Concurrent Supply Chain Network & Manufacturing Systems Design Under Uncertain Parameters

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ABSTRACT

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Concurrent Supply Chain Network & Manufacturing Systems Design Under Uncertain Parameters

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Global supply chain decisions, such as facility location, manufacturing system design, resource allocation, and distribution center location are long-term strategic decisions in nature and involve many uncertainties. Traditionally, a hierarchical approach is used design supply chain networks and manufacturing systems. First, the location of the facilities are determined, and then the manufacturing systems are designed at the selected locations. In this dissertation, a multi-stage supply chain network model is developed where locations of the plants and inner manufacturing system design are determined simultaneously for labor-intensive manufacturing companies. This dissertation aims to develop a decision making framework to integrate manufacturing systems and supply chain network design decisions considering optimal operator assignment and layered cellular manufacturing in mind.

The industry studied is fashion jewelry manufacturing where labor cost is one of the major cost factors. Hence, optimizing the number of workers required for each operation, cell, and plant is critical for the cost efficiency of the entire supply chain. The optimal number of operators are determined for each manufacturing process, and then the optimal cell sizes are found for each manpower level using a heuristic procedure. The optimal number of manufacturing cells required to cover the uncertain demand is

determined with mathematical modeling, and the designed layered cellular manufacturing systems for manufacturing stages are evaluated using Arena simulation models. The results of these models and methods are used as inputs while finding the optimal locations of the plants and allocating the optimal number of cells, workers, and machines for each selected plant. Different supply chain design alternatives considering various factors such as the shortest lead times, minimum capacity allocations, and multiple shifts are also studied.

DEDICATION

To my dear parents, my wife Saliha, my son Levent Seyit, my daughter Reyyan Elif, my brother Muhammed, and my sisters Gunes and Sibel. I love you ALL!!

Bu doktora tezi basimin taci anneme ve babama, sevgili esim Saliha'ya, aslan oglum Levent Seyit'e, sekerpare kizim Reyyan Elif'e, biraderim Muhammed'e ve kardeslerim Gunes ve Sibel'e adanmistir. Iyi ki varsiniz.

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“Two there are who are never satisfied - the lover of the world and the lover of knowledge.” Rumi

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

Supply chains are complex systems that integrate mainly suppliers, manufacturers, distributors and retailers to fulfill customer requirements. Supply chain management consists of management of products from manufacturers to customers, management of money from customers to manufacturers, and management of information in both directions. Obviously, efficient supply chains benefit both companies and customers.

In supply chains, uncertainties originate from either supply or demand sides. In either case, uncertainties make supply chain management more complex. The goal of this research is to develop a methodology to design and implement supply chain networks and manufacturing systems concurrently for global labor-intensive manufacturing industries under uncertain demand environment. A global fashion jewelry manufacturing company with three manufacturing stages which can be performed all over the world is studied and a single market is assumed for the finished products.

Layered cellular manufacturing system design techniques are at the core of the inner plant designs, and mathematical modeling and simulation have been utilized to optimize the cellular manufacturing systems. Optimal operator assignment to machines, optimal number of operators in cells, optimal production rates, optimal number of machines from each machine type are some of the decisions made simultaneously with the locations of the plants.

In this chapter, supply chain management, supply chain network design and cellular manufacturing system design in supply chain network are briefly discussed.

Tools and techniques used and the research methodology followed, and motivations and research objectives of this research are also outlined in this chapter.

1.1 Supply Chain Management

Supply chain is a network of facilities and activities to acquire, produce, transport and distribute products to end users. The system consists of suppliers, manufacturers, distributors, transporters and customers which covers all of the activities starting from not only obtaining raw materials to delivering products to customers, but also from picking up returned products from customers to delivering them to any other tier in the supply chain for reworking processes. This large and integrated network of resources and processes requires many entities including but not limited to raw material suppliers, manufacturing facilities, distribution facilities, contractors, various vendors, logistics companies, wholesalers, etc. Since the scope of the supply chain is too wide, therefore too complex, the researchers usually focus on and study the supply chain partially (Min & Zhou, 2002). Generally, supply chains consist of four tiers: suppliers, manufacturers, distributors, and consumers. Each layer can be in a different country and subject to different rules and regulations (Kumar, Tiwari, & Babiceanu, 2010).

Supply chain management integrates suppliers, manufacturers, distributors, and consumers efficiently in order to produce and distribute the products at the right amounts to the right locations within the specified time frame. The goal of supply chain management is usually either cost minimization or profit maximization while reaching various service levels set by upper management.

Effective supply chain management provides advantages to the entire network in competitive global market. Failure or inefficiency at any activity affects all parts of supply chain. Therefore, designing and controlling effective supply chain networks has been intensively studied in the literature, various approaches, models and techniques have been developed and applied to solve the key problems of the supply chain, such as product development, forecasting, location selection, resource allocation, production planning and scheduling, transportation, supplier selection, pricing, and information technology (IT) selection. Supply chain studies generally include the operations of international companies since globalization is unavoidable in today's global market (Meixell & Gargeya, 2005).

Figure 1.1 shows a general supply chain network which consists of suppliers, plants, warehouses and markets. Every company has its own unique supply chain network which may have more or less elements of this general network (Celikbilek, Erenay, & Suer, 2015).

The industrialization and liberalization of the less developed Asian countries, like China and India, and expansion of global trade allowed multinational companies to establish manufacturing facilities and outsource some of the operations to the manufacturers in those countries (Bhutta, 2004). The most important reason behind these relocations is the pressure on the companies to minimize the operation costs because of intense global competition. Supply chain network design is a sophisticated process as there are many variables to incorporate and many approaches to use. Any local decision that optimizes a tier of a supply chain may not be the optimal decision for the entire supply chain (Chaharsooghi, Heydari, & Kamalabadi, 2011).

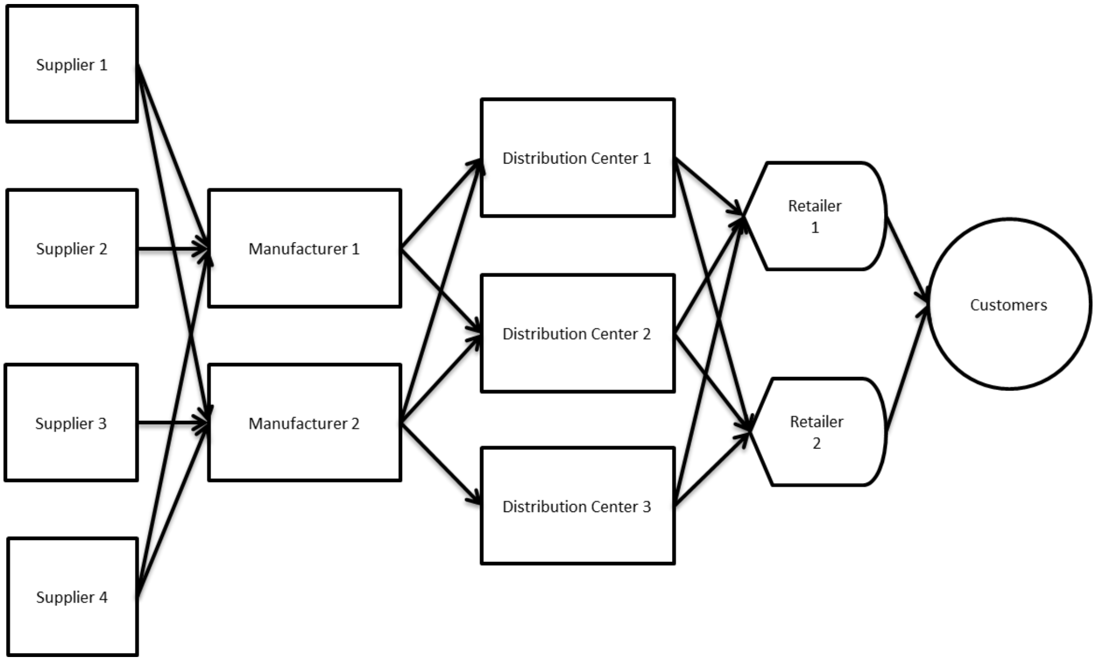

Figure 1.1 A generic supply chain network

1.2 Supply Chain Network Design

The definition of supply chain takes the supply chain network granted, and aims to move the merchandise within the system most efficiently in order to minimize system-wide costs or maximize system-wide profit. However, the physical components of the supply chain network such as plants, warehouses, distribution centers, hubs, etc., affect the performance of the system dramatically, therefore, designing supply chain network efficiently is extremely important. Since the investment costs of these components are high, and these components are considered as long-term investments, these major supply chain network decisions are to be made very carefully.

Supply chain network design refers to involvement and integration of many processes and activities done by many different entities that have their own performance goals. The ultimate goal of this integration is to increase customer satisfaction by meeting their demand while keeping each tier of the supply chain network profitable. Some of the factors considered while designing supply chain network include customers at possible location sites, tax incentives, land costs, investment incentives by local authorities, availability of suppliers, raw material sites, labor costs, labor availability, exchange rates, transportation costs, etc. Supply chain network design decisions include locations of plants, distribution centers and warehouses, capacities of each facility and aggregate determination of the products to be produced at each plant, products to be stored at each warehouse, products to be distributed from each distribution center, amounts to be transported among facilities and modes of transportation, etc.

Supply chain network decisions are classified into three levels: strategic, tactical, and operational. The decisions for facilities such as plants, distribution centers, warehouses, production technology, and information technology are strategic decisions made at supply chain network design phase. Strategic decisions impact the supply chain's direction and efficiency for the long term. Strategic decisions can be made annually or for every 4-5 years by the upper management. Decisions for transportation and distribution, inventory decisions for raw materials, work-in-process (WIP) and finished products, and production planning are tactical decisions. Tactical decisions are made monthly or weekly by the middle management in congruent to the strategic decisions made by upper management. Shop floor decisions such as scheduling and vehicle routing are considered operational level decisions, and can be implemented only after tactical decisions are made. These decisions are routine decisions related to daily operations.

Facility location decisions are considered the most critical decisions in a supply chain network design. Tactical level decisions are relatively easy to change in response to fluctuation in demand, transportation costs, or inventory holding costs. Once a decision is realized for a facility location, e.g., for a plant or a warehouse, it is usually expensive and time consuming to change that decision. However, in recent years there are several examples where companies relocated facilities without much hesitation as a result of expanding globalization. In some situations, it is cost effective to relocate some of the facilities due to changes in demand, transportation, government policies, taxes, and disasters, etc. If the cost of opening a new facility and closing a previous one is within acceptable levels for the planning period like years or quarters, then locations of the facilities can be changed according to changes in aforementioned reasons. The problem becomes similar to evaluating supplier or outsourcing decisions for every planning period where outsourcing companies are evaluated periodically based on some performance measures and upper management decides whether or not to continue with them based on their performances. Similarly, if the cost of relocation is within acceptable levels, these plants can be evaluated periodically according to total costs, and plant location decisions can be made based on the evaluation results.

1.3 Manufacturing System Design in Supply Chain Network

Manufacturing system design, also a strategic decision, is usually completed after facility location decisions. Manufacturing systems are classified into four categories based on their layouts: cellular manufacturing layout, product layout, process layout, and fixed layout. Figure 1.2, which is adopted from Süer, Huang, and Maddisetty (2010), shows these layouts in the context of product variety and product volume.

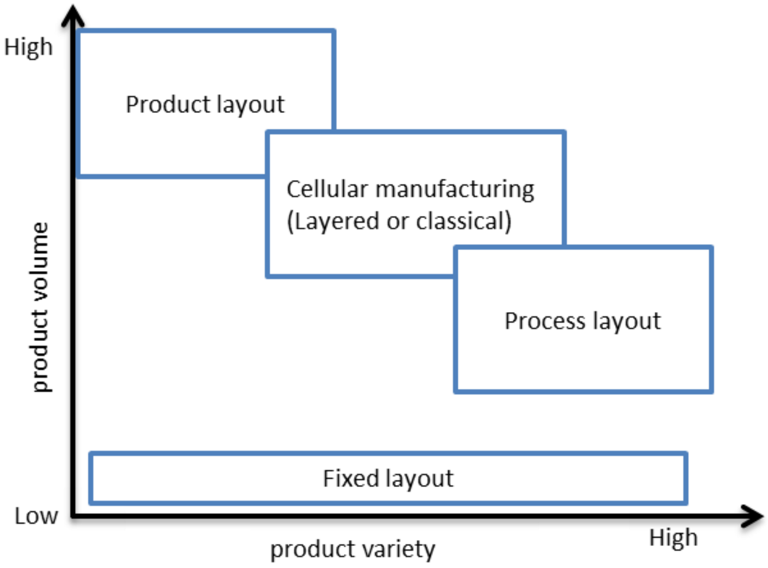

Figure 1.2 Manufacturing systems classification

As product volume increases and product variety decreases, product layout becomes more suitable for the manufacturing systems. This layout type yields lower product flowtime and work-in-process inventory. As product variety increases and product volume decreases process layout becomes a better option. Cellular manufacturing is a solution where product volume and product variety are moderate. In fixed layout, as the name speaks for itself, the product is fixed to a location where the workers and machines are brought to work on the product.

In classical cellular manufacturing systems, each product family is assigned to dedicated cell(s) which is configured according to the machines required to perform all of the operations for the parts which consist of the part families. These dedicated cells have all of the machines, tools and equipment to finish the products completely. However, in some cases machine sharing among cells is allowed, thus leading to intercellular moves. Classical cellular systems yield higher machine and cell utilization values when the demand is stable and predictable. Figure 1.3 presents a classical manufacturing system.

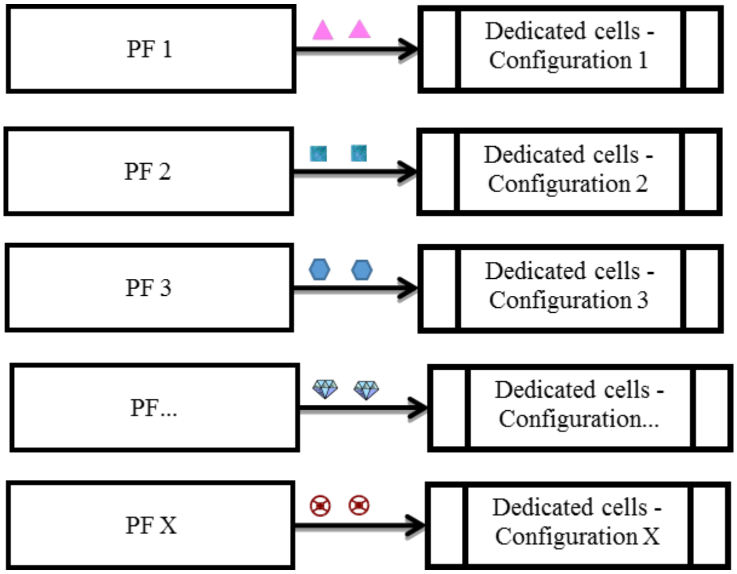

Figure 1.3 Classical cellular manufacturing system with dedicated cells

When the products have fluctuating demands, performing operations in only dedicated cells may not result in higher efficiencies in machine and cell utilizations.

When the demand is lower than the predicted amount, cells are under-utilized, and when it is higher, dedicated cells will not be able to process all of the demand for the product families on time. In order to deal with the fluctuation in the demand, Süer *et al*., (2010) proposed a layered system which consists of dedicated, shared, and remainder cells. These systems are covered in Chapter 4.

1.4 Tools and Techniques Used

In this dissertation, various tools and techniques are employed for the problems at different stages. Deterministic and stochastic mathematical modeling, computer simulation, Monte-Carlo sampling, statistics and heuristic procedures are tools that are used in the following sections. In this section, these tools and techniques are briefly introduced.

Numerous quantitative models have been studied and applied to simulate the behavior of a supply chain. Since it is impossible to develop a model that captures and improves all of the problems of the entire chain, the approaches and models developed aim to optimize only some selected performance measures of the supply chain (Min & Zhou, 2002). Some of the approaches to tackle the problems and improve the performance of supply chains are mathematical optimization, simulation, heuristics, metaheuristic, and artificial intelligence techniques.

Mathematical programming is used to find the optimal solutions for complex supply chain problems. The goals of the studies vary, but generally cost minimization or profit maximization are common goals. In addition to widely used factors such as numbers and locations of facilities in designing supply chains, some of the other factors considered in the recent literature includes social responsibility, environmental effects, public warehouses, private warehouses, for hire transportation, expansion planning, product flow between facilities, transportation modes, cost-time tradeoff between transportation options, opening, closing or enhancing facilities, supplier selection, late delivery fee, demand splitting, and first time quality. Mathematical models have been used for quite long time for optimization purposes. Mostly the drawback of using the mathematical models for complex problems is the time it requires to find the optimal solution. The improvement in computer technology eases this problem; however, at the same time it encourages researchers to tackle even larger and more complex problems.

When the problems aimed take unreasonable time to solve with mathematical modeling, some other methods are employed to handle them. However these methods may require huge efforts and time as well. The methods employed are, including but not limited to, relaxing one or few of the constraints, Lagrangian relaxation, Lagrangian heuristics, Benders' decomposition method, etc. Lagrangian relaxation is a technique where a set of hard-to-solve complicating constraints are removed from the constraints set and plugged into the objective function with fixed multipliers. The fixed multiplier assigned to the removed constraint is called Lagrangian multiplier (Geoffrion, 1974). Lagrangian heuristics are heuristics developed based on Lagrangian relaxation (Nezhad, Manzour, & Salhi, 2013). In Benders' decomposition method, the problems are usually decomposed into smaller problems and solved on that basis (Sirivunnabood, 2010).

Simulation is one other method for designing and analyzing supply chain network models. It is used mostly to design the supply chain network models under some kind of uncertainty, either coming from demand side, or supply side. Simulation is sometimes used to validate the results obtained from another optimization tool (Süer *et al*., 2010). It gives the user the ability to compare designs based on selected performance measures. The drawback of the simulation approach is that it does not guarantee the best solution. Therefore, to improve the quality of the solutions, the optimality/convergence criterion must be emphasized when designing a supply chain network.

Monte Carlo sampling is used for real-world applications where some of the system variables such as demand, capacity, leadtime etc. are probabilistic. Random numbers are generated for a specific distribution in order to simulate the system and to assess the performance of the system.

Heuristics and metaheuristic methods are usually used where the model is too complex to be solved by mathematical modeling. Metaheuristics can provide near-optimal solutions for problems that exact optimization techniques cannot solve. Some of the metaheuristics being used are genetic algorithms, simulated annealing, tabu search, ant colony optimization, artificial bee colony, particle swarm optimization, evolutionary computation, variable neighborhood search, iterated local search, etc. These methods are proved to be powerful tools for various problems where using exact optimization methods is infeasible.

1.5 Methodology

This section explains the steps of the methodology followed in this dissertation. The methodology implemented in this dissertation consists of seven stages as shown in Figure 1.4.

The first two stages involve optimal manpower allocation, optimal cell size determination, and cell loading. In the first stage, the optimal numbers of operators assigned to each operation are found using a mathematical model developed by Süer (1996). The model is run for each product in the multi-stage cellular manufacturing system. Then, the optimal cell sizes for all stages are determined using a heuristic approach developed in the second stage. Cell loading is also performed in the second stage using three different methods.

In the third stage, demand coverage probabilities and expected cell utilizations are calculated using the demand data. In the fourth stage, a mathematical model is used in order to determine the number of cells required. The expected cell utilization and demand coverage probability values are used in the mathematical model in order to determine cell configuration and cell types. The model minimizes the number of cells opened to meet the highly fluctuating demand. It also determines dedicated, shared and remainder cells in the system. A simulation model is developed in order to evaluate the performance measures of proposed cellular manufacturing system in the fifth stage.

In the sixth stage, major supply chain decisions are made using the results of the first, second, and fourth stages. A modified plant location-resource allocation model which integrates the previous stages is proposed for this purpose. In the seventh stage, various manufacturing system and supply chain network alternatives are experimented using the methodologies in the previous chapters.

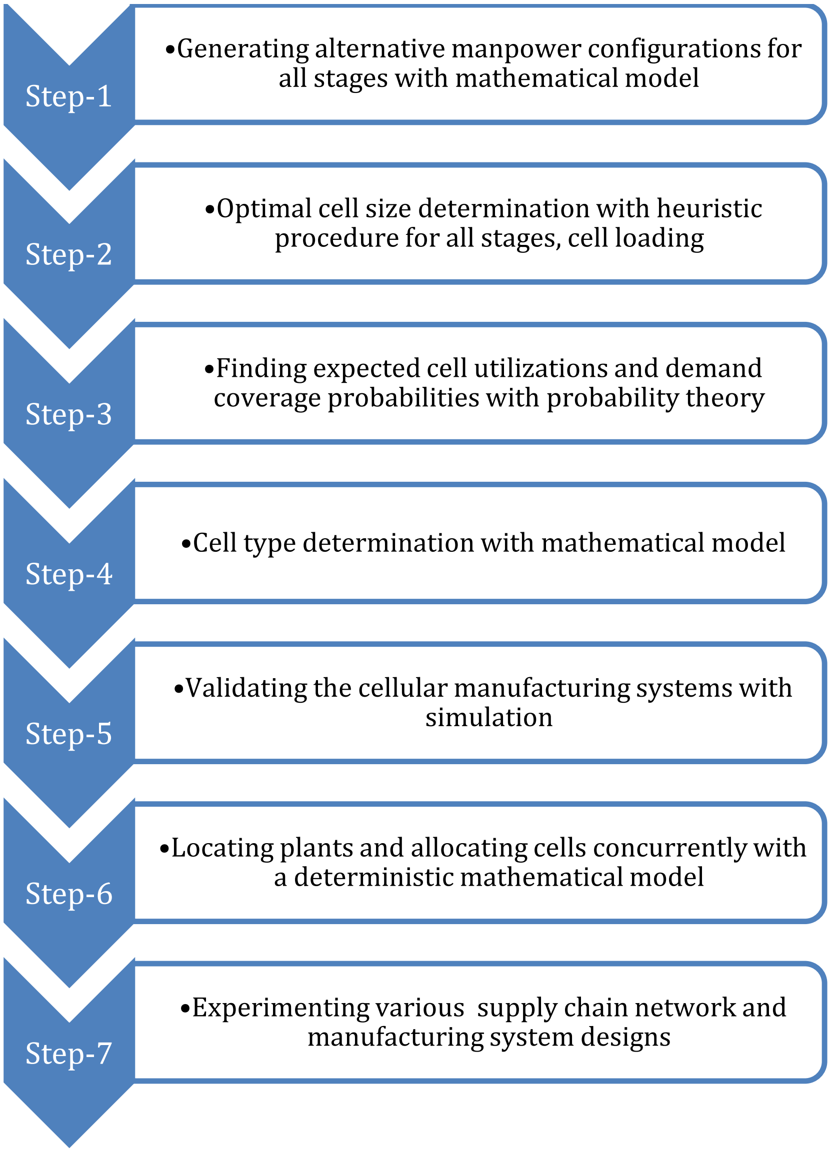

Figure 1.4 Methodology followed in the dissertation

The first and the second steps which are related to the optimal operator assignment for jewelry manufacturing operations are covered in Chapter 3. The third and the fourth stages are covered in Chapter 4. In this chapter, the topics covered are focused on cellular manufacturing system design. However, for shared and remainder cells, the first and the second steps are revisited here. Fifth stage, where the simulation models are developed, is covered in Chapter 5. The sixth stage is covered in Chapter 6. Various supply chain scenarios are studied in Chapter 7.

1.6 Research Motivation

This dissertation proposes an optimal manpower allocation model and the optimal cell size determination approach to assign the optimal number of operators to operations and cells at each manufacturing stage. Manufacturing cells are formed considering probabilistic demand values for the products. Next, manufacturing system and supply chain network design phases are completed concurrently using the results of manpower allocation, cell size determination, and cell design phases.

Strategic decisions like plant location, resource allocation, and distribution center location are long-term decisions in nature and involve many uncertainties. Decision makers utilize forecasting techniques and expert opinion in order to decrease these uncertainties, but it is impossible to eliminate them entirely. Demands of products, costs of raw materials, travel times, construction costs, transportation and labor costs may change significantly by time. Deterministic models do not take the variability into account in these factors and therefore may cause inefficient design of the supply chain network. In deterministic models, all required inputs for the model such as demand, leadtimes, travel times, supply are treated as known and static parameters. These models still provide valuable information to the decision makers, but they do not reflect the uncertainties in real world. Therefore, deterministic and stochastic models produce different results for the same facility location problems.

The uncertainties are handled using two different approaches in the literature: Stochastic programming and robust optimization (Snyder, 2006). The objective of the stochastic programming is expected cost minimization, whereas the objective of robust optimization is worst-case cost or regret minimization. In stochastic programming, uncertain parameters follow a probability distribution and the probability of each scenario is discrete and given. In robust optimization, the scenarios may be discrete or continuous. In this dissertation, stochastic programming approach is used to handle uncertainties in demand.

The lower labor rates in the East Asian countries like China, Thailand, Vietnam, India, Bangladesh etc. made moving manufacturing operations to those countries more profitable for many companies. It was reported that labor rates in China were 30 times lower than labor rates in United States (Lett & Banister, 2006). Even though the labor rates have been increasing especially in China in recent years, they are still very low when compared to industrialized countries. These low rates encourage many companies to move their labor-intensive operations to these countries, while keeping some of high-tech and machine-intensive operations in the homeland or another country. These relocation decisions often lead to finishing the production processes in multi stages dispersed in multiple countries.

In most literature, facility location decision and manufacturing system design are analyzed in two separate stages as shown in Figure 1.5. In the first stage, estimated capacity requirements and demand data are used to locate plants and to roughly allocate production quantities to the opened plants. The second stage, manufacturing system design, is completed after plants' locations are determined, and demand is allocated to those plants. Manpower allocation and optimal cell size determination are not done in all manufacturing system designs.

Unlike most other studies reported in the literature, the proposed approach in this dissertation makes supply chain network and manufacturing system decisions simultaneously. The details of the decisions include locations of the manufacturing facilities, transportation quantities among plants for different manufacturing stages, number of manufacturing cells in each plant, optimal cell sizes, amounts of products to be produced in plants and cells, number of machines from each machine type, number of operators, number of operators assigned to each operation and production rates of products in each cell.

There are studies focusing on integration of manufacturing system design with supply chain design. Rao and Mohanty (2003) proposed an approach to integrate the designs of cellular manufacturing and supply chain and showed the interrelationships between design issues in cellular manufacturing and supply chain. Schaller (2008) provided a mathematical model to integrate cellular manufacturing systems with plant location decision. The proposed model locates the plants and forms cells in the opened plants. These studies focus on single-stage manufacturing. Huang and Süer (2012) developed a mathematical model which integrates cellular manufacturing system design into supply chain design for a multi-stage manufacturing design where demand is probabilistic.

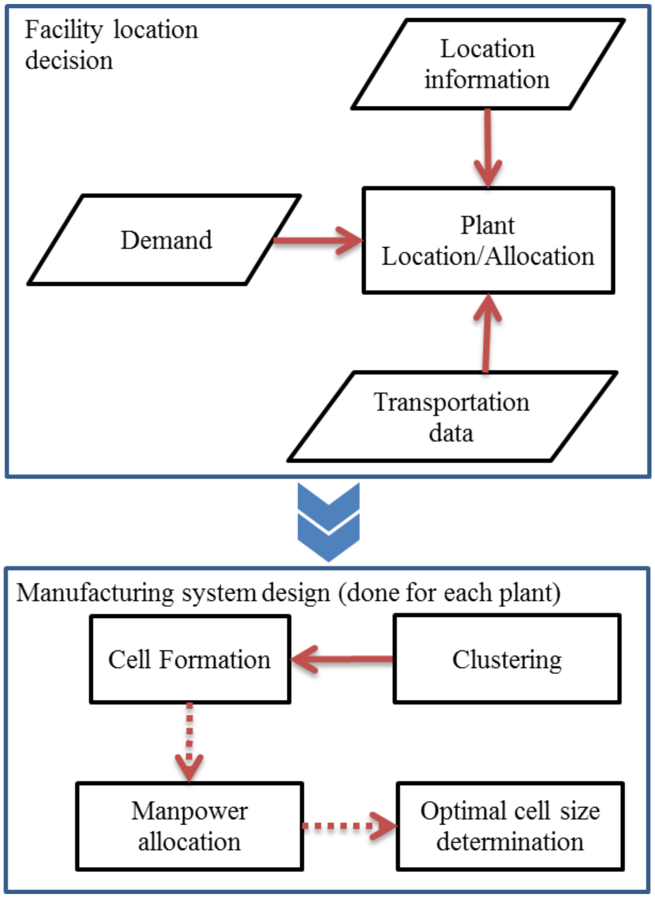

Figure 1.5 Traditional facility location/allocation and cellular manufacturing design

In this dissertation, a multi-stage supply chain network design procedure is proposed for labor-intensive manufacturing companies with a fashion jewelry company in mind. This dissertation aims to integrate manufacturing systems and supply chain network designs considering layered cellular manufacturing, optimal manpower allocation for each operation, cell size determination for each cell, uncertain demand for products, machine setups, individual machine costs, machine duplication, cell installments, in-transit inventory carrying costs, varying transportation costs and minimum percent capacity allocations. Figure 1.6 shows the proposed integrated cellular manufacturing system design with supply chain network design.

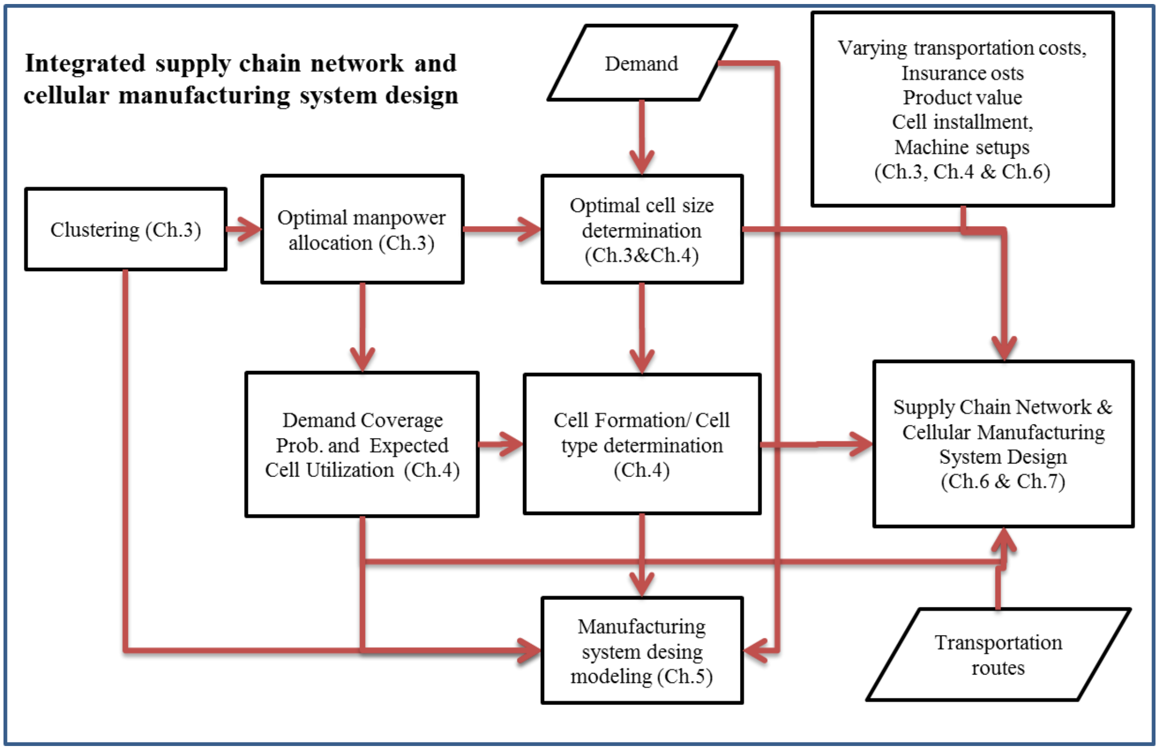

Figure 1.6 Proposed integrated supply chain network and cellular manufacturing systems design

1.7 Research Objectives

This dissertation is expected to contribute to academic literature in cellular manufacturing system design, supply chain network design, manpower allocation, cell loading and stochastic programming areas. The main goal of this dissertation is to design supply chain network and manufacturing systems concurrently while investigating and finding solutions to uncertainties in the system.

- The study finds the optimal operator assignment to each operation and determines the optimal manpower level for each cell in multi-stage cellular manufacturing. A mathematical model is provided for the optimal manpower allocation and a heuristic is proposed to determine the optimal cell sizes for manufacturing cells for each stage.
- Three approaches are proposed for cell loading. For this purpose, two heuristics and a mathematical model are proposed.
- A mathematical model is employed in order to assign part families to cells, and determine types of the cells such as dedicated, shared and remainder cells. Machine duplication, shifting bottleneck machines, and multiple-shift concepts are introduced to layered cellular design, and it is performed by using the number of operators assigned to each operation obtained from the optimal operator assignment phase.
- Simulation models are developed to measure the proposed system's performance with respect to machine and cell utilization

- A global integrated supply chain network model is developed where the manufacturing cells are allocated to the plants. The model considers machine setup cost, individual machine procurement cost, labor costs, in-transit inventory carrying cost, optimal manpower levels for cells, and minimum percent capacity allocations for opened plants. The model treats dedicated, shared and remainder cells separately in order to perform analysis easily when they are directed shared and remainder cells to specified plants. This model integrates cellular manufacturing system design with supply chain network design. The model is based on the model proposed by (Huang & Süer, 2012).

The following problems are also investigated in this dissertation. The global integrated supply chain network model considers the following;

- The effects of minimum percent capacity allocation enforcement for the preferred plant in order to have a plant open for design and prototype production.
- Having minimum percent capacity allocations for each opened plant at each supply chain stage.
- The effects of the fastest and the cheapest transportation routes on SCN design.
- The effects of different number of shifts on supply chain network and manufacturing systems
- Varying transportation costs for different stages: Transportation costs of semi-finished products and finished products cannot be same since finished products require more space and are heavy in weight. Also, plated parts require more

attention than the non-plated parts, and this is reflected in the costs of the items. Domestic and international insurance costs are taken into account while calculating the varying transportation costs.

2 LITERATURE REVIEW

Literature related to supply chain network design, manufacturing system design and cellular manufacturing, and integration of manufacturing system and supply chain network design are reviewed and summarized in this chapter. In manufacturing system design part, cellular manufacturing, and optimal operator assignment are at the focus of the review.

2.1 Supply Chain Network Design, Analysis, and Optimization

In this part, the tools and techniques that have been utilized for supply chain network design, analysis and optimization are provided considering the recent literature. Their strengths and weaknesses are reviewed along with the capabilities that need to be developed in order to address current challenges of supply chain network analysis and optimization.

SCN design problems have been traditionally solved by three primary methods: mathematical programming models, simulation models, heuristics and metaheuristics. Among these solution techniques, optimization has been utilized to produce the optimal solutions for complex supply chain problems. Simulation has been employed for stochastic supply chain problems, and to compare variations in supply chain configurations. Heuristics and metaheuristic methods are usually used where the model is too complex to be solved by optimization methods. According to a study that reviewed the articles published in the Journal of Business Logistics between 2000 and 2012, mathematical programming was utilized in 33% of the analytic works published;

simulation and heuristics/metaheuristics were used in 59% and 15% of the works, respectively. Since some of the works published utilized more than one method, the sum of the percentages exceeds 100% (Griffis, Bell, & Closs, 2012).

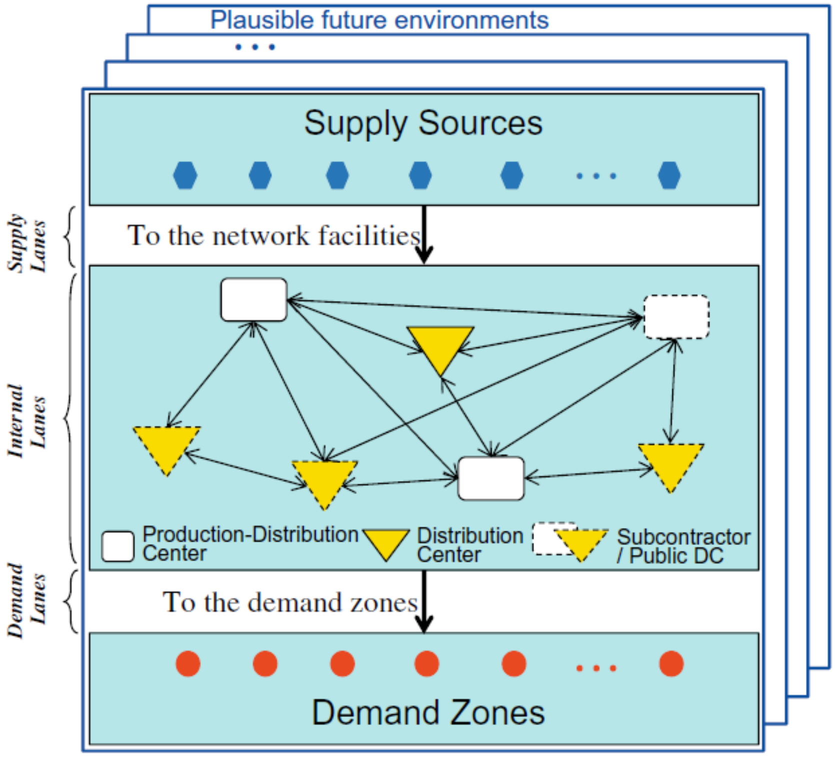

Figure 2.1 Existing and potential supply sources, facilities and demand zones (Klibi, Martel, & Guitouni, 2010)

A typical supply chain network (SCN) consists of four layers; suppliers, plants, warehouses, and markets. It delivers products by transferring them from suppliers to plants, warehouses, and customers, consecutively. Klibi *et al.*, (2010) add transportation components to this typical SCN as a fifth element. They state that subcontractors or public warehouses can be utilized as production or distribution facilities. Moreover, third party logistics can be used alternatively. Therefore, they claim that while designing a new SCN or redesigning an existing SCN, all options must be taken into account (Klibi *et al.*, 2010). The nodes of Figure 2.1 represent existing and potential supply sources, facilities and demand zones.

The main decisions in SCN design are determining the number, locations, and capacities of facilities, product allocation to facilities, and the nature of material and product flow between facilities (Olivares-Benitez, González-Velarde, & Ríos-Mercado, 2012). Klibi *et al.*, (2010) detailed these decisions for a typical SCN design. These decisions include the targeted market for the products, the price and delivery time to these markets, the number and location of plants and warehouses, operations to be outsourced, production, material handling and storage technologies and capacities of them, products to be stored at each facility, the factory/warehouse/markets that should be supplied by each supplier/factory/warehouse, mode and means of transportation. Generally, in research studies, only one or a few of these objectives are addressed.

Recently, environmental and social objectives are studied because of increasing attention to these issues by public and government agencies. The main difficulty with these objectives is the difficulty to measure the improvement. Some of the objectives getting attention are energy cost, carbon emissions, quality of life, noise and pollution, land and water use, tourism, and construction cost. (Elhedhli & Merrick, 2012; Farahani, SteadieSeifi, & Asgari, 2010; Pishvaee, Razmi, & Torabi, 2012)

Supply chain models are classified by the researchers in different ways. Min & Zhou (2002) classify the SCM into four categories as deterministic, stochastic, hybrid and

IT-driven models. It is assumed that there is no uncertainty in the deterministic models. In stochastic models, one or more parameters are uncertain. In hybrid models, usually simulation techniques are used to combine deterministic and stochastic models. Melo, Nickel, & Saldanha-da-Gama (2009) categorized supply chain models according to number of layers, number of periods, and number of products. Models are categorized as single-layer, two-layer, or multi-layer models depending on number of tiers in the model. Models can be single-period or multi-period models based on number of periods they are covering. Single-product family models and multi-product family models make up the third type of the classification.

SCN design using mathematical programming models including Integer Programming (IP), Mixed-integer Programming (MIP), Mixed-integer Linear Programming (MILP), and Stochastic Programming (SP) has been widely studied. These models have been developed to solve various types of problems more accurately.

The global market and competition make the SCNs today more global and complex in structure. This increases the possibility that unpredictable events will occur somewhere in a supply chain network. The stochastic programming method is widely used as a modeling tool for optimization under uncertain conditions. This method is utilized in two stages. In the first stage, strategic decisions such as the number and the location of facilities are addressed, in the second stage tactical level decisions such as production planning, distribution planning are considered. Since these models are usually very large and complex in nature, it is not efficient and generally not possible to solve them as is. Therefore, the problems are usually decomposed into smaller problems and solved on that basis. Two widely used decomposition techniques are the Lagrangian relaxation method and Benders decomposition method (Sirivunnabood, 2010). Benders decomposition algorithm is first proposed by Benders (1962) which is used to solve complicated mixed-integer models with integer variables and coupling constraints. At each iteration, the integer variables are fixed, and the rest of the problem, which is called Benders subproblem, is easily solved. A lower bound and an upper bound for the master problem are found by solving subproblems. The process is repeated until the difference between the upper and lower bounds are negligible or zero (Tang, Jiang, & Saharidis, 2013). Diabat and Richard (2015) studied integration of location and inventory decisions for one warehouse and multiple retailers at a two-echelon supply chain network. Two Lagrangian-relaxation-based algorithms are proposed to make these strategic and tactical decisions concurrently, and the results of these models were compared with those of a branch-and-bound algorithm on various problem sets.

There are numerous studies that employ mathematical modeling in SCN problems. Chan *et al.*, (2008) designed a four-echelon SCN using a dynamic mixed-integer linear programming model with multiple products. The proposed SCN design consists of suppliers, plants, warehouses and customers. The model considers opening, closing or enhancing facilities, material and product flow between tiers of the supply chain, supplier selection. Other features that are included in this model are bill of materials, public warehouses and private warehouses.

Bhutta, Huq, Frazier and Mohamed (2003) developed a mixed-integer linear model focusing on global plant location decisions which involves production capacity and its relation with investment, exchange and tariff rates and distribution. They applied the model to several facility configurations and showed that the developed model is effective.

ElMaraghy and Majety (2008) presented dynamic linear/mixed-integer optimization models to minimize the cost for multi-layer SCN. The model makes decisions about production and inventory quantities, supplier selections, transportation channels and quantities, and also considers late delivery fee, demand splitting, and first time quality. It is designed in terms of periods to include the dynamic nature of the decisions.

Georgiadis, Tsiakis, Longinidis and Sofioglou (2011) proposed a detailed mathematical formulation for the problem of designing supply chain networks comprising multiproduct production facilities with shared production resources, warehouses, distribution centers and customer zones and operating under time varying demand uncertainty.

Pishvaee *et al.*, (2012) studied socially responsible SCN design under uncertain conditions. The purpose of the study is to minimize the total cost of the SCN and to maximize the supply chain social responsibility. They developed bi-objective mathematical programming model to reach these goals simultaneously.

Olivares-Benitez *et al.*, (2012) proposed bi-objective mixed-integer program to optimize a two-echelon single-product SCN design which involves the location of the distribution centers, transportation modes, and the flow between facilities using cost-time tradeoff between transportation options. The studied SCN consists of plants, distribution centers and market, and there are number of transportation mode options between these facilities.

Chen (2012) developed stochastic dynamic optimization model in order to optimize the value of a two-echelon supply chain. It is assumed that the supply chain consists of two major players; a single manufacturing facility which delivers the products to a single retailer that instantly sells them to end users. The effects of inventory holding cost, shipping costs, cost rates, growth rates, demand uncertainty and other important factors on SCN are examined by performing a sensitivity analysis.

Bashiri, Badri, and Talebi (2012) proposed a new mathematical model for strategic and tactical planning in a SCN. The proposed model is multiple-echelon and multiple-product where different time resolutions are considered for strategic and tactical decisions. Some examples are generated and solved with an optimization tool. Results show that the mathematical model can solve small and medium size problems, but for larger problems, other methods need to be developed.

Correia, Melo and Saldanha-Da-Gama (2013) studied a two-echelon supply chain network over a multi-period horizon. Two different objectives are considered; minimizing the total cost, or maximizing the profit. Two mixed-integer linear programming models are developed for the new SCN, one for cost minimization and the other for cost maximization. The goals of the study are to find the optimum locations for the new facilities at upper and intermediate echelons considering the capacities of these locations and product families, and product flow between facilities. The results of these two models are then compared.

Amiri (2006) presented a mixed-integer linear SCN model to optimize the following decisions; the number and location of plants and warehouses, and the capacities of them, locations and capacities of plants and warehouses. SCN is designed for three echelons, single period and single product. A heuristic solution procedure for this SCN is provided to minimize the cost. Ko & Evans (2007) provided a nonlinear mixed-integer program to optimize a two-echelon, multiple-period, and multiple-product capacitated SCN which is a dynamic integrated forward-reverse logistics network. A genetic algorithm is developed to solve the math models in order to find the best SCN design.

Park, Lee and Sung (2010) developed an integer nonlinear programming model for a three-echelon SCN design problem. The SCN have multiple suppliers, distribution centers and retailers. The proposed mathematical model is solved using a heuristic solution algorithm based on the Lagrangian relaxation method. In another study, Badri, Bashiri and Hejazi (2013) provided a mixed-integer linear programming (MILP) model for multiple-echelon, multiple-product SCN design based on the model proposed by Bashiri *et al.*, (2012). Four echelons of the SCN are considered: supplier, plant, warehouse and customer. The goal of the model is to make strategic and tactical decisions for a long-term horizon. The model takes upper and lower limits of facility utilization rates, public warehouses, and potential locations of private warehouses, and gives decisions about supplier selection, plant and distribution center location, production, distribution, and expansion planning in a long-term horizon. The objective of the expansion planning is maximization of cumulative net profit with restricted funding provided by external sources in a long time horizon. A Lagrangian Relaxation method has also been developed, and in order to evaluate and show the performance of the proposed MILP and Lagrangian Relaxation methods, the results are analyzed with numeric methods. More studies can be found in the review of Mula, Peidro, Díaz-Madroñero and Vicens (2010) on mathematical programming models for supply chain production and transportation planning.

Petridis (2013) developed a multi-objective mixed integer non-linear mathematical model to design a supply chain network with the objective of minimizing the total supply chain costs and expected lead times. Lead times and demand of customers are considered as the non-linear component in the model. Four alternative scenarios were developed to evaluate the model with various increasing demand levels. Stockout and overstocking are measured for each scenario. The model is run with four products, four plants, five warehouses, eight distribution centers and ten customers. The author concluded that rapid changes in demand change the supply chain network structure and lead to more stockout occurrences and longer lead times.

Khalili-Damghani, Tavana, and Amirkhan (2014) applied a bi-objective mixed-integer linear model to a multi-layer, multi-product, multi-period food supply chain network. The objectives of the model are to minimize the inventory costs and to maximize the total purchasing value under vague parameters and ambiguous goals. The methodology determines the suppliers at each echelon, amount of raw materials to be purchased, total inventory, and amount of materials distributed to plants.

Abbasi, Hosnavi, Babazadeh (2014) studied the agility and flexibility in supply chain design considering production, outsourcing, discount, flexibility and distribution activities. They used robust optimization to solve the problem where demand of customers, transportation costs and outsourcing costs are uncertain. The results of the robust model have less deviation than other alternative models which leads more confident and accurate decisions.

Niknamfar, Niaki, and Pasandideh (2014) studied aggregate production-distribution planning in a three-echelon supply chain network using robust optimization approach in order to minimize the total cost of the supply chain with multiple plants, DCs, and customers. They applied the proposed methodology on a case problem with probabilistic parameters in several economic scenarios.

Gan, Li, and Chen (2014) formulated a two-layer multi-product supply chain network design as a network flow problem and solved it using a classic algorithm. They applied their methodology to a very interesting area: blood collection in China. They considered the blood types A, B, 0, and AB as products, the blood collections sites as plants, the facilities where blood is tested, processed, stored and distributed as DCs, and the urban hospitals as customers.

Cost of quality is another important aspect in supply chain network design. Castillo-Villar, Smith, and Herbert-Acero (2014) studied the importance of choosing the right partners that benefits the entire health of the supply chain network. They developed a mathematical model to design a supply chain network considering factors relating to manufacturing, capacity allowances, and retailer capabilities. The objective of the model is to minimize the total cost of recalls, rework and poor customer experience by reducing financial risks by meeting quality standards in the manufacturing and distribution levels. The manufacturing and distribution levels of the supply chain network measures the quality issues and their financial implications using same methods.

Ogier, Chan, Chung, Cung, and Boissière (2015) presented a mixed integer mathematical model to solve a decentralised capacitated lot-sizing problem in a two-echelon supply chain problem where the goal is to minimize the cost, information sharing between the suppliers and retailers are limited, suppliers are responsible from manufacturing, and retailers are responsible from transportations. Each echelon of the supply chain manage storage activities at their level. They focused on the quality of service punishing the lost sales with high penalty. Several lot-sizing strategies are experimented and then compared.

Yu, Normasari and Luong (2015) proposed a pure integer linear mathematical model to solve a supply chain network problem which consists of suppliers, manufacturing facilities and distribution centers with the objective of minimizing total cost of the supply chain including transportation costs. They found out that the transportation and facility opening costs have the lowest impact on supply chain design, while customer demand has the highest impact.

2.2 Heuristics/Metaheuristic in Supply Chain Network Design

In SCN design problems, when the model involves multiple layers, multiple products or multiple periods, and consequently a large number of variables, the models usually become too complex to be solved in reasonable time frames by optimization methods. That kind of problems can be solved only with heuristic/metaheuristic methods. Pure heuristics, Lagrangian heuristics, linear programming based heuristics and metaheuristics are among the most popular techniques (Badri *et al.*, 2013). In this part of this study, the focus is on metaheuristics and Lagrangian relaxation only since pure heuristics is not widely used for this kind of complex problems. Metaheuristics are powerful tools which can provide near-optimal solutions for problems that exact optimization techniques cannot solve.

Griffis *et al.*, (2012) focuses on the utilization of metaheuristics development in SCN and logistics problem. They consider mainly the four most used metaheuristic methods; the ant colony optimization, genetic algorithm (GA), simulated annealing, and Tabu search. But there are other metaheuristics available to use for complex problems such as harmony search, glow worm optimization, artificial bee colony, intelligent water drops, firefly algorithm, monkey search, and the cuckoo search (Griffis *et al.*, 2012).

Dias, Eugénia Captivo and Clímaco (2007) proposed primal-dual heuristics to redesign a two-echelon SCN that consists of facilities and customers for three capacity related options. It is assumed that the facilities in the supply chain can be opened and closed more than once during the considered period. Ross and Jayaraman (2008) proposed a new heuristic approach in order to optimize the locations of distribution centers and cross-docks in a SCN. The model considers various product families, multiple cross-docking and distribution centers and one plant. Montoya-Torres, Aponte and Rosas (2011) proposed a Greedy Randomized Adaptive Search Procedure (GRASP) to solve the three-echelon SCN model which consists of plants, warehouses and customers. Nagurney (2010) proposed a SCN design with oligopolistic firms using game theory modeling. The model considers capacities and quantities for production, storage and delivery of a product to numerous markets in the SCN model.

Lin and Wang (2011) developed an L-shaped decomposition for a SCN design under supply and demand uncertainty. In the model, to minimize the expected operating cost, the operations of the supply, manufacturing and demand are integrated. The model considers some strategies to mitigate the risks coming from unexpected disruptions. Elhedhli and Merrick (2012) proposed a SCN design considering CO2 emissions cost with other costs such as production cost, fixed and variable location costs. A concave function is utilized to model the relationship between CO2 emissions and vehicle weight. The problem is a concave minimization problem. Lagrangian relaxation is used to decompose the problem, and the problem becomes a capacitated facility location problem with single sourcing. Then a Lagrangian heuristic is developed to solve this sub-problem. The solution methodology proved to obtain solutions within 1% of the optimal. Pan and Nagi (2013) considered a multiple-echelon and multiple-period SCN design problem in an agile manufacturing where customers do not accept backorders. A Lagrangian heuristic is proposed as a solution methodology. The objective of the model is to minimize the total cost of inventory holding cost, production cost, fixed alliance cost and transportation cost. The model contains features such as capacity limits for production and transportation, no-backorder allowance, establishing alliance between companies which make the problem complex.

Altiparmak, Gen, Lin and Paksoy (2006) developed a GA to design a multiple layer SCN with single-source, multi-product, and then compared the results with CPLEX, Lagrangian heuristics, hybrid GA and SA. Chan, Chung and Choy (2006) developed a GA to solve a stochastic multi-objective model that optimizes a combined objective function with weights. The model optimizes transportation time, which is a linear function of the quantity transported, and the costs, including the cost of transportation channel options simultaneously without containing facility location. Every transportation channel has a cost-time tradeoff. Kumar *et al.*, (2010) developed genetic algorithms, particle swarm optimization and artificial bee colony to minimize the cost for a multiple-echelon SCN model where suppliers, manufacturers, warehouses and markets are located in different countries and compared them. Zegordi, Abadi and Nia (2010) developed a GA for a two-layer SCN in order to optimize the production plans and transportation plans. More studies can be reviewed in the study of Griffis *et al.*, (2012) on metaheuristics in logistics and supply chain management. Khalaj, Modarres, Tavakkoli-Moghaddam (2014) studied a multi-echelon supply chain network that consists of cross-dock, plant, distribution center and customers considering fixed manufacturing sequence. A five-echelon supply chain network of a car manufacturer is used as an example problem. Their focus was to find the optimal number of cross-docks and distribution centers in the supply chain network. Due to the high number of variables and constraints, the mathematical model couldn’t find the optimal solution for larger problem sets, hence a generic algorithm was proposed to solve the problem.

Mousavi, Alikar, Niaki, and Bahreininejad (2015) studied an integrated location-allocation and inventory control problem considering the distances between the distribution centers and customers Euclidean. They developed a mixed integer nonlinear mathematical model whose objective is to minimize the inventory cost and to find the optimal locations of the distribution centers. Distribution centers and manufacturers have limited capacities and customers buy the products from the distribution centers under incremental quantity discount contracts. For larger problems, three metaheuristics are proposed, namely particle swarm optimization, fruit fly optimization and simulated annealing. Fruit fly optimization approach performed better than the others.

In summary, metaheuristics are used to find near-optimal solutions for complex SCN design problems where exact optimization techniques are not efficient to use. Genetic algorithms, ant colony optimization, simulated annealing, and tabu search are some of the most widely used metaheuristics. In addition to the metaheuristics, there are some heuristics used for SCN problems as well such as Greedy Randomized Adaptive Search Procedure, etc.

Table 2.1 gives a brief comparison of mathematical programming, metaheuristics, and simulation techniques from different perspectives such as speed, real world reflection ability, solution quality, software availability, etc.

Table 2.1 Comparison table for tools utilized in SCN design

Mathematical Programming	Metaheuristics	Simulation
Searches for the optimal solutions	Searches for near optimal solutions	Searches for the optimal solutions (if the goal is optimization)
Guarantees the optimal solutions for solvable problems	Does not guarantee the optimal solutions	Does not guarantee the optimal solutions
Most large, complex problems cannot be solved in real time	Solves most large, complex problems that cannot be solved by math modeling	Solves most large, complex problems
Reflects the real world limitedly	Reflects the real world better than math modeling	Reflects the real world best
Fast (depends on the complexity)	Slower (depends on the complexity)	Slower (depends on the complexity)
Ready to use on the shelf software is available	Ready to use on the shelf software is mostly NOT available	Ready to use on the shelf software is available
Changing and fine tuning the parameters is easier than metaheuristics	It is not easy to change and fine tune the parameters	Easiest to change and fine tune the parameters
Offers only one solution	Offers alternative solutions	Offers alternative solutions

2.3 Manufacturing System Design

Various types of cellular manufacturing systems have been proposed in the literature. Examples include dynamic cellular manufacturing (Rheault, Drolet, & Abdulnour, 1996), virtual cellular manufacturing, holonic manufacturing (Nomden, Slomp, & Suresh, 2005), fractal cellular manufacturing (Montreuil, Venkatadri, & Rardin, 1999), layered cellular manufacturing with dedicated, shared and remainder cells (Süer *et al.*, 2010). In a virtual manufacturing cell, a group of machines and/or operators are assigned to produce a part family, but machines are not physically put together. Dynamic cells are introduced to deal with turbulent environment and the physical locations of the machines may be changed anytime as needed to respond to the fluctuation in the demand (Rheault *et al.*, 1996). In fractal cell configuration, fractal cells contain workstations which have two or three machines. Then, a few of these workstations form similar fractal cells that have the ability of manufacturing most or all of the product families (Montreuil *et al.,* 1999). All of the fractal cells can be identical, but to avoid having duplicate machines some workstations can be shared by two different fractal cells. Süer *et al*., (2010) made a hierarchical classification of manufacturing cells as dedicated, shared and remainder cells. Dedicated cells are aimed to process only one part family, whereas shared cells have the ability to process two part families and remainder cells can process more than two part families. Cellular manufacturing systems are categorized also as single-stage and multi-stage cellular manufacturing systems (Süer, Saiz, Dagli, & Gonzalez, 1995). In single-stage cells, all operations are completed in one cell. According to Süer *et al.*, (1995), if the output of a cell is used as an input by another cell, i.e., more than one cell is involved in finishing the end product; these cells are called connected cells. In connected cells, operations are completed in different cells in multi stages that are connected to each other (Süer & Lobo, 2012). Another categorization was introduced considering the involvement of labor force in the process (Süer & Bera, 1998). In this regard, manufacturing cells were categorized as labor or machine-intensive cells. In machine-intensive cells most or all of the work is done by machines and the responsibilities of the workers are limited to loading, unloading, transferring etc. In labor-intensive cells, workers carry out the operations for the products. In labor-intensive cells, average flowtimes for the products have more variability than the machine-intensive cells due to variations in the skill, and experience of the workers.

Mathematical models are widely used in deterministic cellular manufacturing literature for cell design. Purcheck (1974) developed a linear mathematical model for the manufacturing cell design problem. Kusiak (1987) developed integer programming models for part families and machine cells. Shtubt (1989) proved that the cell formation problem is equal to the Generalized Assignment Problem. Wei and Gaither (1990) developed an integer model for a cell design problem with the objective of cost minimization of the products which are not manufactured in the cellular system. Rajamani, Singh and Aneja (1990) proposed three integer programming models to form part families and machine groups simultaneously. Kamrani, Parsaei and Leep (1995) proposed a three-stage hierarchical methodology for cell formation to optimize the resources. In the first stage, manufacturing cells are formed based on part dissimilarity. In the second stage, machines are assigned to the cells. Finally, a simulation model is developed to validate the proposed mathematical model. Chen (1998) developed an integer programming model with the objective of total cost minimization of material handling, machine and reconfiguration for a multi-period planning horizon. Heragu and Chen (1998) designed a cellular system using Bender's decomposition technique to a large scale mathematical model. Sofianopoulou (1999) used mathematical modeling and simulated annealing for cell formation and process planning while enforcing some design constraints. Akturk and Turkcan (2000) developed an algorithm which simultaneously attempts to form part families and machine cell in the cellular system. Albadawi, Bashir and Chen (2005) developed a two-phase mathematical model. They applied factor analysis to identify the cells and assigned the parts to the cells. In another work, Süer, Cosner and Patten (2008) developed a three-phase approach to deal with cell loading and product sequencing problem in labor-intensive cells. The objectives were minimizing number of machines, intra-cell manpower movement and makespan using mathematical models. They compared the results with previously proposed heuristic methods and reported better results. Adenso-Díaz and Lozano (2008) developed a mathematical model based on the operation types to achieve high quality products by utilizing the learning effect. They assigned similar operations to the cells as an alternative to part types. Ghotboddini, Rabbani and Rahimian (2011) proposed a multi-objective mixed-integer mathematical model to form part families, design cells, and allocate manpower simultaneously. Since the model is non-linear, the authors employed Bender's decomposition technique to solve the model. Fallahalipour, Mahdavi, Shamsi and Paydar (2011) developed a mathematical model and a simulated annealing algorithm for cell design to increase cell utilization.

Renna and Ambrico (2014) developed a methodology to tackle fluctuating demand using reconfigurable machines in cellular manufacturing system. Three mathematical models are proposed for CMS design, reconfiguration and scheduling activities. The first model is used to design the manufacturing system under uncertain demand environment. The second model is a variant of first model and used to reconfigure the CMS at fixed periods. The third model is used to assign the jobs to the machines. They used simulation models to show effectiveness of their approach.

Won and Logendran (2015) improved the Jaccard's similarity coefficient by considering lot sizes, duplicate machines, setup times, processing times and machine sequences for cell formation. They used a two-phase p-median model to assign machines to the cells. After cells are formed, a proposed heuristic procedure is utilized for cell loading with the objective of balancing cell loads. They showed that their approach is effective for medium sized problems.

Wu and Suzuki (2015) proposed a two-phase methodology for the cell design problem considering the sequence of operations to form part families. A new mathematical model, which takes part process routes, processing times, capacities and demand into account, was developed to design the cellular manufacturing system. Then the model is decomposed into sub-problems to reduce computation times. The model allows lot splitting and the objective of the model is to minimize sum of machine acquisition, production and inter-cell movement costs and to maximize workload balance and machine utilization. The model analyzes the trade-off between using duplicate machines and part movement among cells, and produces a manufacturing schedule with the optimal processing routes.

Uncertainty in cellular manufacturing system design has not been widely studied. Seifoddini (1990) developed a mathematical model to design cells with the objective of minimizing inter-cell material handling cost where product mix is probabilistic. Jeon and Leep (2006) considered uncertain demand to find out number of machines of cells for the current and future periods where three mixed-integer programming models were utilized. Saidi-Mehrabad and Ghezavati (2009) designed a cellular manufacturing system which has uncertainties using queuing theory. The model consists of servers (machines) and customers (parts), and the goal is to minimize the total cost of underutilization, idleness, and subcontracting. Arkat, Naseri and Ahmadizar (2011) focused on machine reliability while solving the generalized cell formation problem. They utilized chance-constrained programming and compared the results of their study with the expected value and generalized cell formation models. Eğilmez, Süer and Özgüner (2012) provided a stochastic mathematical model based on Kusiak's (1987) generalized p-median model. They considered probabilistic capacity requirements and demand for the products. A Genetic Algorithm model is also provided and the results of both models are simulated to compare the performance measures. In another study, a genetic algorithm model is developed to solve a dynamic multi-objective cell formation problem with the objectives of minimizing cost and cell loads (Javadian, Aghajani, Rezaeian, & Sebdani, 2011).

Egilmez, Süer and Huang (2012) proposed a mathematical model to design a stochastic cellular manufacturing system where production rates and demand of products are uncertain. The objective of the study is to minimize the number of cells and machines subject to a maximum overutilization risk level. Both stochastic and deterministic systems are simulated to make comparisons in terms of cell utilization, WIP, etc. Chattopadhyay, Sengupta, Ghosh, Dan and Mazumdar (2013) provided an in-depth review and analysis of the impact of Artificial Neural Networks and Genetic Algorithms on cellular manufacturing system design. Egilmez and Süer (2014) studied the effects of uncertainty on the cellular manufacturing system design and control. Two stochastic non-linear mathematical models are proposed where demand of the products and processing times of manufacturing processes are considered probabilistic. They developed a two-phase methodology where they analyzed the chain effect of risks in the cellular manufacturing system design and control phases. They solved 300 scheduling problems with various design and control risk scenarios and compared them using number of tardy jobs as a performance measure. They showed that if higher risk is taken at the design phase, the decision makers at the control phase take lower risks. Erenay, Suer, Huang and Maddisetty (2015) developed a methodology to design a stochastic layered cellular manufacturing system. They compared their findings with a previous study, and showed that their methodology outperforms with respect to number of machines. In other performance measures, average flow time and work-in-process inventory, they reported mixed results.

Metaheuristics methods are widely used to solve CMS problems as well. Renzi, Leali, Cavazzuti, and Andrisano (2014) presented a state-of-art review of cellular manufacturing systems by focusing on the studies on dedicated and reconfigurable cellular manufacturing systems. They compared the techniques and methodologies of metaheuristics used to solve various CMS problems such as cell formation, layout, design, etc., and listed their benefits and shortcomings. Deep and Singh (2015) developed a mathematical model to design robust manufacturing cells considering various processing routes for parts and multi-period production planning. The objective of the model is to minimize the sum of machine cost, production cost, material handling cost and subcontracting cost. The model determines the optimal production plan for each part at each planning period. Subcontracting is used to avoid frequent changes in the cell designs when demand fluctuates. A Genetic Algorithm based heuristic was proposed to solve larger problems. Mar-Ortiz, Adenso-Díaz and González-Velarde (2015) studied the difference between robust cellular manufacturing system problem and robust disassembly cell formation problem. A mathematical model was developed and a Tabu Search algorithm was utilized to solve both problems. The data obtained from the solutions of both designs were then analyzed with factorial design using total cost, cell size, utilization and part moves among cells as dependent variables. Results show that the quality of the outsourced components affects all of the response variables, and machine utilization and cell size are affected by the production environment.

2.4 Simulation in Manufacturing and Supply Chain Network Design

Simulation is mostly used to validate the developed designs produced by other optimization methods such as mathematical modeling and genetic algorithms. However, there are some studies in the literature where simulation is used for optimization purposes as well. This section of the dissertation reviews some of the studies that used simulation as a validation or optimization tool in manufacturing system and supply chain network designs.

In addition to deterministic and stochastic cell formation approaches, it is critical to simulate the results or integrate simulation into the proposed methodology to check the proposed solutions' validity. Fewer works exist in the literature compared to studies that are based on only-optimization-based approaches. For example, Ertay and Ruan (2005) simulated a cellular manufacturing system and used number of operators, batch size and demand as inputs and results of the simulation model as outputs in a data envelopment analysis model to determine the optimal operator assignment for the system. Azadeh and

Anvari (2009) employed multivariate methods to determine the optimal number of operators in a CMS by using results of simulation models. Reeb, Baker, Brunner, Funck, and Reiter (2010) designed a CMS and then excluded some part families from job-shop floor in a wood manufacturing facility with simulation by using leadtime and work-in-process inventory. Azadeh, Anvari, Ziaei and Sadeghi (2009) developed simulation models in order to optimize worker assignment in cellular manufacturing systems considering different layouts. The results of the simulation models are then investigated using fuzzy data envelopment analysis and fuzzy C-means method to evaluate and compare simulation models according to uncertainty levels. The results of the U-shape layout were also compared with those of L, W, Z, zigzag, straight and spiral shape production systems. In a follow-up study integrated simulation and Genetic Algorithms to assign optimum number of operators and select a production layout in cellular manufacturing systems. The results showed that U-shape system is more effective than the other alternatives (Azadeh, Nokhandan, Asadzadeh, & Fathi, 2011).

Most of the studies employed simulation to validate and compare various CMS designs developed by using other methods such as mathematical modeling and metaheuristics. Siemiatkowski and Przybylski (2007) used fuzzy clustering to design alternative cellular manufacturing systems with limited capacities. They developed simulation models to compare these alternative systems and assessed them for various performance measures using the simulation results. Ranaiefar, Mohagheghzadeh, Chitsaz, Ardakani and Shahbazi (2009) proposed simulation models to increase the capacity and to optimize the material flow between cells in a cellular manufacturing system. Süer *et* *al.*, (2010) designed alternative cellular manufacturing systems with different number of part families using mathematical modeling and a heuristic method. They simulated these alternatives to compare and determine the best design using number of machines, average flow time and work-in-process inventory. Savory and Williams (2010) integrated simulation and activity-based costing to estimate the cost drivers of a U-shaped cellular manufacturing system. Durmusoglu and Satoglu (2011) used simulation to confirm the available resource capacities in a hybrid cellular manufacturing system where demands of the parts are probabilistic. The results of the simulation models are then used to show that the proposed system performed better than the current system in terms of leadtime. In another study, Egilmez *et al.*, (2012a) developed simulation models for various capacity risk levels for a cellular manufacturing system with uncertain demands. They compared these risk levels using average flow time, total waiting time, work-in-process inventory and cell utilization which are obtained from simulation results. Renna and Ambrico (2014) developed simulation models to compare the proposed methodology with reconfigurable machines in cellular manufacturing system to a model without reconfiguration in with respect to various cost factors such as material handling and machine movement, and profit. The results indicated that the proposed methodology is superior to the other model. Xie and Allen (2015) provided a comprehensive review on use of simulation in job shop scheduling problems. They especially focused on online and offline job shop scheduling with material handling problems where the material transfer times between different machines are considered an essential part of the manufacturing. Erenay *et al.*, (2015) compared two layered cellular manufacturing system methodologies using simulation results. They used average flow time and WIP inventory as performance measures.

Simulation is also used to compare cellular manufacturing layout and process layout in many studies in the literature. Chtourou, Jerbi and Maalej (2008) provided a review on these studies and presented taxonomy of performance measures and key factors used in them. They focused on the conflicting results of these studies and claim that results of some of the studies in the literature cannot be generalized and the proposed models are applicable in only limited circumstances. They further provided simulation models in order to illustrate these conflicting results using a sample study from the literature. Pitchuka, Adil and Ananthakumar (2006) studied the effects of transition from process layout to cellular layout using queue times as a performance measure. They studied single stage and multi-stage manufacturing systems and used queuing theory for single stage and simulation for multi-stage to acquire queue times for both systems. The results showed that cellular manufacturing yielded better queue times than process layout in some circumstances even though the conditions were not favorable to cellular manufacturing layout.

Chan and Chan (2005) developed simulation models to evaluate different SCN designs which have volatile demands. Three different SCN designs with four echelons; supplier, manufacturers, retailers, and customers are investigated. The first design, which is called interorganizational supply chain model, consists of one supplier, manufacturer, retailer, and customer for each product type. The second one, a network supply chain model, improves the first model and allows suppliers and customers material/product transfer and among each other and work together to satisfy the manufacturer. The third one, regional clustering supply chain model, can have more than one supplier, manufacturer, retailer, and customer for each product. These three models are compared based on average order leadtime, transportation cost, resource utilization, and inventory level performance measures. The results show that the SCN models do not outperform each other at all performance measures (Chan & Chan, 2005). Deleris and Erhun (2005) presented simulation models of SCN models with uncertain supplies. They considered that the supplier would not be able supply the plant because of four types of risks at the supplier level: strikes, shortage of components, political instability, and disruption caused by natural disasters. The comparison was made according to production volume cost, and financial losses. Mele, Guillén, Espuña and Puigjaner (2007) proposed a simulation model to design and evaluate a SCN model. Monte-Carlo simulation is used to generate demand uncertainty in the model. The configuration and inventory control policy is considered together. A genetic algorithm is developed and employed in order to optimize the total profit for each SCN, then the parameters obtained from the GA are used as inputs in the agent-based simulation models where the expected profits of these SCN models are computed. This simulation is terminated once the optimal expected profit is reached. The SCN and inventory control strategy with the optimal profit is selected (Mele *et al.*, 2007).

In SCN design problems, simulation is usually used along with other optimization methods such as mathematical programming, heuristics, and metaheuristic methods due to practical reasons. The power of simulation comes from its ability to solve problems with some kind of uncertainty in any part or parts of SCN. Simulation allows users to compare different SCN designs, effects of parameter changes using desired performance measures such as total output, WIP, average flowtime, inventory turnover, etc.

2.5 Optimal Operator Assignment in Manufacturing Systems

The literature on optimal operator assignment in manufacturing is extensive. Dagli and Süer (1986) developed a two-level solution methodology to determine the manpower level in an assembly line. Russell, Huang and Leu (1991) studied different labor scheduling and allocation methods in a 3-cell group technology shop using two simulation models in order to study the overall system performance. The best performance was achieved with the skillful operators that are able to run all the machines. Wirth, Mahmoodi and Mosier (1993) and Lee and Vairaktarakis (1993) proposed heuristic methods to optimize manpower level. Cesani and Steudel (2005) studied the impacts of various manpower allocation policies on the cellular manufacturing system considering intra-cell operator's mobility. The labor assignment policies are classified as dedicated, shared and combined based on number of operators assigned to machine or group of machines. In another work, Ertay and Ruan (2005) utilized data envelopment analysis for manpower allocation using the number of operators, transfer batch size and demand as the input variables.

The literature about combined optimization of manpower allocation and cell loading is not extensive. Süer and Bera (1998) presented a two-phase solution methodology to maximize the output of labor-intensive cells in a multi-period environment. In the first phase, the optimal manpower level is achieved, and in the second phase integer programming models were developed to optimize cell loading and cell size simultaneously. They used the same cell for the same product at all periods to take advantage of learning curve and setup times. Babayigit (2004) developed a genetic algorithm (GA) approach to optimize the manpower allocation and cell loading problem, in which GA outperformed the mathematical model with larger problems in terms of execution time. Later, Süer and Dagli (2005) studied on the number of intra-cell manpower transfers and cell loading in labor-intensive cells and introduced a three-phase methodology to minimize the total manpower transfers. The main focus was on making the scheduling and the manpower allocation decisions simultaneously in order to minimize the makespan, machine and space requirements. A similarity coefficient method was utilized which was developed earlier by Süer and Ortega (1994). In another work, Süer, Arikan, and Babayigit (2009) developed four fuzzy mathematical models that have two contradictory objectives in a cellular manufacturing system; minimizing number of workers and number of tardy jobs. The proposed fuzzy mathematical models which consist of multiple objective functions used to optimize the number of cells, manpower allocation and cell loading for each cell. In another work, Süer *et al.*(2009) developed a three-phase approach to deal with cell loading and product sequencing problem in labor-intensive cells. The objectives were minimizing number of machines, intra-cell manpower movement and makespan using mathematical models. They compared the results with previously proposed heuristic methods and reported better results.

Skill-based deterministic manpower allocation cellular manufacturing has been studied by a few researchers previously. Süer (1996) developed a deterministic hierarchical methodology in which he proposed a mixed-integer programming model to generate various cell configurations and an integer programming model to load cells and find the optimal operator assignment. Norman, Tharmmaphornphilas, Needy, Bidanda, and Warner (2002) considered the human skills and technical skills together. The workers were allowed to improve their skill levels with training in the study. They developed a mixed-integer mathematical model in order to maximize the profitability using productivity, quality and training costs. The purpose of the study was to find out the influence of different skill levels to the productivity, manpower allocation and training plan. As a result, better worker assignment was obtained when compared to studies that considered technical skills only. Süer and Tummaluri (2008) developed a three-phase hierarchical approach which considers learning and forgetting to find the optimal cell sizes, cell loading and manpower allocation in labor-intensive cells. The methodology consisted of mixed-integer mathematical models and two heuristic methods**.** In this study, the authors defined each operator with a different skill set, which are essentially used to determine the operation times instead of standard times. Aryanezhad, Deljoo and Al-e-Hashem (2008) studied dynamic cell formation and manpower allocation simultaneously. They proposed a mathematical model with the objective of minimizing various types of costs including machine costs, production cost, inventory cost, hiring and firing costs, training cost and salary. Workers assumed to have different productivity rates depending on their skill levels. Workers are expected to increase their skill levels by training. In a recent work, Süer and Alhawari (2012) utilized two assignment strategies (min-max and max) in a dynamic multi-period cellular manufacturing environment. The objective is to minimize makespan while assigning operators to operations considering dynamic skill change. Costa, Cappadonna, and Fichera (2014) studied effects of skill-based operator assignment on a flow-shop sequence-dependent group scheduling problem using a mixed integer linear mathematical model. The objective of the model is to minimize the total processing time of products. They developed three GA based metaheuristic models and applied them to a known problem from the literature to select the best method among them. They also studied the relationship between labor cost and makespan using the results of the model. Azadeh, Rezaei-Malek, Evazabadian, and Sheikhalishahi (2014) incorporated personal characteristics and skills of workers for the cell formation problem. They developed a mathematical problem with two objectives: to minimize the total cost, and to assign workers with similar characteristics to the cells. They applied their method on an assembly line, and used DEA to find the optimal solution among alternatives. The authors claim that their methodology allows decision makers to make better decisions by taking worker satisfaction and skills into consideration on the shop floor.

Renna and Ambrico (2011) proposed new methods to deal with high variability in market conditions and in output times of the products in three different cellular manufacturing systems. They compared classical cellular manufacturing system (CMS) to fractal cellular manufacturing system (FCMS) and remainder cellular manufacturing system (RCMS) when unexpected events such as machine failures, production mix changes, unstable demands, and processing time variability happen. The authors performed simulation experiments with various scenarios using the number of total output, total processing times of the parts through the system, WIP, utilization of the machines and tardiness of the parts as performance measures. They developed new approaches to control RCMS and FCMS. The main goal of the study was to present an alternative method to the costly reconfiguration of the cells when the changes in the internal and external conditions affect the manufacturing system. In the initial conditions, CMS outperformed its alternatives. In unstable conditions, FCMS performed worst and RCMS with the proposed control system had the best results in performance measures.

Egilmez and Süer (2011) developed two non-linear stochastic programming models to deal with the cell loading and manpower allocation problem where demand and processing times were probabilistic for a labor intensive manufacturing company. Later, Egilmez, Erenay and Süer (2014) extended this study by considering variability in the performance of individual workers. The processing times of individual workers and demand of the products were considered to follow normal distribution. A hierarchical four-phase methodology was implemented. In the first phase, a stochastic non-linear mathematical model is developed to generate alternative operator levels with the objective of production rate maximization. In the second phase, probabilistic capacity requirements for products are calculated by using probabilistic demand with independent and identically distributed (IID) sampling. In the third phase, the optimal manpower levels and cell loads are found using another stochastic non-linear mathematical model. In the fourth phase, individual workers assignments to manufacturing cells are optimized with a third stochastic model by considering normally distributed processing times where workers have varying processing times and the objective is to maximize the productions rate. Erenay & Süer (2014) studied the optimal manpower allocation in manufacturing cells using production rates. They employed a mathematical model to determine the optimal number of operators to be assigned to each job, and used the results and demand of products in order to find the optimal number of operators for manufacturing cells.

3 OPTIMAL OPERATOR ASSIGNMENT IN SINGLE-STAGE AND MULTI-STAGE MANUFACTURING[1]

Manufacturing cells are classified as machine-intensive cells and labor-intensive cells (Süer & Bera, 1998). In machine-intensive cells, the number and types of machines determine the performance of the cells. Since the operator involvement is limited, the effect of the operators on the output of the cells is not as significant as the effect of machines. On the contrary, in labor-intensive cells, the number of operators assigned to a cell and to an operation determines the performance of the cell.

Labor-intensive manufacturing cells require heavy involvement of the operators at almost all manufacturing operations. The machines and the equipment used in the manufacturing are usually small, light-weight, portable, simple and inexpensive. Since each operation has different processing time, assigning the same number of operators to each operation results in low levels of output. In order to increase the efficiency of the cell, it is extremely important to assign the optimal number of operators for each operation. Determining the optimal cell sizes and assigning product families to the cells are also critical decisions for manufacturing facilities.

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[1] This chapter is partly adopted from (Erenay & Süer, 2014), a study published in the proceedings of Computers and Industrial Engineering Conference.

3.1 Research Motivation

Assigning the optimal number of operators to operations of a product is an important task to be executed for the supervisors on the shop floor in cellular manufacturing systems. This assignment determines the production rates of the manufacturing cells. The production rates of the cells increase as better assignment decisions are made for the operations. Poor assignment decisions lead to lower production rates and lower labor and machine utilizations. On the other hand, a cell usually processes one or more part families which usually consist of more than one part, thus makes the problem more complex. The optimal number of operators for each operation would be different since processing times of the parts at different machines are different than each other. Besides, manufacturing systems consist of many cells. In that case, the number of operators assigned to individual cells should be optimized in order to lower labor costs.

Süer (1996) provided two mathematical models to determine the optimal operator assignment and cell loading. The first model determines the optimal number of operators for each operation, and the second model finds the optimal cell size and cell load simultaneously. Egilmez and Süer (2011) developed two non-linear stochastic programming models to deal with the same problem considering probabilistic demand and processing times. However, these studies consider single-stage manufacturing systems. In this dissertation, a multi-stage cellular manufacturing system is considered while finding the optimal manpower allocation for operations. Also, in Süer’s study, the second model does the cell loading and optimal cell size determination concurrently

(Süer, 1996). In this dissertation, first, part families are determined, and then the optimal operator assignment is determined for all manufacturing stages considering the demand for part families. The optimal cell sizes are found with a heuristic approach developed.

In addition to optimal cell size determination, cell loading is also performed in this chapter. This work is done as an extension of the optimal cell size determination stage. The results of the cell loading experiments will not be used in the following chapters of the dissertation. Product families are assigned to manufacturing cells with two proposed heuristic approaches and a modified mathematical model developed by Süer (1996).

A three-stage hierarchical methodology is proposed for the optimal operator assignment, optimal cell size determination, and cell loading in this dissertation. The objective is to find the optimal number of operators for each operation using a mathematical model at the first stage. In the second stage, a heuristic approach is developed in order to determine an optimal cell size for each cell using cell size efficiency values. In the third stage, cell loading is performed using three different approaches; common cell size approach, optimal cell size approach, and a modified mathematical model approach.

3.2 Background

Shoe, apparel, medical device and jewelry manufacturing industries are labor-intensive industries and require high involvement of workers. Jewelry manufacturing is classified into two types based on the value of the materials used: fashion jewelry and precious jewelry manufacturing. In this dissertation, fashion jewelry manufacturing is used to conduct the research.

Jewelries, such as rings, bracelets, earrings, pendants, and necklaces are used for personal adornment. Precious jewelry is made of, as the name suggests, precious metals such as gold, silver etc., and decorated with precious stones such as diamond, pearl, and other precious stones. Fashion jewelry is made of non-precious metals and decorated with synthetic or imitation of precious stones.

Fashion jewelry is classified into 2 types as well; imitation, and ornamental. Imitation items look like precious jewelry counterparts, but are made of cheaper metals. Ornamental items can be made of any material, such as wood, glass or plastic. Table 3.1 shows the materials used for fashion jewelry manufacturing and some of the items produced with these materials (United States International Trade Commission, 1986).

Table 3.1 General information about fashion jewelry manufacturing

Property	Fashion jewelry (imitation and ornamental)
Materials used (including but not limited to)	Base metals such as aluminum, iron, copper etc., plated metals, plastics, wood, glass, leather, textiles, bones, shells, nuts, etc.
Materials not used (including but not limited to)	precious metal, precious stones, natural pearls, cameos, intaglios, amber, coral, etc.
items made (including but not limited to)	rings, earrings, bracelets, necklaces, neck chains, watch chains, key chains, collar pins and clips, tie pins and clips, medals, fobs, pendants, emblems, chain, religious items, card cases, combs, money clips etc.

Table 3.2 shows the possible processes required in fashion jewelry manufacturing. Please note that not all of the processes are required for each part. There are precedence relations among some operations in fashion jewelry manufacturing. If the part goes through finding operation, next operation for that part is deburring and that part does not require casting, degating or tumbling. Similarly, if the first operation of the part is casting, next operations are degating and tumbling and that part does not require finding and deburring.

Table 3.2 Fashion jewelry manufacturing processes

Stages	Operations preceding plating	Plating	Operations following plating
Operations	Finding, deburring, casting, degating, tumbling	chain plating, barrel plating manual plating (Racking the parts and placing spaghetti, plating, and unracking and removing spaghetti)	Oven, buffing, linking, stone settings, enameling, finishing, carding and packing, inspection, combination

Some of the operations have to be finished before plating. Plating is an expensive and time consuming operation; therefore it is one of the critical operations in fashion jewelry manufacturing process. There are three types of plating operations: chain plating, barrel plating, and manual plating. Barrel plating is usually used for small parts. Parts are put in a barrel to go through the plating process. In chain plating, parts are put on chains to be plated. The most time consuming plating process is manual plating as it requires more labor involvement in the operations. Manual plating is completed in three steps: racking the parts and placing spaghetti; plating; and unracking the parts and removing spaghetti.

The objective is to find the optimal number of operators for each cell at various operator levels and use them for manufacturing cells to meet the demand of the customers.

3.3 Solution Methodology

A three-phase methodology is proposed to find the optimal number of operators for each operation in a cell at various operator levels. First, ALINK clustering algorithm is used in order to form part families. Second, a mathematical model is employed to generate alternative operator levels. Finally, the results are analyzed to find the most efficient operator level for each part family/cell. The proposed methodology is illustrated with an example problem drawn from a real cellular system focused on fashion jewelry manufacturing.

3.3.1 Part Family Formation

Pairwise similarities are calculated using a modified Jaccard's similarity coefficient which is suggested by (McAuley, 1972). In Jaccard's similarity coefficient, similarity between parts is used to form part families. In this study, instead of using parts; machines are used to find the similarity coefficient values. The formulation is shown in Equation 3.1.

$$MS_{ij} = \frac{No. of\ machines\ processing\ parts\ i\ and\ j}{No. of\ machines\ processing\ parts\ either\ i\ or\ j} \tag{3.1}$$

ALINK similarity coefficient method, which is proposed by (Seifoddini & Wolfe, 1986), is used in this dissertation. In this method, averages of similarity coefficients are used to form part families. Similarity coefficient values show how much the processes of the parts are similar to each other. Having more similar processes means higher similarity coefficients. The parts with similarity coefficient values above the similarity threshold value are grouped in the same part family. The parts whose similarities are not high enough to join in any part family form the remainder part family.

The ALINK algorithm is explained using a sample group of six parts that require six different machines. Table 3.3 shows the part-machine matrix for this example problem. In the table, number "1" in column i and row j indicates that machine i is required for part j. For example, part 1 requires machines 2, 3, and 4. This binary part-machine matrix is used to form the modified Jaccard's similarity coefficient matrix.

Table 3.3 Part-machine matrix for the ALINK algorithm

	Parts					
Machines	P1	P2	P3	P4	P5	P6
M1	-	1	1	-	1	-
M2	1	1	1	1	1	1
M3	1	-	1	1	1	1
M4	1	1	-	1	1	1
M5	-	1	1	1	-	-
M6	-	-	1	-	1	-

In order to calculate the similarity coefficient for parts 1 and 2, two values are required: the number of machines that processes both parts 1 and 2, and the number of machines that processes either part. Machines 2 and 4 process both parts, thus the number of machines that process both parts is 2. Machines 1, 2, 3, 4, and 5 process either part 1 or part 2, thus the number of machines that process either part is 5. The similarity coefficient for parts 1 and 2 is $MS_{12} = 2/5 = 0.40$. This calculation is done for all parts. Table 3.4 shows the initial similarities for this part-machine matrix.

Table 3.4 Initial similarity matrix for the ALINK algorithm

Parts	P1	P2	P3	P4	P5	P6
P1	-	0.40	0.33	0.75	0.60	1
P2	0.40	-	0.50	0.60	0.50	0.40
P3	0.33	0.50	-	0.50	0.67	0.33
P4	0.75	0.60	0.50	-	0.50	0.75
P5	0.60	0.50	0.67	0.50	-	0.60
P6	1	0.40	0.33	0.75	0.6	-

The similarity threshold value is assumed to be 0.60 for this dissertation. In the initial similarity matrix, the highest similarity value is 1, which is the similarity coefficient for parts 1 and 6. This value is bigger than the threshold value (1>0.60), therefore parts 1 ad 6 are combined and grouped into a part-family. Then the similarity matrix is updated considering this newly formed part-family instead of considering parts 1 and 6 separately. The similarity coefficient values of this part family are calculated by taking the averages of similarity coefficients of parts 1 and 6. Table 3.5 presents the updated similarity values after grouping parts 1 and 6.

Table 3.5 Iteration 1: Updated similarity matrix for the ALINK algorithm

Parts	P1,P6	P2	P3	P4	P5
P1,P6	-	0.40	0.33	0.75	0.60
P2	0.40	-	0.50	0.60	0.50
P3	0.33	0.50	-	0.50	0.67
P4	0.75	0.60	0.50	-	0.50
P5	0.60	0.50	0.67	0.50	-

In the updated similarity matrix, the highest similarity value is 0.75, which is the similarity between part 4 and the part-family of parts 1 and 6. Since 0.75>0.60, part 4 and the part-family of parts 1 and 6 are combined into a new part family. The similarity matrix is updated again after this new grouping. Table 3.6 shows the similarity matrix after the second iteration of ALINK algorithm.

Table 3.6 Iteration 2: Updated similarity matrix for the ALINK algorithm

Parts	P1,P6,P4	P2	P3	P5
P1,P6,P4	-	0.50	0.42	0.55
P2	0.50	-	0.50	0.50
P3	0.42	0.50	-	0.67
P5	0.55	0.50	0.67	-

In the updated similarity matrix after the second iteration, the highest similarity value is 0.67, which is the similarity between parts 3 and 5. This value is bigger than the similarity threshold value (0.67>0.60). Therefore, parts 3 and 5 form a new part-family and the similarity matrix is updated after this new grouping. Table 3.7 shows the similarity values after the third iteration.

Table 3.7 Iteration 3: Updated similarity matrix for the ALINK algorithm

Parts	P1,P6,P4	P2	P3,P5
P1,P6,P4	-	0.50	0.48
P2	0.50	-	0.50
P3,P5	0.48	0.50	-

In the updated similarity matrix after the third iteration, none of the similarity values are bigger than the similarity threshold value, therefore part 2 is not included any of the part families and forms the remainder part family. As a result, parts 1, 4, and 6 form part-family 1, parts 3 and 5 form part-family 2, and part-family 3 or the remainder part-family consists of only part 2. Table 3.8 shows the part families formed with ALINK clustering algorithm for the similarity threshold value of 0.60. Machines needed in the corresponding cells are also presented assuming independent cells (i.e., no machine sharing is allowed among cells).

Table 3.8 Part-families and required machines

Families	Parts	Machines in cells
Part-family 1	P1, P4, P6	M2, M3, M4, M5
Part-family 2	P3, P5	M1, M2, M3, M4, M5, M6
Part-family 3	P2	M1, M2, M4, M5

3.3.2 Optimal Operator Assignment

After part families are formed using ALINK algorithm, a mathematical model developed by (Süer, 1996) is used to assign the optimal number of operators to each operation for each product. The mathematical model used is explained below.

Notation:

Index

j Operation index

Parameters

N Number of operations

T Total number of operators available for cell

U_j Total number of operators allowed for operation j

t_j Processing time of for operation j

Decision variables

R Production rate

X_j Number of operators for operation j

Objective Function:

$$Max\ Z = R \tag{3.2}$$

Subject to:

$$\left[(\mathrm{X_j}) * \left(\frac{1}{\mathrm{t_j}}\right)\right] - \mathrm{R} \geq 0 \qquad \mathrm{j} = 1,2,3, \dots, \mathrm{N} \tag{3.3}$$

$$X_j \leq U_j \qquad j = 1,2, \dots, N \tag{3.4}$$

$$\sum_{j=1}^{N} X_j \leq T \tag{3.5}$$

$$X_j \in (1, U) \qquad j = 1,2, \dots, N \tag{3.6}$$

$$R \geq 0 \tag{3.7}$$

The objective function is to maximize the production rate as shown in Equation (3.2). Equation (3.3) forces sufficient number of operators to be assigned to each operation such that the maximum production rate is achieved. Equation (3.4) prevents the number of operators assigned to an operation to exceed the number of operators available to perform the operation. Total number of operators assigned to all operations cannot be more than the total number of available operators (Equation (3.5)). Equation (3.6) ensures that the number of operators assigned to operations take positive integer values up to the maximum number of available operators. Equation (3.7) forces production rates of parts to take positive values.

3.3.3 Heuristic Procedure for Optimal Cell Size Determination

In this stage, a simple heuristic approach is developed to find the optimal cell size of each cell at each stage for a multi-stage cellular manufacturing system using cell size efficiency values of cell sizes. Manpower levels, number of operators assigned to each operation, and production rate values obtained from the mathematical model results are used in order to calculate the efficiency values. The procedure followed to find the cell size efficiency value for a cell size is explained below.

The total number of operators assigned to a cell is found by adding up all of the number of assigned operators to all operations in the cell as shown in Equation (3.8) where j is operation index, N is the number of operations in a cell and n_j is the number of operators assigned to operation j. This value is, usually but not necessarily, equal to the available number of operators in the cell.

$$Total\ Number\ of\ Operators\ Assigned\ in\ Cell = \sum_{j=1}^{N} n_j \tag{3.8}$$

Operator time in cell is the amount time one operator spends in the manufacturing cell. Hence, total operator time in cell per minute is equal to the total number of operators assigned to the cell as shown in Equation (3.9). For example, if the cell size is 15 operators, total number of operators assigned to cell is 15 operators, and these operators spend a total of 15 minutes in the cells, thus total operator time in cell per minute is 15 minutes.

$$\begin{aligned} &Total\ Operator\ Time\ in\ Cell\ per\ Minute \\ &\qquad = 1(min)x\ Total\ Number\ of\ Operators\ Assigned\ in\ Cell \end{aligned} \tag{3.9}$$

Theoretical time spent per unit is obtained by finding the sum of processing times of all required operations for the part in the cell. This value is calculated by using the Equation (3.10) where j is the number of operations for the part, and p_j represents the processing time of the part for operation j.

$$Theoretical\ Time\ Per\ Unit\ = \sum_{j=1}^{N} p_j \tag{3.10}$$

Efficiency value shows how much of the available operator time is used to produce the part. It is the ratio of the amount of time spent to produce the part to the amount of time available as shown in Equation (3.11).

$$Efficiency = \frac{Theoretical\ time\ per\ unit\ *\ Production\ Rate}{Total\ Operator\ Time\ in\ Cell} \tag{3.11}$$

After finding efficiency values for each part, now we can find the efficiency value for the entire cell which processes not only one part but the part family. Cell size efficiency is found by using the Equation (3.12) where L is the number of parts in that part family, and *i* is the part index.

$$Cell\ Size\ Efficiency = \sum_{i=1}^{L} Efficiency_i * Weight_i \tag{3.12}$$

In order to calculate the cell size efficiency, two values are required: efficiency of the cell for part *i* ($efficiency_i$) and weight of part *i* ($weight_i$) in the part family. Weight is the ratio of the total production time of part *i* to the total production time of all parts in the part family of part *i* as shown in Equation (3.13).

$$Weight_i = \frac{Total\ production\ time\ of\ part\ i}{Total\ production\ time\ of\ part\ family} \tag{3.13}$$

Total production time of the part is found by multiplying the demand with the actual processing time per unit, which is different than the theoretical time per unit. Theoretical time is the time that would be spent if the operator assignments to the operations are perfectly balanced.

However, since the processing times of the operations are not multiples of each other, it is almost impossible to design a perfectly balanced operator allocation. Therefore, the balance based actual processing times are used to calculate the total production time of parts by using Equation (3.14).

$$Total\ prod.time\ of\ part_i = Demand_i * Actual\ time\ spent\ per\ unit_i \tag{3.14}$$

Actual time spent per unit is the ratio of total operator time in cell per minute to the production rate as shown in the Equation (3.15).

$$Actual\ time\ spent\ per\ unit_i = \frac{Total\ Operator\ Time\ in\ Cell\ per\ Minute}{Production\ Rate_i} \tag{3.15}$$

Total production time of a part family is the sum of total production times of all of the parts in the part family and cell as shown in Equation (3.16).

$$\text{Total production time of PF} = \sum_{\mathrm{i=1}}^{\mathrm{L}} \text{Total production time of part}_{\mathrm{i}} \tag{3.16}$$

Steps of the heuristic procedure are illustrated in Figure 3.2. Each input is represented by a number, and the equations to calculate some of the inputs are shown under each input by using these numbers.

After providing the equations used in calculations, the heuristic procedure is explained step by step below.

Step 1. Retrieve the production rate for the part from the mathematical model results.

Step 2. Retrieve number of operators assigned to operations from the mathematical model results.

Step 3. Find total number of operators assigned to cell using Equation (3.8).

Step 4. Find total operator time in cell per minute using Equation (3.9).

Step 5. Find theoretical time spent per unit by using the processing times of the operations required for the part from the data table (Table 3.4) with Equation (3.10).

Step 6. Find efficiency values using Equation (3.11).

Step 7. Calculate actual time spent per unit using Equation (3.15).

Step 8. Calculate total production time of the part using Equation (3.14).

Step 9. Repeat steps 1-8 for all other parts in the part family.

Step 10. Find total production time of PF by using Equation (3.16).

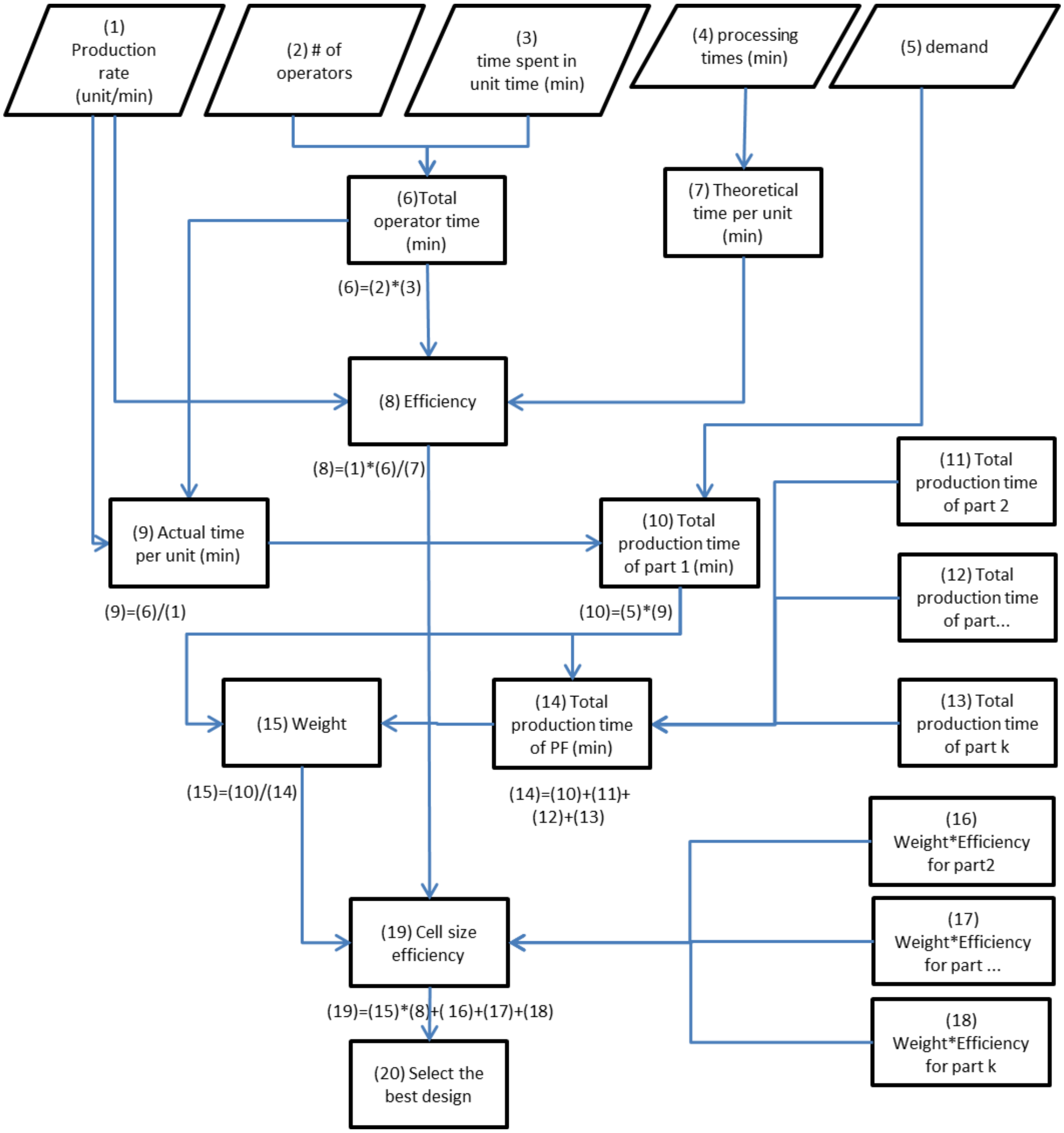

Figure 3.1 Steps of the heuristic procedure

Step 11. Find weight of the part by using Equation (3.13).

Step 12. Repeat step 11 for all parts in the part family.

Step 13. Find cell size efficiency for the part using Equation (3.12).

Step 14. Repeat steps 1-13 for other operator levels, i.e., cell sizes.

Step 15. Prepare a summary table that presents cell size efficiency values of other part families in the manufacturing stage, and determine the best cell size efficiency value for each cell/part family.

The results of the heuristic procedure are presented for a part family that consists of four parts for cell sizes of 15, 20, 25 and 30 operators in Table 3.9. The values in the columns are either retrieved from the mathematical model results or calculated using these values. Please note that Table 3.9 is prepared for illustration purposes only considering all of the 19 operations. The steps of the heuristic procedure are explained below for the cell size of 15 operators by using Table 3.9.

Step 1. Retrieve the production rate for part 1 from the mathematical model results. Production rate = 4.35 items/min (obtained from mathematical model results for part 1)

Step 2. Retrieve the number of operators assigned to operations from the mathematical model results.

Step 3. Find the total number of operators assigned to cell using Equation (3.8). (From Step 2) Total number of operators assigned to cell = 15

Step 4. Find the total operator time in cell per minute using Equation (3.9).

Total operator time in cell per minute = 1(min) * 15 = 15 minutes

Step 5. Find the sum of theoretical time spent per unit by using the processing times of the operations required for the part with Equation (3.10).

Theoretical time spent per unit = 2.57 min

Step 6. Find the efficiency value of part 1 using Equation (3.11).

Efficiency = (4.35 * 2.57) / 15 = 74.49%

Step 7. Calculate the actual operator time spent per unit using Equation (3.15).

Actual time per unit = 15 / 4.35 = 3.45 min.

Step 8. Calculate the total production time of part 1 using Equation (3.14).

Total production time of part 1 = 4950* 3.45 = 17077.5 min.

Step 9. Repeat Steps 1-8 for all other parts in the part family. See Table 3.9 for the values found for other parts 2, 3, and 4.

Total production time of part 2 = 6150 * 8.625 = 53043.8 min.

Total production time of part 3 = 6750 * 2.775 = 18731.3 min.

Total production time of part 4 = 5550 * 5.625 = 31218.7 min.

Step 10. Find the total production time of part family 1 by using Equation (3.16).

Total production time of PF1 = 120,071 min.

Step 11. Find the weight of part 1 by using Equation (3.13).

Weight of part 1 = 17077.5 / 120,071 = 14.22%

Step 12. Repeat step 11 for all parts in the part family.

Weight of part 2 = 53043.8 / 120,071 = 44.18 %

Weight of part 3 = 18731.3 / 120,071 = 15.6 %

Weight of part 4 = 31218.7 / 120,071 = 26 %

Table 3.9 Heuristic procedure illustration for Part Family 1 for single stage

PF1	Parts	Total # of Operators Assigned in Cell	Prod Rate	Total operator time in cell per minute	Theoretical time spent per unit	Efficiency	Actual time spent per unit	demand	Total Production Time of the Part	Total production time of PF	Weight	Cell Size Efficiency
15 workers	Part 1	15	4.35	15	2.57	74.49%	3.450	4950	17077.5	120,071	14.22%	68%
	Part 2	15	1.74	15	5.28	61.22%	8.625	6150	53043.8		44.18%	
	Part 3	15	5.41	15	1.95	70.27%	2.775	6750	18731.3		15.60%	
	Part 4	15	2.67	15	4.27	75.91%	5.625	5550	31218.7		26.00%	
20 workers	Part 1	20	6.06	20	2.57	77.88%	3.300	4950	16335.0	107,955	15.13%	76%
	Part 2	20	2.67	20	5.28	70.40%	7.500	6150	46125.0		42.73%	
	Part 3	20	8.70	20	1.95	84.78%	2.300	6750	15525.0		14.38%	
	Part 4	20	3.70	20	4.27	79.07%	5.400	5550	29970.0		27.76%	
25 workers	Part 1	25	8.00	25	2.57	82.24%	3.125	4950	15468.8	103,181	14.99%	80%
	Part 2	25	3.57	25	5.28	75.43%	7.000	6150	43050.0		41.72%	
	Part 3	23	10.00	23	1.95	84.78%	2.300	6750	15525.0		15.05%	
	Part 4	25	4.76	25	4.27	81.33%	5.250	5550	29137.5		28.24%	
30 workers	Part 1	30	9.80	30	2.57	83.99%	3.060	4950	15147.0	98,100	15.44%	84%
	Part 2	30	4.46	30	5.28	78.57%	6.720	6150	41328.0		42.13%	
	Part 3	30	13.51	30	1.95	87.84%	2.220	6750	14985.0		15.28%	
	Part 4	30	6.25	30	4.27	88.96%	4.800	5550	26640.0		27.16%	

Step 13. Find cell size efficiency for part family 1 for 15 operators using Equation (3.12).

Cell Size Efficiency for 15 operators = 74.49%*14.22% + 61.22%*44.18% + 70.27%*15.60% + 75.91%*26%

Cell Size Efficiency for 15 operators = 68 %

Step 14. Repeat Steps 1-13 for other cell sizes, i.e., operator levels.

Cell Size Efficiency for 20 operators = 76 %

Cell Size Efficiency for 25 operators = 80 %

Cell Size Efficiency for 30 operators = 84 %

Step 15. Prepare a summary table that presents cell size efficiency values of other part families in the manufacturing stage, and select the best cell size efficiency.

Summary tables for single-stage and multi-stage experiments are provided in the experimentation section later in this chapter.

3.3.4 Optimal Manpower Allocation to Manufacturing Cells

The work in this section of the dissertation is an extension of the optimal cell size determination stage. The results of this section will not be used in the following chapters of the dissertation.

In this section, the optimal number of workers and the minimum number of cells required to meet the customer demand for all product families are determined. Three different methods are used for the cell loading problem in this study. In the first method, common cell size is considered for all of the part families in order to find the number of cells and number of workers. In the second method, optimal cell size for each part family is considered. In the third method, a modified mathematical model is used to determine the number of cells and number of workers. Then these three methods are compared with each other.

3.3.4.1 Method 1: Common Cell Size for All Part Families

In this method, the common cell sizes which were determined using the hybrid approach developed in the first and second stages are used to find the number of cells and the number of workers required in the manufacturing system.

3.3.4.2 Method 2: Optimal Cell Size for All Part Families

In this method, instead of the common cell size for the entire stage for all part families, optimal cell sizes found for each part family are used to find the number of cells and the number of workers required in the manufacturing system.

3.3.4.3 Method 3: Using Mathematical Model for Optimal Manpower Allocation and Cell Loading

A modified mathematical model is proposed in this section. The modified model is based on the mathematical model developed in the study of Süer (1996) which finds the optimal crew size and loads the products to cells. In the model proposed in this section, instead of parts, part families are assigned to cells. Each part family can be produced in more than one cell, hence job splitting is allowed. Efficiency of the cell sizes are not considered in this section. The outcomes of the proposed model are to minimize the number of cells opened, to assign part families to cells, and to find the optimal number of operators for opened cells, simultaneously.

The first stage of the multi-stage manufacturing is considered here. In the previous sections, part families are formed, the optimal production rates for each product at each manpower level are determined, and total production times, i.e., annual capacity requirements of part families for the given demand are calculated. Manpower levels vary between 5 and 12 workers for stage 1. These values are used as inputs in the mathematical model. The model is run for each product family separately. The indices, parameters, decision variables, objective function and constraints of the mathematical model are given as follows.

Indices

j: Cell index

k: Configuration index

Parameters

m: Number cells

h: Annual capacity of a cell (min)

a_j: number of alternative configurations for cell j

p_{jk}: time required to produce the part family in cell j with configuration k

Decision Variables

b_{jk}: The manpower level required for the configuration *k* and cell *j*.

Y_{jk}: 1 if alternative configuration k is assigned to cell *j*, 0 otherwise.

X_{jk}: 1 if cell *j* assigned to configuration *k,* 0 otherwise.

Objective Function:

$$\mathrm{Min\ Z} = \sum_{j=1}^{m}\sum_{k=1}^{a_j} b_{jk} * Y_{jk} \tag{3.18}$$

Subject to:

$$\sum_{j=1}^{m}\sum_{k}^{a_j} X_{jk} = 1 \tag{3.18}$$

$$\sum_{k=1}^{a_j} Y_{jk} \leq 1 \qquad j = 1,2,3,\dots,m \tag{3.19}$$

$$p_{jk} * X_{jk} \leq h * Y_{jk} \qquad j = 1,2,3,\dots,m \qquad k = 1,2,3,\dots,a_j \tag{3.20}$$

$$X_{jk} \geq 0 \tag{3.21}$$

$$Y_{jk} \in (0,1) \tag{3.22}$$

The objective function is to minimize the number of workers in the open cells (Equation 3.17). Equation (3.18) states that the total of assignments to all manpower configurations for each product family must be equal to 1. Each cell partially covers the demand for a product family and this constraint makes sure that the total of these percentages adds up to 100%. Equation (3.19) ensures that each cell is assigned to one configuration only. The production times required in assigned cells cannot be bigger than the available capacity of opened cells as shown in Equation (3.20). Equation (3.21) assures that the cell assignments to manpower configurations take positive values only. Finally, the part family and manpower configuration assignments can be only binary values (Equation 3.22).

3.4 Description of the System Studied

The proposed methodology in this dissertation can be applied to all labor-intensive industries such as shoe, apparel, electronics, and medical device manufacturing industry. The system considered is a cellular manufacturing system that was located in Puerto Rico and specialized in fashion jewelry manufacturing. In the system considered in this dissertation, there are 40 parts that go through 19 possible operations.

Table 3.10 shows the processing times of the operations for all parts. The processing times in this study are generated based on the values presented in Süer's (1996) study on the same fashion jewelry manufacturing company. As can be seen in the table, not all operations are required for all parts. Some of the operations are combined and shown in one column where a part requires either the first or the second operation. For example, if welding operation is required for a part, then soldering operation is not performed.

In single-stage cellular manufacturing, all of the required operations starting from finding or casting to inspection and combination and packing are performed in one cell. Components and raw materials enter a cell and leave it as finished products in single-stage cellular manufacturing.

Table 3.10 Processing times of parts at operations in fashion jewelry industry

Ops/ Part	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1		.22	.24	.13		.12	.30		.18		.20				.24		.25				.30	.29		.22	.16	.17		.12	.22		.30		.15						.25	.14
2		.48	.43	.36		.46	.46		.26		.28				.40		.31				.44	.35		.36	.27	.25		.37	.49		.38		.38						.50	.47
3	.15				.11			.13		.13		.15	.11	.15		.11		.10	.13	.11			.10				.12			.10		.12		.11	.10	.12	.10	.15		
4	.15				.15			.15		.15		.12	.10	.15		.12		.15	.15	.10			.10				.15			.10		.11		.13	.14	.10	.15	.13		
5	.10				.11			.13		.11		.14	.14	.14		.12		.13	.13	.12			.08				.14			.13		.14		.13	.10	.12	.14	.11		
6	.22	.30	.50	.50	.24	.39	.20	.20	.22	.28	.26		.21	.30	.29	.22	.33	.23	.28	.26	.24	.29	.25	.23		.22		.21	.30	.22	.21	.25	.33	.30	.25	.25	.27		.34	.38
7							.42	.49							.57				.43			.47				.25			.47		.40	.10			.47				.45	.38
8		.19							.18		.21		.12	.17		.12				.10				.19									.12	.16						
9	.30		.50	.50																	.44		.50					.44		.30						.45				
10					.30	.17				.19		.25					.30	.16							.24		.18										.30	.27		
11	.51			.41	.35	.48		.38	.51			.48	.51	.52	.44	.51						.36	.52	.38	.37	.37		.45	.45			.43	.53	.42	.38		.38	.39	.45	.46
12		.75	1.18	1.18	.57		.46		.55		.68				.75			.63	.88				1.12		.63	.58					.75	.48	.68			1.12	.44	.65	.59	.42
13		.86	1.35	1.25		.50	.49	1.02	.65	.50	.65	.42		.52	1.32			.62		.53		.35	1.15				.56				1.12		.59		.75	1.08	.62	.75	.43	
14	.43	.41			.20	.27	.41	.38	.25				.25		.37	.25	.40	.30	.30			.37	.33	.31		.26	.44			.37	.40	.44					.34		.42	
15	.23	.27	.29	.27		.20	.29	.21		.24	.29	.30			.26	.24	.27	.22	.24	.26	.20	.23	.29	.24			.25	.29		.23	.23				.27	.21	.27	.28	.20	.27
16	.33		.46	.47		.36		.39	.44	.33			.43	.41	.32	.38			.47	.33	.30	.38	.44					.47	.45	.34	.38		.39		.28	.37				
17	.25	.37	.70	.75	.20	.25	.39		.22	.38	.26	.31	.43	.26		.38	.36	.28		.31	.38	.21	.75	.40	.44	.29	.35	.43	.29	.26		.36	.36	.34	.39	.75	.34	.38	.38	
18			.20	.20	.20			.15							.20	.20			.15				.15								.20	.20		.20		.15				
19	.20							.50			.50			.50	.50				.50	.50	.15			.50				.15		.20	.50						.50			.25

On the other hand, however, in multi-stage cellular manufacturing, the operations are divided into multiple stages. In fashion jewelry manufacturing, plating is a natural division point of all operations. The operations before plating such as finding, casting and deburring have to take place before plating process. Similarly, some operations such as enameling, stone settings, oven and packing are not done before plating. Therefore in multi-stage cellular manufacturing, the fashion jewelry manufacturing operations can be divided into three stages; 1) operations before plating 2) plating operations 3) operations after plating.

3.5 Part Family Formation

ALINK clustering algorithm is performed in order to form part families based on single stage similarity coefficients. The similarity threshold for ALINK algorithm is set to 0.60 for this study. Table 3.11 shows the part families. The remainder part family, which is named as Part Family 10 in the table, includes the parts which are not similar enough to be assigned to other part families.

3.6 Experimentation and Results

The results of the mathematical model for optimal operator assignment, the heuristic procedure for optimal cell size determination, and cell loading approaches are provided in this section.

The mathematical model is run for each product at all manufacturing stages for all manpower levels. Four different manpower levels are considered; 15, 20, 25, and 30 operators for single stage cellular manufacturing. Manpower level of 15 operators means that there are 15 operators available who can be assigned to the operations required for the parts. For stage 1 of multi-stage cellular manufacturing, six different manpower levels, namely 5, 6, 7, 8, 10, and 12, are considered. For stage 3 of multi-stage cellular manufacturing, five different manpower levels, namely 10, 12, 15, 18, and 20, are considered.

Table 3.11 ALINK clustering results: Part families formed

Part family	Parts
Part family 1	Part 1, Part 30, Part 23, Part 36
Part family 2	Part 2, Part 11, Part 9, Part 33
Part family 3	Part 3, Part 4, Part 21, Part 28
Part family 4	Part 5, Part 32, Part 13, Part 16, Part 34
Part family 5	Part 6, Part 22, Part 7, Part 39, Part 26, Part 29
Part family 6	Part 8, Part 19
Part family 7	Part 10, Part 35, Part 14, Part 20
Part family 8	Part 12, Part 38, Part 27, Part 18, Part 37
Part family 9	Part 15, Part 31, Part 40
Part family 10 (Remainder PF)	Part 17, Part 24, Part 25

Demands for the parts are randomly generated between [2500, 5000] with uniform distribution. The efficiency values and the production volume based weights are used to find the cell size efficiency values for each manpower level.

3.6.1 Single-Stage Cellular Manufacturing System Results

In single-stage cellular manufacturing, all operations required for the parts are performed in one cell. The parts are not transferred to another cell for further operations, i.e., the products are ready to be shipped to the warehouses or retailers after they leave the cells. Optimal operator assignment is performed for four different operator levels in the first stage: 15, 20, 25 and 30 operators. Table 3.12 shows the mathematical model results for all parts in single-stage cellular manufacturing system for 20 operators. Tables for other manpower levels in single-stage manufacturing and multi-stage manufacturing are provided in Appendix A.

In addition to the number of operators for each operation, mathematical model provides the maximum production rate that can be achieved by using this many operators in the cell. Production rates of the parts at each operator level are shown in Table 3.13. The production rate for Part 1 in a cell size of 20 operators is 6.06 parts per minute. Production rates increase as the available number of operators, i.e., manpower levels, increase as expected.

By adding up the number of operators assigned to each operation, the total number of operators required is found. Total number of operators assigned to cells at each operator level are shown in Table 3.14. Maximum number of operators required cannot be bigger than the available number of operators for the cell, but can be smaller as observed in the case of part 28. Highlighted cells indicate the cases where number of operators assigned are lower than available numbers of operators.

Table 3.12 Number of assigned operators to operations in single-stage manufacturing system for 20 operators

20	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	1	1	1	0	1	2	0	1	0	1	0	0	0	1	0	2	0	0	0	3	2	0	2	2	2	0	1	2	0	2	0	1	0	0	0	0	0	2	1
2	0	3	2	1	0	3	3	0	2	0	2	0	0	0	2	0	3	0	0	0	4	2	0	3	3	2	0	3	4	0	2	0	2	0	0	0	0	0	3	4
3	1	0	0	0	1	0	0	1	0	1	0	2	1	1	0	1	0	1	1	1	0	0	1	0	0	0	1	0	0	1	0	1	0	2	1	1	1	1	0	0
4	1	0	0	0	1	0	0	1	0	2	0	1	1	2	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	2	1	1	1	1	0	0
5	1	0	0	0	1	0	0	1	0	1	0	1	2	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	2	0	1	0	2	1	1	1	1	0	0
6	2	2	2	2	2	2	2	1	1	2	2	0	2	2	1	2	3	2	2	2	2	2	1	2	0	2	0	2	3	2	1	2	2	3	2	1	1	0	2	3
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	2	1	0	0	0	2	0	2	0	0	0	0	3	1	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	2	2	0	0
11	4	0	0	2	3	3	0	2	4	0	0	4	4	3	2	3	0	0	0	0	0	2	2	3	3	3	0	3	4	0	0	3	3	5	3	0	2	3	3	4
12	0	4	4	4	4	0	3	0	3	0	4	0	0	0	3	0	0	4	4	0	0	0	3	0	6	5	0	0	0	0	3	4	4	0	0	5	2	4	3	4
13	0	4	4	4	0	3	3	5	3	4	4	4	0	3	4	0	0	4	0	4	0	2	4	0	0	0	4	0	0	0	4	0	4	0	5	4	3	4	2	0
14	3	2	0	0	2	2	3	2	2	0	0	0	2	0	2	2	3	2	2	0	0	3	1	2	0	3	4	0	0	4	2	3	0	0	0	0	2	0	2	0
15	2	2	1	1	0	1	2	1	0	2	2	3	0	0	1	2	3	2	2	2	2	2	1	2	0	0	2	2	0	2	1	0	0	0	2	1	1	2	1	2
16	2	0	2	2	0	2	0	2	2	3	0	0	4	3	1	3	0	0	3	3	3	3	2	0	0	0	0	4	4	3	2	0	2	0	2	2	0	0	0	0
17	2	2	3	2	2	2	2	0	1	3	2	3	4	2	0	3	3	2	0	2	4	2	2	3	4	3	3	3	3	3	0	3	2	4	3	3	2	2	2	0
18	0	0	1	1	2	0	0	1	0	0	0	0	0	0	1	2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	2	0	2	0	1	0	0	0	0
19	2	0	0	0	0	0	0	3	0	0	3	0	0	3	2	0	0	0	3	4	2	0	0	3	0	0	0	1	0	2	2	0	0	0	0	0	2	0	0	2

Efficiency values of the parts are independent of the demand. The efficiency results and their corresponding weights for each part in part family 1 are shown in Table 3.15. The steps to be followed to achieve these results are explained in detail in previous sections. The weights are used to find cell size efficiency values and they depend on demand of products. Hence, cell size efficiency values change when demand to any of the parts in the part family changes. Similar tables are formed for part families 2 to 10 for single stage and multi-stage manufacturing which are provided in Appendix B.

Cell size efficiency values for different level operators for part family 1 are calculated as shown below. Similarly, these values are calculated for the rest of the part families for all operator levels as well. Cell size efficiency values are found summing up the products of the efficiencies (Equation (3.11) and weights (Equation (3.13)) of all of the parts in the part family.

15 operators = 74.5%*14.2% + 61.2%*44.2% + 70.3%*15.6% +75.9%*26% = 68.3%

20 operators = 77.9%*15.1%+70.4%*42.7%+84.8%*14.4%+79.1%*27.8% = 76%

25 operators = 82.2%*15%+75.4%*41.7%+84.8%*15%+81.3%*28.2% = 79.5%

30 operators = 84%*15.4%+78.6%*42.1%+87.8%*15.3%+89%*27.2% = 83.6%

Table 3.13 Production rates at manpower levels in single-stage manufacturing

Part	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**
15 ops.	4.35	3.33	2.17	2	5	3.7	4.08	2.63	3.85	5.26	3.85	6.25	4.76	3.85	2.27	4.17	5.56	3.57	3.41	3.85
20 ops.	6.06	4.55	2.96	2.67	6.67	5	5.13	4.76	4.55	7.14	5	7.14	7.84	5.77	3.03	5.88	7.5	6.25	4.55	6.45
25 ops.	8	5.81	4.17	4	8.77	6.25	6.9	5.26	6.15	9.09	7.14	9.68	9.52	7.14	4	8.33	10	7.14	6.67	8.33
30 ops.	9.8	7.32	4.65	4.8	10	8	8.7	6.86	7.84	10.71	8	12.5	11.76	8	5	9.8	12.12	9.09	7.69	10
Part	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**	**P31**	**P32**	**P33**	**P34**	**P35**	**P36**	**P37**	**P38**	**P39**	**P40**
15 ops.	6.67	3.45	1.74	4.35	6.25	5.41	5.56	4.65	6.12	5.41	2.63	4.55	3.03	7.69	4	2.67	2.63	3.57	2.94	4.76
20 ops.	8.33	5.56	2.67	6	8.11	8	7.14	6.67	8.16	8.7	3.57	6.82	5.13	10	6.67	3.7	3.7	5.26	4.65	7.14
25 ops.	10.53	7.89	3.57	8.33	11.11	10.34	9.09	8.51	10.2	10	4.76	8.33	6.06	14.29	7.89	4.76	5.26	7.14	5.88	8.7
30 ops.	13.33	8.7	4.46	10	12.7	12.07	12	10.64	13.33	13.51	5.33	10	7.69	16.67	10	6.25	6.67	7.89	7.14	11.11

Table 3.14 Total number of assigned operators at manpower levels in single-stage manufacturing

Parts	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**
15 ops.	15	15	15	15	15	15	15	15	15	15	15	15	15	14	15	15	15	15	15	15
20 ops.	20	20	20	20	20	20	20	20	**19**	20	20	20	20	20	20	20	20	20	20	20
25 ops.	25	25	25	25	25	25	25	**24**	25	25	25	25	25	25	25	25	25	25	25	25
30 ops.	30	30	30	30	30	**29**	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Parts	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**	**P31**	**P32**	**P33**	**P34**	**P35**	**P36**	**P37**	**P38**	**P39**	**P40**
15 ops.	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
20 ops.	20	20	20	20	20	20	20	19	**20**	20	20	20	20	20	20	20	20	20	20	20
25 ops.	25	25	25	25	25	25	25	**25**	25	23	25	24	25	25	25	25	25	25	25	25
30 ops.	30	30	30	30	30	**30**	30	30	30	30	30	30	30	30	29	30	30	30	30	30

Table 3.15 Heuristic procedure results for part family 1 in single-stage manufacturing

Operator level	PF1 Parts	Production rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight
15	1	4.35	15	2.57	74.50%	3.45	4950	17078	120071	14.20%
	23	1.74	15	5.28	61.20%	8.63	6150	53044	120071	44.20%
	30	5.41	15	1.95	70.30%	2.78	6750	18731	120071	15.60%
	36	2.67	15	4.27	75.90%	5.62	5550	31219	120071	26.00%
20	1	6.06	20	2.57	77.90%	3.3	4950	16335	107955	15.10%
	23	2.67	20	5.28	70.40%	7.5	6150	46125	107955	42.70%
	30	8.7	20	1.95	84.80%	2.3	6750	15525	107955	14.40%
	36	3.7	20	4.27	79.10%	5.4	5550	29970	107955	27.80%
25	1	8	25	2.57	82.20%	3.13	4950	15469	103181	15.00%
	23	3.57	25	5.28	75.40%	7	6150	43050	103181	41.70%
	30	10	23	1.95	84.80%	2.3	6750	15525	103181	15.00%
	36	4.76	25	4.27	81.30%	5.25	5550	29137	103181	28.20%
30	1	9.8	30	2.57	84.00%	3.06	4950	15147	98100	15.40%
	23	4.46	30	5.28	78.60%	6.72	6150	41328	98100	42.10%
	30	13.51	30	1.95	87.80%	2.22	6750	14985	98100	15.30%
	36	6.25	30	4.27	89.00%	4.8	5550	26640	98100	27.20%

Table 3.16 shows the cell size efficiency values of all part families at single-stage cellular manufacturing for all manpower levels. Cells with highlighted and bold values represent highest cell sizes efficiencies for part families. Cells with only bold values represent the second best efficiency scores for part families. As expected, generally, when the number of operators in a cell increases, the efficiency of that cell increases as well. The reason for this is that the number of operators assigned to operations fits better to the processing times of those operations when more operators are available to be assigned to the cell. The difference between the cell efficiency values of 15 operators and 20 operators are more than the difference between the cell efficiency values of 25 and 30 operators. For example, for PF7 the difference in cell efficiencies between 15 and 20 operators is 10.8%, however it drops to 0.1% when it comes to 25 and 30 operators. This is an indication for better fit with increasing number of operators.

Table 3.16 Cell size efficiency values at single-stage cellular manufacturing

Operator Level	**PF1**	**PF2**	**PF3**	**PF4**	**PF5**	**PF6**	**PF7**	**PF8**	**PF9**	**PF10**
15	68.3%	78.7%	77.2%	75.7%	76.0%	70.7%	73.7%	74.6%	77.6%	81.2%
20	76.0%	81.7%	78.6%	81.7%	81.7%	78.8%	84.5%	78.6%	79.7%	82.1%
25	79.5%	84.1%	87.6%	85.9%	84.8%	83.7%	84.1%	82.8%	84.1%	89.8%
30	83.6%	86.7%	86.5%	84.0%	87.2%	83.9%	84.2%	86.0%	82.3%	88.9%

However, because of the same fitting reason, at almost half of the part families, higher operator levels are more efficient than the highest operator levels. For example, at PF 7, operator level 20 is more efficient than operator levels 25 and 30. In single-stage manufacturing, the optimal operator level is 25 operators for PF3, PF4, PF9, and PF10. For PF1, PF2, PF5, PF6, and PF8, the optimal operator level is 30 operators.

3.6.2 Multi-Stage Cellular Manufacturing System Results

In single stage cellular manufacturing system, all of the required operations for a finished product are performed in one cell. However, this is not the case for most of the manufacturing systems. Final products may be completed by assembling parts produced in other manufacturing companies. Hence, the finished product is actually manufactured in multiple stages at various locations. Similarly, operations of the fashion jewelry manufacturing are divided into three stages. The first stage consists of 10 operations which are required before plating. Second stage has one of the three types of plating operations only; manual plating, barrel plating and chain plating. The operations after plating are in the third stage of multi-stage manufacturing system. Part families used in multi-stage manufacturing were defined based on the single-stage manufacturing system.

Optimal operator assignment is performed for six operator levels in the first stage: 5, 6, 7, 8, 10 and 12 operators. In the second stage, since the plating operations are performed mostly by machines and the number of workers has little effect on the production rate, optimal operator assignment is not performed. In the third stage, 5 operator levels are considered: 10, 12, 15, 18 and 20 operators.

Summary of the results of the mathematical model in stage 1 of the multi-stage cellular manufacturing system for operator level 5 is shown in Table 3.17. There are 6 different operations that can be performed in stage 1, but not all of them are required for each part. For example, operations 3, 4, 5 and 6 are required for Part 1, but operations 1 and 2 are not required. It can be seen from the table that operators are assigned to only these operations. The results of the mathematical model for other operator levels for stage 1 and stage 3 of multi-stage manufacturing system are provided in Appendix A.

Table 3.17 Number of assigned operators to operations in Stage 1 of multi-stage manufacturing system for operator level 5

Ops	**Parts**																			
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	0	1	1	1	0	1	2	0	1	0	1	0	0	0	1	0	1	0	0	0
2	0	2	2	2	0	2	2	0	2	0	2	0	0	0	2	0	2	0	0	0
3	1	0	0	0	1	0	0	1	0	1	0	2	1	1	0	1	0	1	1	1
4	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	1	0	1	1	1
5	1	0	0	0	1	0	0	1	0	1	0	2	1	1	0	1	0	1	1	1
6	2	2	2	2	2	2	1	2	2	2	2	0	2	2	2	2	2	2	2	2
Ops	**Parts**																			
	21	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
1	2	2	0	1	2	1	0	1	1	0	2	0	1	0	0	0	0	0	1	1
2	2	2	0	2	3	2	0	2	2	0	2	0	2	0	0	0	0	0	2	2
3	0	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	1	2	0	0
4	0	0	1	0	0	0	2	0	0	1	0	1	0	1	1	1	1	2	0	0
5	0	0	1	0	0	0	2	0	0	1	0	1	0	1	1	1	1	1	0	0
6	1	1	2	2	0	2	0	2	2	2	1	2	2	2	2	2	2	0	2	2

Table 3.18 presents the production rates of the parts for the first stage of multi-stage manufacturing. The production rates increase as the number of available operators increases.

Table 3.18 Production rates in the first stage of multi-stage manufacturing

Parts/ # of operators	**5 ops.**	**6 ops.**	**7 ops.**	**8 ops.**	**10 ops.**	**12 ops.**
Part 1	6.67	6.67	9.09	10.00	13.33	18.18
Part 2	4.17	4.55	6.25	6.67	9.09	10.42
Part 3	4.00	4.17	4.65	6.00	8.00	9.30
Part 4	4.00	5.56	6.00	7.69	8.33	11.11
Part 5	6.67	8.33	9.09	9.09	13.33	18.18
Part 6	4.35	5.13	6.52	7.69	8.70	10.87
Part 7	4.35	5.00	6.52	6.67	10.00	10.87
Part 8	6.67	7.69	7.69	10.00	15.00	15.38
Part 9	5.56	7.69	9.09	11.11	13.64	16.67
Part 10	6.67	7.14	7.69	9.09	13.33	15.38
Part 11	5.00	7.14	7.69	10.00	11.54	15.00
Part 12	8.33	13.33	14.29	16.67	21.43	26.67
Part 13	7.14	9.09	9.52	10.00	14.29	19.05
Part 14	6.67	6.67	6.67	7.14	13.33	13.33
Part 15	4.17	5.00	6.90	7.50	10.00	12.50
Part 16	8.33	8.33	9.09	9.09	16.67	18.18
Part 17	4.00	6.06	6.45	8.00	9.68	12.12
Part 18	6.67	7.69	8.70	10.00	13.33	17.39
Part 19	6.67	7.14	7.69	7.69	13.33	15.38
Part 20	7.69	8.33	9.09	10.00	15.38	18.18
Part 21	4.17	4.55	6.67	6.82	9.09	11.36
Part 22	3.45	5.71	6.90	6.90	10.34	11.43
Part 23	8.00	10.00	10.00	12.00	16.00	20.00
Part 24	4.55	5.56	8.33	8.70	11.11	13.64
Part 25	11.11	12.50	14.81	18.52	22.22	25.93
Part 26	5.88	8.00	9.09	11.76	13.64	17.65
Part 27	8.33	13.33	14.29	16.67	21.43	26.67
Part 28	5.41	8.11	8.33	9.52	13.51	16.22
Part 29	4.08	4.55	6.12	6.67	9.09	10.20
Part 30	7.69	9.09	10.00	10.00	15.38	20.00
Part 31	4.76	5.26	6.67	7.89	10.00	13.16
Part 32	7.14	8.00	8.33	9.09	14.29	16.67
Part 33	5.26	6.06	6.67	7.89	10.53	13.16
Part 34	6.67	7.69	7.69	9.09	13.33	15.38
Part 35	7.14	8.00	10.00	10.00	14.29	20.00
Part 36	8.00	8.33	8.33	10.00	16.00	16.67
Part 37	6.67	7.14	7.41	10.00	13.33	14.81
Part 38	9.09	13.33	15.38	18.18	23.08	27.27
Part 39	4.00	4.00	5.88	6.00	8.00	10.00
Part 40	4.26	5.26	6.38	7.14	8.51	10.64

Table 3.19 presents total number of assigned operators out of number of available operators for the first stage of multi-stage manufacturing. For some parts, the total number of assigned operators is less than the number of available operators.

Table 3.19 Total number of assigned operators at manpower levels in the first stage of multi-stage manufacturing

Parts	**5 ops.**	**6 ops.**	**7 ops.**	**8 ops.**	**10 ops.**	**12 ops.**	**Parts**	**5 ops.**	**6 ops.**	**7 ops.**	**8 ops.**	**10 ops.**	**12 ops.**
1	5	**5**	7	8	10	12	**21**	5	6	7	8	10	12
2	5	6	7	8	10	12	**22**	5	6	7	8	10	12
3	5	6	7	8	10	12	**23**	5	6	**6**	8	10	12
4	5	6	7	8	10	12	**24**	5	6	7	8	10	12
5	5	6	7	8	10	12	**25**	5	6	7	8	10	12
6	5	6	7	8	10	12	**26**	5	6	7	8	10	12
7	5	6	7	8	10	12	**27**	5	6	7	8	10	12
8	5	6	7	8	10	12	**28**	5	6	7	8	10	12
9	5	6	7	8	10	12	**29**	5	6	7	8	10	12
10	5	6	7	8	10	12	**30**	5	6	7	8	10	12
11	5	6	7	8	10	12	**31**	5	6	7	8	10	12
12	5	6	7	8	10	12	**32**	5	6	7	8	10	12
13	5	6	7	8	10	12	**33**	5	6	7	8	10	12
14	5	6	7	8	10	12	**34**	5	6	7	8	10	12
15	5	6	7	8	10	12	**35**	5	6	7	8	10	12
16	5	**5**	7	8	10	12	**36**	5	6	7	8	10	12
17	5	6	7	8	10	12	**37**	5	6	7	8	10	12
18	5	6	7	8	10	12	**38**	5	6	7	8	10	12
19	5	6	7	8	10	12	**39**	5	6	7	8	10	12
20	5	6	7	8	10	12	**40**	5	6	7	8	10	12

Table 3.20 presents the production rates of the parts for the third stage of multi-stage manufacturing. The same observation is made here; as the production rates increase, the number of available operators increases as well.

Table 3.20 Production rates in the third stage of multi-stage manufacturing

Parts/ # of operators	**10 ops.**	**12 ops.**	**15 ops.**	**18 ops.**	**20 ops.**
Part 1	4.00	4.65	6.06	8.00	9.09
Part 2	2.70	3.70	4.88	5.81	6.98
Part 3	1.69	2.22	2.96	3.70	4.29
Part 4	1.60	2.13	2.54	3.39	4.00
Part 5	5.00	5.00	6.67	8.77	10.00
Part 6	3.70	4.00	5.56	6.25	8.00
Part 7	4.08	4.88	6.52	7.69	8.70
Part 8	2.56	2.63	4.00	5.13	5.26
Part 9	3.08	3.92	4.55	5.88	6.82
Part 10	5.26	6.00	8.00	10.00	10.53
Part 11	3.45	4.00	5.88	6.90	7.69
Part 12	4.17	6.25	7.14	9.52	10.00
Part 13	4.65	6.98	8.00	9.80	11.63
Part 14	3.85	4.00	5.77	7.69	7.69
Part 15	1.52	2.27	2.70	3.79	4.00
Part 16	4.00	5.00	5.88	7.89	8.33
Part 17	6.67	7.50	10.00	12.50	13.89
Part 18	3.33	4.55	6.25	6.67	7.94
Part 19	3.33	4.00	4.55	6.38	6.67
Part 20	3.85	5.66	6.45	8.00	9.43
Part 21	7.89	10.00	13.33	15.79	18.42
Part 22	4.35	5.26	5.71	8.33	8.70
Part 23	1.33	1.79	2.61	3.03	3.48
Part 24	4.17	5.26	7.50	8.33	10.00
Part 25	4.76	6.35	8.11	9.52	11.11
Part 26	5.41	6.90	8.62	10.81	12.07
Part 27	4.55	5.56	7.14	8.93	10.71
Part 28	4.44	6.38	6.90	8.89	10.34
Part 29	6.90	8.89	11.11	13.79	15.56
Part 30	5.41	7.69	8.82	11.54	13.04
Part 31	2.00	2.63	3.57	4.35	5.00
Part 32	4.55	5.00	6.82	8.33	9.30
Part 33	2.94	3.77	5.13	5.88	7.35
Part 34	9.52	11.76	14.71	17.65	20.00
Part 35	3.70	5.13	6.67	7.69	8.00
Part 36	1.85	2.68	3.57	4.46	4.76
Part 37	2.27	2.94	3.33	4.55	5.26
Part 38	2.67	3.57	4.62	5.33	6.67
Part 39	2.63	4.44	5.00	6.67	6.98
Part 40	6.52	7.41	9.52	11.90	13.04

Table 3.21 presents total number of assigned operators out of number of available operators for the third stage of multi-stage manufacturing. For some parts, the total number of assigned operators is less than the number of available operators.

The results of the heuristic procedure for Part-Family 1 in stage three of multi-stage cellular manufacturing are presented in Table 3.22. The values show similar trends to those of single-stage cellular manufacturing.

Generally, as the number of available operators in a cell increases, the production rate and efficiency increases as well. But there are exceptions to this trend. For example, for Part 1 in Table 3.19, as the operator level moves from 10 to 12 operators, the production rate increases from 4.00 to 4.65, but the efficiency decreases from 78% to 75.58%.

The results of the heuristic procedure for all of the other part families in the first and third stage of multi-stage cellular manufacturing are provided in Appendix B.

Table 3.21 Total number of assigned operators at manpower levels in the third stage of multi-stage manufacturing

Parts	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**	**P20**
10 ops.	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
12 ops.	12	12	12	12	10	12	12	12	**12**	12	12	12	12	12	12	12	12	12	12	12
15 ops.	15	15	15	15	15	15	15	**15**	15	15	15	15	15	15	15	15	15	15	15	15
18 ops.	18	18	18	18	18	**18**	18	18	18	18	18	18	18	18	18	17	18	18	18	18
20 ops.	20	20	20	20	19	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
Parts	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**	**P31**	**P32**	**P33**	**P34**	**P35**	**P36**	**P37**	**P38**	**P39**	**P40**
10 ops.	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
12 ops.	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
15 ops.	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
18 ops.	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18
20 ops.	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

Table 3.22 Heuristic procedure results for PF 1 in the third stage of multi-stage manufacturing

Operator level	PF1 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 1	4.00	10	1.95	78.0%	2.50	4950	12375	100958	12.3%	68.1%
	Part 23	1.33	10	4.75	63.3%	7.50	6150	46125	100958	45.7%	
	Part 30	5.41	10	1.40	75.7%	1.85	6750	12488	100958	12.4%	
	Part 36	1.85	10	3.68	68.1%	5.40	5550	29970	100958	29.7%	
12	Part 1	4.65	12	1.95	75.6%	2.58	4950	12771	89493	14.3%	76.8%
	Part 23	1.79	12	4.75	70.7%	6.72	6150	41328	89493	46.2%	
	Part 30	7.69	12	1.40	89.7%	1.56	6750	10530	89493	11.8%	
	Part 36	2.68	12	3.68	82.1%	4.48	5550	24864	89493	27.8%	
15	Part 1	6.06	15	1.95	78.8%	2.48	4950	12251	82399	14.9%	83.4%
	Part 23	2.61	15	4.75	82.6%	5.75	6150	35362	82399	42.9%	
	Part 30	8.82	15	1.40	82.4%	1.70	6750	11475	82399	13.9%	
	Part 36	3.57	15	3.68	87.6%	4.20	5550	23310	82399	28.3%	
18	Part 1	8.00	18	1.95	86.7%	2.25	4950	11138	80576	13.8%	85.3%
	Part 23	3.03	18	4.75	80.0%	5.94	6150	36531	80576	45.3%	
	Part 30	11.54	18	1.40	89.7%	1.56	6750	10530	80576	13.1%	
	Part 36	4.46	18	3.68	91.3%	4.03	5550	22378	80576	27.8%	
20	Part 1	9.09	20	1.95	88.6%	2.20	4950	10890	79912	13.6%	86.0%
	Part 23	3.48	20	4.75	82.6%	5.75	6150	35362	79912	44.3%	
	Part 30	13.04	20	1.40	91.3%	1.53	6750	10350	79912	13.0%	
	Part 36	4.76	20	3.68	87.6%	4.20	5550	23310	79912	29.2%	

Cell size efficiency values for stage 1 and stage 3 of multi-stage manufacturing are shown in Tables 3.23 and 3.24. Similar trends to single-stage manufacturing results are observed in both stages. In stage 1 of multi-stage manufacturing, the optimal operator levels are achieved mostly at the highest operator level, 12, with the exception of PF5 and PF7. For PF7, best efficiency value is 90.5% for operator levels 5 and 10.

Table 3.23 . Cell size efficiency values at the first stage of multi-stage cellular manufacturing

Operator Level	**PF1**	**PF2**	**PF3**	**PF4**	**PF5**	**PF6**	**PF7**	**PF8**	**PF9**	**PF10**
5	86.4%	80.5%	83.0%	85.4%	79.8%	87.2%	90.5%	75.4%	82.7%	89.4%
6	84.0%	82.1%	84.1%	85.9%	79.9%	80.5%	80.6%	84.2%	78.8%	82.9%
7	78.8%	85.2%	84.1%	75.8%	89.4%	75.8%	75.8%	78.5%	84.4%	89.2%
8	74.4%	87.0%	87.7%	70.1%	84.8%	70.1%	72.2%	82.9%	83.3%	90.4%
10	86.4%	89.5%	89.4%	85.4%	90.1%	87.2%	90.5%	86.6%	90.3%	89.4%
12	88.8%	90.5%	92.1%	88.4%	88.6%	88.4%	88.5%	87.7%	94.7%	91.3%

Table 3.24 Cell size efficiency values at the third stage of multi-stage cellular manufacturing

Operator Level	**PF1**	**PF2**	**PF3**	**PF4**	**PF5**	**PF6**	**PF7**	**PF8**	**PF9**	**PF10**
10	68.1%	76.7%	73.5%	84.0%	77.8%	79.8%	79.9%	74.3%	69.8%	92.3%
12	76.8%	82.1%	81.6%	87.8%	83.6%	84.3%	83.3%	82.8%	78.8%	83.6%
15	83.4%	85.7%	80.7%	83.5%	82.9%	82.5%	87.0%	81.7%	81.0%	90.5%
18	85.3%	86.2%	86.4%	89.4%	86.6%	86.5%	89.8%	84.2%	87.2%	87.9%
20	86.0%	91.8%	90.9%	91.3%	87.9%	85.9%	86.0%	88.7%	86.8%	92.3%

In stage 3, similar to stage 1, the optimal operator levels are achieved mostly at the highest operator level, 20, this time with more exceptions. For PF6, PF7 and PF9, the best cell efficiency value is achieved at the operator level 18. For PF 10, there is a tie between operator levels 10 and 20.

3.6.3 Results of the Manpower Allocation Approaches

The results of the three methods including the proposed mathematical model to determine the number of cells required to cover the demand for product families, and the number of operators assigned to these cells are presented in this section. The results for only stage 1 are shown in this section.

3.6.3.1 Results of the Common Cell Size Approach

The most efficient cell size is 12 workers for most of the product families at stage 1 as shown in Table 3.23, hence the common cell size is 12 workers for stage 1. Similarly, Table 3.24 shows that the common cell size for stage 3 is 20 workers.

Annual production times are calculated in order to find the number of cells required. It is assumed that the manufacturing facility works for 50 weeks per year. Hence, the weekly production times for product families are multiplied by 50 in order to find the annual production times. Then, annual production times are divided by the available production time for each cell to find the number of cells required for production. The available production time for one cell is considered to be 40 hours per week, hence 2,000 hours, or 120,000 minutes per year.

Table 3.25 shows the weekly production times, annual production times, number of cells required for each part family, cell size for each part family, and the total number of workers for the cellular manufacturing system of stage 1 for the common cell size approach. Total number of cells required for stage 1 for the common cell size approach is 80. Total number of workers for the manufacturing system is found by multiplying the cell size (number of operators in one cell) with the total number of cells, which is 960 workers. The efficiency of manufacturing cells with this cell size quite high, optimal for almost all of the part families. Since each cell has equal number of workers, the supervision and cell loading is easier for the middle management.

Table 3.25 Number of cells required for the common cell size 12 workers

Stage 1	weekly production times (min)	annual production times (min)	number of cells required	Cell size	Total number of workers
PF1	15,003	750,150	7	12	84
PF2	19,118	955,920	8	12	96
PF3	21,143	1,057,140	9	12	108
PF4	17,730	886,500	8	12	96
PF5	35,838	1,791,885	15	12	180
PF6	9,211	460,575	4	12	48
PF7	19,773	988,650	9	12	108
PF8	17,070	853,500	8	12	96
PF9	13,630	681,480	6	12	72
PF10	13,670	683,497	6	12	72

3.6.3.2 Results of the Optimal Cell Size Approach

At most of the part families, optimal cell sizes are obtained mostly at the highest operator level, 12, with the exception of PF5 and PF7 which has 10 workers as the optimal cell size with respect to cell efficiency values. PF7 has the same efficiency for 5 workers as well.

Table 3.26 shows the weekly production times, annual production times, number of cells required for each part family, cell size for each part family, and the total number of workers for the cellular manufacturing system of stage 1 for the optimal cell size approach.

Table 3.26 Number of cells required for the optimal cell sizes in stage 1

Stage 1	weekly production times (min)	annual production times (min)	number of cells required	Cell size	Total number of workers
PF1	15,003	750,150	7	12	84
PF2	19,118	955,920	8	12	96
PF3	21,143	1,057,140	9	12	108
PF4	17,730	886,500	8	12	96
PF5	35,015	1,750,750	15	10	150
PF6	9,211	460,575	4	12	48
PF7	19,328	966,375	9	10	90
PF8	17,070	853,500	8	12	96
PF9	13,630	681,480	6	12	72
PF10	13,670	683,497	6	12	72

Total number of cells required for stage 1 is 80 if the optimal cell size approach is used. Total number of workers for the manufacturing system is 912 if operator level 10 is used for PF7, and 867 if operator level 5 is used. This method is very similar to method 1 where common cell size was used instead of the optimal cell size since the common cell sizes and the optimal cell sizes are the same for most part families.

3.6.3.3 Results of the Mathematical Modelling Approach

The results of the mathematical model showed that the model assigned the manpower configurations which minimized the total number of workers required for the opened cells. Table 3.27 shows the configurations selected, number of cells opened at each manpower level, the percentage of production times covered by the cells at each manpower level, and total number of workers required for the cells opened for each part family.

Table 3.27 Table 12 Results of the mathematical model

Part family	Configuration (# of workers in a cell)	# of cells	Assigned production	Total # of workers
PF1	5	7	100%	35
PF2	5	9	100%	45
PF3	5	10	100%	50
PF4	5	8	100%	40
PF5	5	1	5.90%	5
	7	14	94.10%	98
PF6	5	4	100%	20
PF7	5	9	100%	45
PF8	5	5	59.50%	25
	6	3	40.50%	18
PF9	5	7	100%	35
PF10	5	7	100%	35

The minimum manpower level, 5 workers, are assigned to the opened cells for most of the part families. For PF5 and PF8, two different configurations are assigned to cells. For PF5, almost all of the cells have 7 workers, for PF8 configuration with 6 workers are assigned to cells along with configuration with 5 workers. The average percentages of cells with higher number of workers are higher than the average percentages with lower number of workers.

The total number of opened cells is 84. The total number of operators assigned to these cells is 451. The number of cells opened is higher than the previous two approaches. Since manpower configurations with lower number of operators are assigned to the opened cells, the total number of operators in the cellular system are way lower than the first two approaches.

However, the efficiency values of these cells are way lower than the common cell size and optimal cell size approaches. The mathematical model aims to minimize the number of workers in the system considering that the workers assigned to the operations will work with 100% efficiency. The optimal operator assignment results show that this is rarely the case.

3.7 Conclusions

In this chapter, optimal operator assignment to all operations of parts in a cell is determined for single-stage and multi-stage cellular manufacturing systems. A heuristic procedure is developed in order to find the optimal cell size for each part family in dedicated cells. Then, a modified mathematical model along with two other methods are used for cell loading.

A three-stage methodology is proposed for optimal operator assignment, optimal and common cell size determination, and optimal manpower allocation. In the first stage, a mathematical model developed by Süer (1996) is utilized. The objective is of the mathematical model is to find the optimal number of operators for each operation and to maximize the production rate of the part with the assigned number of operators. In the second stage, a heuristic approach is developed to determine the optimal cell sizes and a common cell size for each stage using cell efficiency values. The methodology is implemented for a single-stage and three-stage cellular manufacturing system. The same methodology is used to find the optimal cell sizes for shared and remainder cells in Chapter 4. In the third stage, three different methods are used to determine the number of cells opened and the number of operators required for these cells. The first two methods utilize the results of the optimal cell size and common cell size approaches that consider the cell efficiency values. A mathematical model is proposed to determine the number of cells opened in the third method. The goal of the mathematical model is to optimize the number of operators assigned to each cell among crew size alternatives.

Generally, when the number of operators in a cell increases, the efficiency of that cell increases as well. The reason for this is that the number of operators assigned to operations fits better to the processing times of those operations when more operators are available to be assigned in the cell. However, because the same fitting reason, for some of the part families, higher operator levels are more efficient than the highest operator levels.

The three methods proposed to determine the number of cells required to cover the customer demands and to assign the optimal manpower allocation to these opened cells have advantages over each other. The common cell size approach makes cell loading easier for supervisors. The optimal cell size approach has the highest production rates, thus cell efficiencies. But it is relatively more difficult to load cells and supervise the workers since some cells have different crew sizes. A mathematical model is employed for the third approach. This approach has the lowest number of workers for the cellular manufacturing system. This means this approach leads to the lowest labor cost among alternatives. However, the cells opened in this approach have the lowest cell size efficiencies, and cell sizes vary as well.

This study can be improved by comparing these results with other cell size determination approaches from the literature. Efficiency values can be used for crew size determination.

4 LAYERED CELLULAR MANUFACTURING SYSTEM DESIGN WITH MATHEMATICAL MODELING[2]

In this chapter, a mathematical model is used to create a layered cellular manufacturing system with the objective of minimizing the number of cells in highly fluctuating stochastic demand environment. The proposed methodology improves the study of Erenay *et al.*, (2015) in many aspects. To be specific, machine duplication and system-wide multiple shifts are introduced in the layered cellular manufacturing system design. In this study, the number of machines required for each operation in each cell is determined using the results of the mathematical model discussed in Chapter 3.

The rest of this chapter is organized as follows. Section 4.1 briefly explains categories of manufacturing systems and compares classical cellular manufacturing system with the layered cellular manufacturing system. Section 4.2 describes the manufacturing system studied. The methodology followed is explained in Section 4.3. The results of the proposed mathematical and simulation models are presented in Section 4.4. Section 4.5 discusses the conclusions and work to be done in this chapter of the dissertation.

4.1 Introduction and Research Motivation

Manufacturing systems are classified into four categories based on their layouts: cellular manufacturing layout, product layout, process layout, and fixed layout. In classical cellular manufacturing systems, each product family is assigned to its own

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[2] This chapter is partly adopted from (Erenay *et al.*, 2015), an article published in Computers and Industrial Engineering Journal.

dedicated cell(s) which ideally has all of the machines, tools and manpower to process all of the products in the product family completely. These systems work efficiently in terms of machine and cell utilization when the demand is steady and predictable. Figure 4.1 represents an example of classical cellular manufacturing system with four part families and their dedicated cells.

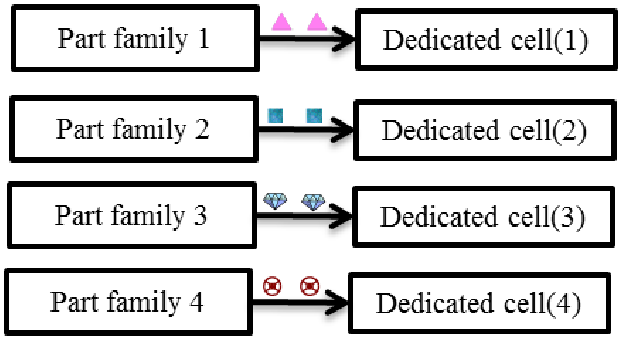


Figure 4.1 A classical cellular manufacturing system

However, when the demand fluctuates, performing operations in only dedicated cells may not yield the same efficiency. When the demand is lower than the expected amount, cells are under-utilized, and when it is higher, dedicated cells will not be able to process all of the products in a family on time. In order to deal with the fluctuating demand, Süer *et al.*, (2010) proposed a layered system which consists of dedicated, shared, and remainder cells. Dedicated cells are defined the same as in classical manufacturing systems; dedicated cells process only their assigned product families. Shared cells process two product families, and remainder cells process more than two product families. Hence, a product family can be processed in dedicated cells, shared cells, and remainder cells at the same time. Figure 4.2 presents an example of the layered cellular system. In the study of Süer *et al.* (2010), a heuristic procedure is used to create dedicated, shared and remainder cells considering expected utilization of cells, demand coverage probabilities and the similarities among part families. Their study showed that, in high demand fluctuation, the layered design yields better results than the classical design in terms of WIP and average flowtime, and the classical design was better in terms of number of machines. However, in low demand fluctuation, the classical design performed better than the layered design at all performance measures. Later, Erenay *et al.*, (2015) used a mathematical model developed by Maddisetty (2005) to design a layered cellular manufacturing system instead of heuristic procedure, and compared the results with those of Süer *et al.*, (2010) for a highly fluctuated uncertain demand data. The results showed that the layered cellular design with mathematical model yielded lower number of machines and higher WIP inventory and average flow time.

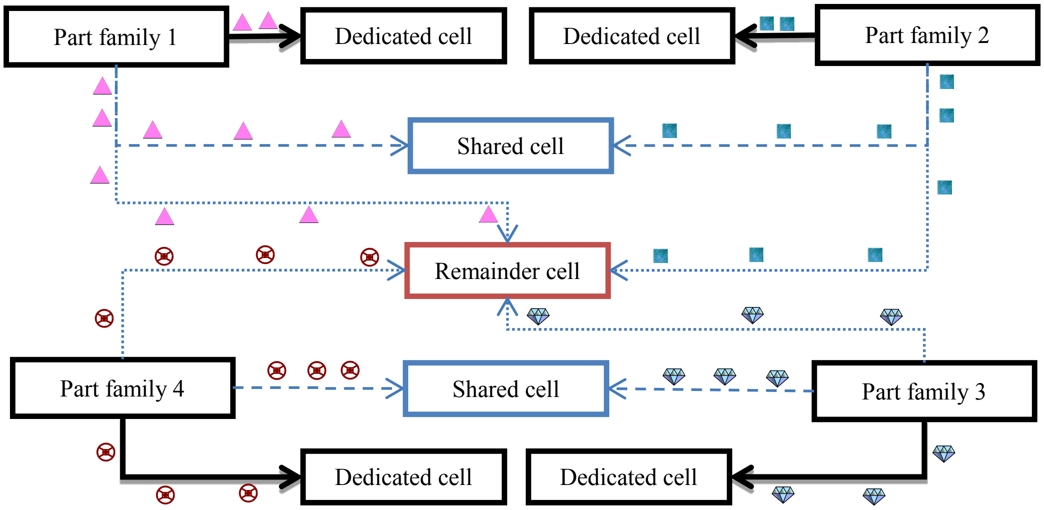


Figure 4.2 A layered cellular manufacturing system

In this dissertation, the methodology developed by Erenay *et al.*, (2015) is improved in many aspects. First, machine duplication is introduced to layered cellular manufacturing system by using the heuristic procedure developed and the mathematical model used in Chapter 3. Number of machines required in the cells are calculated using the results of the same mathematical model. Second, double/triple shifts are used where the demand requires opening too many cells. This leads a more cost effective cellular system considering the reduction in space and number of machines required. Finally, in the previous study a static bottleneck machine was used even for a multi-stage cellular manufacturing system. In this section, shifting and multiple bottleneck machines are considered for each cell and product.

4.2 Description of the System Studied

The cellular system considered in this study processes 40 parts with 19 machines. The processing times in this study are generated based on the values provided in Süer's (1996) study on fashion jewelry manufacturing. Each cell has a bottleneck machine which has the highest processing time of the system. Parts move in one direction in the system, i.e., no back-tracking is allowed. Additionally, following assumptions are made:

- Cells are independent, parts are finished in the assigned cells and don't need to go other cells for further processing.
- Each cell is visited only once by the parts.
- No setup is required for the machines to process parts, i.e., setup times are zero.

- Parts arrive and move in the system in units.
- Fifty weeks a year, 5 working days a week and 8 hours a day are considered as operating parameters for the cells.

Table 4.1 presents the demand information for products. It is assumed that demand of products follow normal distribution, and mean values are generated with [3750, 7500] units randomly. Standard deviation is considered to be 25% of the mean demand of the parts.

Table 4.1 Mean and standard deviation of demand for parts

Parts	**Mean Demand**	**Std.Dev**	**Parts**	**Mean Demand**	**Std.Dev**
P1	4950	1237.5	**P21**	4800	1200
P2	6450	1612.5	**P22**	3750	937.5
P3	5100	1275	**P23**	6150	1537.5
P4	5400	1350	**P24**	6450	1612.5
P5	7350	1837.5	**P25**	5400	1350
P6	4800	1200	**P26**	4200	1050
P7	4500	1125	**P27**	7050	1762.5
P8	5700	1425	**P28**	4950	1237.5
P9	5700	1425	**P29**	4650	1162.5
P10	6900	1725	**P30**	6750	1687.5
P11	4350	1087.5	**P31**	6300	1575
P12	7350	1837.5	**P32**	4350	1087.5
P13	6000	1500	**P33**	4500	1125
P14	6150	1537.5	**P34**	4350	1087.5
P15	4950	1237.5	**P35**	7500	1875
P16	3900	975	**P36**	5550	1387.5
P17	5550	1387.5	**P37**	5250	1312.5
P18	5550	1387.5	**P38**	5700	1425
P19	6900	1725	**P39**	4500	1125
P20	6600	1650	**P40**	4500	1125

4.3 Methodology

The methodology followed in this chapter is explained in this section. The proposed approach consists of following phases: identifying part families for alternative designs, determining cell configurations, determining cell types with the proposed mathematical model, determining operational parameters of the cellular system and values of performance measures using simulation models, and selecting the best design with statistical analysis. The steps of the methodology used in this study are shown in Table 4.2. Each step is described in detail in the following subsections.

Table 4.2 . Phases and methods used in Chapter 4 and 5

Phase#	Phases	Methods
1	Identify part families for alternative designs	Clustering algorithm
2	Determine cell configurations	Mathematical model 1, Probability theory, Heuristic procedure
3	a. Determine cell types	Mathematical model 2
	b. Determine number of machines	Mathematical models 1-2, Heuristic procedure
4	a. Determine operational parameters	Simulation
	b. Determine value of performance measures	Simulation
5	Compare the cellular designs	Statistical analysis

Two different mathematical models are used. The results of the mathematical model employed in Chapter 3 are used in machine duplication process, capacity calculations, and determining total number of machines. Mathematical model employed in this chapter is used to determine cell configurations and cell types.

4.3.1 Identifying Part Families and Determining Cell Configurations

A similarity matrix is formed using the proposed modified Jaccard's similarity coefficient (McAuley, 1972). Part families are determined in Chapter 3 using ALINK clustering algorithm which was proposed by Seifoddini and Wolfe (1986). Table 4.3 shows parts that form 10-part family configuration along with required machine information obtained by using these methods.

Table 4.3 Parts and machines of part families in 10-part family configuration

Part family	Parts	Machine Types		
		Stage 1	Stage 2	Stage 3
Part family 1	Part 1, Part 30, Part 23, Part 36	3, 4, 5, 6	9	11, 12, 13, 14, 15, 16, 17, 18, 19
Part family 2	Part 2, Part 11, Part 9, Part 33	1, 2, 6	8	11, 12, 13, 14, 15, 16, 17, 19
Part family 3	Part 3, Part 4, Part 21, Part 28	1, 2, 6	9	10, 11, 12, 13, 15, 16, 17, 18, 19
Part family 4	Part 5, Part 32, Part 13, Part 16, Part 34	3, 4, 5	7, 8	10, 11, 12, 14, 15, 16, 17, 18
Part family 5	Part 6, Part 22, Part 7, Part 39, Part 26, Part 29	1, 2, 6	7	10, 11, 12, 13, 14, 15, 16, 17
Part family 6	Part 8, Part 19	3, 4, 5, 6	7	10, 12, 13, 14, 15, 16, 17, 18, 19
Part family 7	Part 10, Part 35, Part 14, Part 20	3, 4, 5, 6	7, 8	10, 11, 13, 15, 16, 17, 19
Part family 8	Part 12, Part 38, Part 27, Part 18, Part 37	3, 4, 5, 6	-	10, 11, 12, 13, 14, 15, 17, 19
Part family 9	Part 15, Part 31, Part 40	1, 2, 3, 4, 5, 6	7	11, 12, 13, 14, 15, 16, 17, 18, 19
Part family 10	Part 17, Part 24, Part 25	1, 2, 6	8	10, 11, 12, 14, 15, 17, 19

Capacity requirements for a part family are found using the mean and standard deviation of the demand of each part in a family. The expected cell utilization and demand coverage probability of each part is calculated using the methodology proposed by Süer and Ortega (1996).

4.3.2 Mean Capacity Requirements

The demands for parts are considered probabilistic in this dissertation. The manufacturing systems are designed for a single set of demand data, hence the variability in demand in future years is not considered. However, since fashion jewelry manufacturing is labor-intensive, and the machines for fashion jewelry manufacturing are inexpensive, it is relatively easier to open/close cells if demand increases/decreases in the following years. Also, most of the jobs do not require highly skilled workers; this gives flexibility to manufacturers to increase or decrease the capacity if needed.

Demands for the parts follow normal distribution, and standard deviations of the demands are assumed to be 25% of the mean demands of the parts. Since the parts are grouped into part families, first the mean and standard deviation of demand for each part family need to be determined. The expected value of n independent random variables X1, X_2, X_3, …, and X_n each having a mean of μ_1, μ_2, μ_3, …, and μ_n, respectively, are found by using Equation (4.1);

$$E(X_1+X_2+X_3+ \ldots +X_n) = \mu_1 + \mu_2 + \mu_3 + \ldots + \mu_n \tag{4.1}$$

The variance value of n independent random variables X_1, X_2, X_3, …, X_n each having a variance of σ_1^2, σ_2^2, σ_3^2, … σ_n^2 , respectively, are found by using Equation (4.2)

$$Variance(X_1+X_2+X_3+ \ldots +X_n) = \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \ldots + \sigma_n^2 \tag{4.2}$$

Standard deviation of the demands for part families are simply found by getting the square roots of the variances.

After determining the standard deviations of the parts, the mean capacity requirements (MCR) and standard deviations of the part families are calculated. Mean capacity requirements for the products are calculated using Equation (4.3) (Maddisety, 2005). Here, BPT is the processing time for the bottleneck operation of the part. Equation (4.4) determines the variance of mean capacity requirement of parts.

$$MCR = \mu_{demand} \times {}^{BPT}/_{60} \ (in\ hours) \tag{4.3}$$

$$Variance_{capacity} = \sigma_{demand}^2 \times {}^{BPT^2}/_{3600} \ (in\ hours) \tag{4.4}$$

Since the processing times of the parts for each operation are in minutes, the bottleneck machine processing time is divided by 60 and converted into hours. The product of mean demand and BPT is the mean capacity requirement for that particular part in hours.

The standard deviation and the variance of the capacity of the part families are calculated in a similar fashion. After calculating the mean capacity requirements and the variances for the parts, the mean capacity requirement, variance and the standard deviation of capacities for a part family are found. Table 4.4 shows the MCR, variance of capacities, and standard deviation of capacities for each part in part family 1 as well as the entire part family. The MCR for PF1 is 1250.25 hours with a standard deviation of 156.8 hours.

Table 4.4 Mean capacity requirement, variance and standard deviation of capacities for part family 1

Parts	MCR	Variance of capacity	Standard Deviation of capacity
Part 1	272.25	4632.5	68.1
Part 23	307.5	5909.8	76.9
Part 30	337.5	7119.1	84.4
Part 36	333	6930.6	83.3
Part family 1	**1250.25**	**24592.0**	**156.8**

Table 4.5 shows the mean capacity requirements, variances and standard deviations of capacities for all of the part families. PF5 has the highest MCR, and PF6 has the lowest MCR.

Table 4.5 Mean capacity requirements, variances and standard deviations of capacities for part families

PF	MCR	Variance of capacity	Standard Deviation of capacity
PF1	1,250.25	24,591.97	156.82
PF2	1,593.20	43,839.79	209.38
PF3	1,761.90	50,523.34	224.77
PF4	1,477.50	28,545.12	168.95
PF5	2,746.50	81,969.55	286.30
PF6	809.25	20,705.80	143.90
PF7	1,932.75	58,763.99	242.41
PF8	1,422.50	26,060.42	161.43
PF9	1,283.70	34,579.04	185.95
PF10	1,139.16	29,797.59	172.62

4.3.3 Demand Coverage Probabilities

After determining the MCRs and their standard deviation for all of the part families, the probabilities of covering the demand for those part families are calculated. The total available number of hours at stage j ($THCell_j$) in a manufacturing cell for one shift is considered as 2000 hours/year, for two shifts 4000 hours/year, and for three shifts 6000 hours/year. The first and the third manufacturing stages work on shift, while the second shift works two or three shifts. The mean and the standard deviation of capacity requirements and Microsoft Excel's NORMDIST, which returns the standard normal cumulative distribution function, are used to find the demand coverage probabilities (DemCovProb) for cell i, as show in Equation (4.5) (Ates, 2013).

$$DemCovProb_i = NORMDIST\ (THCell_j\ x\ i - {}^{\mu_{capacity}}/_{\sigma_{capacity}}) \qquad (4.5)$$

For example the demand coverage probability for the first manufacturing cell for part family 3 is 85.5% as calculated below. First stage works for one shift; hence total available time for this cell is 2000 hours. If a second cell is allocated for part family 3, the demand would be covered entirely by these two cells.

$$DemCovProb_1 = NORMDIST\left(2000\ x\ 1 - {}^{1761.9}/_{224.77}\right) = 0.855$$

Table 4.6, Table 4.7, and Table 4.8 shows the demand coverage probabilities for the first, second and third manufacturing stages for all of the part families, respectively.

Table 4.6 Demand covering probabilities for manufacturing stage 1

Part family	1st cell	2nd cell
PF1	1.0000	
PF2	0.9740	1.0000
PF3	0.8553	1.0000
PF4	0.9990	1.0000
PF5	0.0046	1.0000
PF6	1.0000	
PF7	0.6093	1.0000
PF8	0.9998	1.0000
PF9	0.9999	1.0000
PF10	1.0000	

Table 4.7 Demand covering probabilities for manufacturing stage 2

Part family	1st cell	2nd cell	3rd cell	4th cell
PF1	0.0000073	0.1779566	0.9935788	1.0000000
PF2	0.7307447	1.0000000		
PF3	0.0000019	0.0994765	0.9799117	1.0000000
PF4	1.0000000			
PF5	0.0000007	0.1854510	0.9987585	1.0000000
PF6	0.9181376	1.0000000		
PF7	0.0938167	0.9984894	1.0000000	
PF8	1.0000000			
PF9	0.0310140	0.9902450	1.0000000	
PF10	1.0000000			

Table 4.8 Demand covering probabilities for manufacturing stage 3

Part family	1st cell	2nd cell	3rd cell
PF1	0.0042840	0.9935788	1.0000000
PF2	0.9999991	1.0000000	
PF3	0.0015747	0.9799117	1.0000000
PF4	1.0000000		
PF5	0.0021526	0.9987585	1.0000000
PF6	0.9999783	1.0000000	
PF7	0.7950235	1.0000000	
PF8	1.0000000		
PF9	0.5928071	1.0000000	
PF10	1.0000000		

Most of the part families require opening the second cells to fully cover the demands. For only PF1 and PF6, one cell is enough to cover the demand.

4.3.4 Expected Cell Utilization Computations

In this section, the demand coverage probabilities for the first, second, and third manufacturing stages are calculated in the previous section are used to determine the expected utilizations of the cells. A methodology developed by Süer and Ortega (1996) is utilized. This methodology considers demand coverage probabilities and expected cell utilizations of previous and additional cells to calculate the expected utilization of the current cell, as presented in Equation (4.6);

$$E(\mathrm{C}=\mathrm{X}) = P(\mathrm{CR}>\mathrm{X}) * PU_1 + P(\mathrm{X}-1 \leq \mathrm{CR} \leq \mathrm{X}) * PU_2 + P(\mathrm{CR}<\mathrm{X}-1) * PU_3 \quad (4.6)$$

where,

$E(\mathrm{C} = \mathrm{X})$	Expected utilization for the X^{th} cell assigned to a part family
$P\,(\mathrm{CR} > \mathrm{X})$	Probability that the number of cells required (CR) is greater than X
PU_1	Percent utilization of cell X when CR > X, i.e. PU1 = 1
$P\,(\mathrm{X}\text{-}1 \leq \mathrm{CR} \leq \mathrm{X})$	Probability that the number of cells required falls within X-1 and X
PU_2	Percent utilization of cell X when $\mathrm{X}\text{-}1 \leq \mathrm{CR} \leq \mathrm{X}$
$P\,(\mathrm{CR} < \mathrm{X}\text{-}1)$	Probability that the number of cells required is less than X-1
PU_3	Percent utilization of cell X when CR < X-1, i.e. PU3 = 0

PU2 is calculated using Equation (4.7). Here, for the manufacturing cells that work for one shift, the upper and lower bounds of the integral is 2000 hours, for the cells that work two shifts, they are 4000 hours, and for the cells that work three shifts, they are 6000 hours.

$$PU_2 = \int_{2000(X-1)}^{2000X} \frac{y * f(y)}{2000 * A}\, dy - (X - 1) \tag{4.7}$$

where,

f(y)	Probability density function for the number of cells required
y	Random variable representing the number of cells required
A	Probability that cells required is between X-1 and X, i.e. P (X-1 ≤ CR ≤ X)

The probability density function, f(y), follows normal distribution which is represented by the equation 4.8.

$$f(y) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-(y-\mu)^2 \frac{1}{2\sigma^2}} \tag{4.8}$$

Equation (4.7) is solved via MATLAB Software by using means and standard deviations of each part family and each cell. Then the result of Equation (4.7) is plugged in Equation (4.6) to find the expected utilization of the cell for the part family.

Table 4.9 shows the expected cell utilization values for the first manufacturing stage. This stage works for one shift per day.

Table 4.9 Expected cell utilization for manufacturing stage 1

Part family	1st cell	2nd cell	3rd cell	4^{th} cell
PF1	0.625100	0.000000		
PF2	0.799545	0.013525	0.000000	
PF3	0.867831	0.076550	0.000000	
PF4	0.737767	0.000508	0.000000	
PF5	1.004357	0.684459	0.000004	0.0000000
PF6	0.383800	0.000000		
PF7	0.932251	0.212049	0.000000	
PF8	0.711077	0.000089	0.000000	
PF9	0.641762	0.000030	0.000000	
PF10	0.569600	0.000000		

Table 4.10 shows the expected cell utilization values for the second manufacturing stage. Please note that manufacturing stage 2 works for double shifts, and part family 8 do not require any operations at stage 2.

Table 4.10 Expected cell utilization for manufacturing stage 2

Part family	1st cell	2nd cell	3rd cell	4th cell	5th cell
PF1	1.000000	0.983856	0.647419	0.004968	0.000000
PF2	0.907282	0.144482	0.000000		
PF3	1.000000	0.992422	0.732625	0.015619	0.000000
PF4	0.579800	0.000000			
PF5	1.000000	0.982524	0.627732	0.000953	0.000000
PF6	0.732979	0.044386	0.000000		
PF7	0.993581	0.610473	0.001041	0.000000	
PF8					
PF9	0.998142	0.707841	0.006765	0.000000	
PF10	0.306400	0.000000			

Table 4.11 shows the expected cell utilization values for the third manufacturing stages. This stage works for one shift per day.

Table 4.11 Expected cell utilization for manufacturing stage 3

Part family	1st cell	2nd cell	3rd cell	4th cell	5th cell
PF1	1.000000	0.943332	0.368242	0.000138	0.000000
PF2	0.995794	0.731570	0.001578	0.000000	
PF3	1.000000	0.815050	0.043830	0.000000	
PF4	0.992494	0.564785	0.000000		
PF5	1.000000	0.904246	0.129392	0.000000	
PF6	0.908279	0.224230	0.000000		
PF7	1.000000	0.820127	0.030006	0.000000	
PF8	1.000000	0.948255	0.325831	0.000000	
PF9	1.000000	0.776279	0.028456	0.000000	
PF10	0.765970	0.009676	0.000000		

4.3.5 Machine Duplication

Machine duplication is introduced to layered cellular manufacturing system in this section. In Chapter 3, number of operators assigned to each operation for each part that yields the maximum production rate is determined by the mathematical model proposed by Süer (1996). The optimal total number of operators in manufacturing cells is determined using the heuristic procedure developed in Chapter 3. In order to get the maximum production rate for the determined cell size for each part, the optimal number of operators needs to be assigned to the operations. It is assumed that each machine is used by one operator, and each operator operates one machine only. Therefore, the number of machines required for each operation in a cell is assumed to be the same as the number of operators assigned to that operation.

There may be more than one machine for each operation after machine duplication is allowed; therefore this has to be taken into consideration while finding the capacity requirements. The processing times of the operations are divided to the number of machines determined by the mathematical model. Table 4.12 shows the original processing times, the number of operators assigned to part-family 2 for the cell size of 20 operators, which is determined as the optimal cell size by using the heuristic procedure in Chapter 3, and the new processing times to be used in order to find the capacity requirements for each part and part family. For example, the original processing time of Part 2 for linking operation is 0.75 min/part. The heuristic procedure developed in chapter 3 determined 20 operators as the most efficient cell size for part-family 2. For 20 operators, mathematical model assigns 6 operators to linking operation. Hence 6 machines are required. The original processing time is divided by 6, and the new processing time is found as 0.125 min/part. Bottleneck operations also change for some parts after assigning multiple operators.

Plant-wise multiple shifts are introduced to layered cellular manufacturing concept. Demand for a part family may require too many cells to be opened which may not be possible for companies with limited space in facilities. It also requires more investment for machine and equipment. In this chapter, in order to avoid these inconvenient situations, it is assumed that when the demand for part families requires too may cells, the cells work for two or three shifts per day. Cells work 16 hours/day or 24 hours/day instead of 8 hours/day, which means that the capacities of the cells are doubled or tripled.

Table 4.12 Finding new processing times for parts in part-family 2

Operations	Dying/ Frosting	Welding/ Soldering	Linking	Stone Settings	Enameling	Finishing	Oven	Carding & Packing	Inspection	Combination	Parts
Original processing times	0	0	**0.75**	0.86	0.41	0.27	0	0.37	0	0	Part 2
	0	0.51	0.55	0.65	0.25	0	0.44	0.22	0	0	Part 9
	0	0	0.68	0.65	0	0.29	0	0.26	0	0.5	Part 11
	0	0.53	0.68	0.59	0	0	0.39	0.36	0	0	Part 33
Number of operators assigned	0	0	**6**	6	3	2	0	3	0	0	Part 2
	0	4	4	5	2	0	3	2	0	0	Part 9
	0	0	6	5	0	3	0	2	0	4	Part 11
	0	4	5	5	0	0	3	3	0	0	Part 33
New processing times	0	0	**0.125**	0.143	0.137	0.135	0	0.123	0	0	Part 2
	0	0.128	0.138	0.13	0.125	0	0.147	0.11	0	0	Part 9
	0	0	0.113	0.13	0	0.097	0	0.13	0	0.125	Part 11
	0	0.133	0.136	0.118	0	0	0.13	0.12	0	0	Part 33

Table 4.13 presents demand coverage probabilities and expected cell utilizations for part family 10 in stage 3 of multi-stage manufacturing system. Part family 10 requires two cells to cover the demand. The probability that one cell covers the entire demand is 98.1%. When the second cell is opened, the probability to cover the demand increases to almost 100%. Please note that 100% values in the tables are approximate since the demand values are normally distributed. The expected cell utilization of the first cell of part family 10 is 76.6% which means that the demand of part family 10 needs 76.6% of the capacity of the first cell. Similarly, the rest of the demand of part family 10 requires on the average 1% of the capacity of the second cell.

Table 4.13 Demand coverage probability and expected cell utilization values

Part Family	Mean Cap Req. (hr)	Std. Dev. of Cap Req	Demand Coverage Probability			Expected Cell Utilization		
			Cell 1	Cell 2	Cell 3	Cell 1	Cell 2	Cell 3
PF10	1530.6	225	0.981	1		0.766	0.010	

4.3.6 Determining Cell Types

A mathematical model developed by Erenay *et al.*, (2015) is used to determine the cell types. Expected cell utilization and demand coverage probability values are used as inputs in the mathematical model in order to determine cell configuration and cell types. The model minimizes the number of cells opened to meet the highly fluctuating demand. It also allows us to determine whether the cells are dedicated, shared or remainder cells in the system. The model, solved in IBM ILOG-CPLEX software, is explained in detail below. The indices, parameters and decision variables are listed as follows.

Notation:

Indices

i	Family index
j	Coverage segment index
k	Cell index

Parameters

p	Number of families
q	Number of coverage segments
r	Number of cells
b_{ij}	Expected cell utilization of part family i and coverage segment j
c_{ij}	Probability of covering demand for part family i and coverage segment j
m	Maximum allowable expected cell utilization for a cell
n	Minimum demand coverage probability for each family

Decision variables

$X_{ijk} = 1$, if part family i is assigned to coverage segment j and cell k, 0 otherwise

$Y_k = 1$, if cell k is opened, 0 otherwise

Objective function:

$$Min\ Z = \sum_{k=1}^{r} Y_k \tag{4.9}$$

Subject to:

$$\sum_{j=1}^{q} X_{ijk} \leq Y_k \quad for \begin{cases} i = 1,2,\dots,p \\ k = 1,2,\dots,r \end{cases} \tag{4.10}$$

$$\sum_{j=1}^{q} \sum_{i=1}^{p} b_{ij} * X_{ijk} \ \leq \ Y_k * m \quad for \ k = 1,2,\dots,r \tag{4.11}$$

$$\sum_{j=1}^{q} c_{ij} \left[\sum_{k=1}^{r} X_{ijk}\right] \geq n \quad for \ i = 1,2,\dots,p \tag{4.12}$$

$$\sum_{k=1}^{r} X_{ijk} \leq 1 \qquad for \begin{cases} i = 1,2,\dots,p \\ j = 1,2,\dots,q \end{cases} \tag{4.13}$$

$$\sum_{k=1}^{r} X_{i,j-1,k} \geq \sum_{k=1}^{r} X_{ijk} \qquad for \begin{cases} i = 1,2,\dots,p \\ j = 2,3,\dots,q \end{cases} \tag{4.14}$$

$$X_{ijk} \in [0,1], \ Y_k \in [0,1] \qquad (4.15)\ (4.16)$$

The objective is to minimize the number of cells opened as given in Equation (4.9). Equation (4.10) guarantees that number of coverage segments assigned to a cell from the same part family cannot exceed 1. This also depends on the cell forming decision, so that if the cell is not opened, the coverage segment is not assigned to that cell. Equation (4.11) prevents expected cell utilization from exceeding the upper limit for cell utilization and Equation (4.12) forces demand coverage probability for each part family to be higher than the minimum value. Each coverage segment of a part family can be assigned to only one cell as shown in Equation (4.13). Equation (4.14) states that the coverage segments of a part family are assigned consecutively to the cells.

In order to determine the total number of machines required in each cell, the results obtained in Chapter 3 is used. In Chapter 3, the optimal cell sizes, i.e. total number of operators in each cell, are found using a mathematical model and a heuristic procedure for each part family. The mathematical model determines the optimal number of operators assigned to each operation for a part while maximizing the production rates. The heuristic procedure finds the optimal total number of operators for the part family considering the production rates and the assigned number of operators found by the mathematical model, and demand of the parts. It is assumed that each operator uses only one machine, and each machine is operated by only one operator. Hence, at any point in time, total number of machines being used is equal to number of operators in cells. This means that some machines are idle and waiting to be used for other products.

After the optimal cells sizes are found using the heuristic procedure, the number of machines required for each type in dedicated cells is found by taking the maximum number of operators assigned to each operation among all parts of the part family. Total number of machines is found by adding up all of the maximum number of machines for each type. Table 4.14 shows the maximum number of machines required for each operation and total number of machines in a dedicated cell for part-family 2.

Table 4.14 Finding the total number of machines for a dedicated cell

Operations	Parts	Op 10	Op 11	Op 12	Op 13	Op 14	Op 15	Op 16	Op 17	Op 18	Op 19	
Number of operators assigned	Part 2	0	0	6	6	3	2	0	3	0	0	
	Part 9	0	4	4	5	2	0	3	2	0	0	
	Part 11	0	0	6	5	0	3	0	2	0	4	
	Part 33	0	4	5	5	0	0	3	3	0	0	Total
Maximum		0	4	6	6	3	3	3	3	0	4	32

The numbers of machines required for each operation of each part family at stages 1, 2 and 3 are presented for the optimal cell sizes in Table 4.15, Table 4.16, Table 4.17, respectively. The total number of machines for each part family is also provided.

Table 4.15 Maximum number of operators assigned to operations for part families at stage 1

Part family	Optimal Cell size	Op 1	Op 2	Op 3	Op 4	Op 5	Op 6	Total
PF1	12	0	0	3	3	3	6	15
PF2	12	3	5	0	0	0	5	13
PF3	12	4	6	0	0	0	6	16
PF4	12	0	0	3	3	3	5	14
PF5	10	3	5	0	0	0	4	12
PF6	12	0	0	2	3	3	5	13
PF7	10	0	0	2	2	2	4	10
PF8	12	0	0	5	4	4	4	17
PF9	12	4	5	0	0	0	5	14
PF10	12	5	7	0	0	0	4	16

Table 4.16 . Maximum number of operators assigned to operations for part families at stage 2

Part family	Optimal Cell size	Op 7	Op 8	Op 9	Total
PF1	5	0	0	5	5
PF2	3	0	3	0	3
PF3	5	0	0	5	5
PF4	3	3	3	0	6
PF5	3	3	0	0	3
PF6	3	3	0	0	3
PF7	3	3	3	0	6
PF8	0	0	0	0	0
PF9	3	3	0	0	3
PF10	3	0	3	0	3

Table 4.17 Maximum number of operators assigned to operations for part families at stage 3

Part family	Optimal Cell size	Op 10	Op 11	Op 12	Op 13	Op 14	Op 15	Op 16	Op 17	Op 18	Op 19	Total
PF1	20	0	5	6	6	5	3	5	4	1	3	38
PF2	20	0	4	6	6	3	3	3	3	0	4	32
PF3	20	0	5	6	6	0	4	6	7	1	3	38
PF4	20	3	9	6	0	5	2	5	7	4	0	41
PF5	20	2	8	7	5	4	3	7	5	0	0	41
PF6	18	2	0	6	5	2	2	3	2	1	4	27
PF7	18	2	4	0	6	0	3	4	4	0	4	27
PF8	20	3	5	5	6	5	3	0	4	0	3	34
PF9	18	0	6	5	5	2	4	2	0	1	3	28
PF10	20	5	5	7	0	6	4	0	5	0	5	37

As seen from the tables, total number of machines required and total number of operators assigned, i.e., cell size, is not same. The total number of machines is more than the total number of operators for all part families. But this does not mean that the operators use more than one machine at a time. Each operator uses only one machine, and vice versa. Since parts are processed separately, not simultaneously, and need different machines, number of machines in a cell is usually higher than number of operators.

4.4 Results of the Proposed Mathematical Modeling-Based Layered Cellular Manufacturing System

The results of the cellular designs obtained are explained in detail in this section. Part family configuration is found using ALINK algorithm and 0.60 is used as the similarity coefficient value. Number of cells, demand coverage probabilities of the cells, and expected utilizations of each cell are obtained using the methodology developed by Süer and Ortega (1996). Then these values are used as inputs to the mathematical model.

Cell capacity is 2000 hours for cells working one shift, 4000 hours for cells working double shifts, and 6000 hours for cells working for three shifts. This means opening one more cell increases the capacity to process the demand of a part family by 2000 hours for one shift, and 4000 hours for double shifts, and 6000 hours for three shifts. In this study, in order to decrease the investment cost and machine costs, multiple shifts are used in the stages where the capacity requirements for the demand require opening too many manufacturing cells. In stages 1 and 3, single-shift is considered. In stage 2, two and three shifts are considered.

Table 4.18 shows demand coverage probabilities and expected cell utilization values for stage 1. Table 4.19 and Table 4.20 shows demand coverage probabilities and expected cell utilization values of stage 2 for two shifts and three shifts, respectively. Increasing number of shifts from two to three shifts decreased the number of opened cells from 16 to 10. Table 4.21 provide demand coverage probabilities and expected cell utilization values for stage 3. Mean capacity requirements and standard deviation of capacity requirements for each part family are also displayed in the tables.

Table 4.18 Cell configurations for minimum 95% demand coverage probability for part families at stage 1

10 Part Families	Mean Cap Req. (hr)	Std. Dev. of Cap Req (hr)	Demand Coverage Prob.			Expected Cell Utilization		
			Cell 1	Cell 2	Cell 3	Cell 1	Cell 2	Cell 3
PF1	1250.3	156.8	1.000			0.625		
PF2	1593.2	209.4	0.974			0.800		
PF3	1761.9	224.8	0.855	1.000		0.868	0.077	
PF4	1477.5	169.0	0.999			0.738		
PF5	2746.5	286.3	0.005	1.000		1.000	0.684	
PF6	767.6	137.6	1.000			0.384		
PF7	1932.8	242.4	0.609	1.000		0.932	0.212	
PF8	1422.5	161.4	1.000			0.711		
PF9	1283.7	186.0	1.000			0.642		
PF10	1139.2	172.6	1.000			0.570		

Table 4.19 Cell configuration for minimum 95% demand coverage probability for part families at stage 2 - Two shifts case

10 Part Families	Mean Cap Req. (hr)	Std. Dev. of Cap Req (hr)	Demand Coverage Prob.			Expected Cell Utilization		
			Cell 1	Cell 2	Cell 3	Cell 1	Cell 2	Cell 3
PF1	9082.5	1172.6	0.000	0.178	0.994	1.000	0.984	0.647
PF2	3705.0	479.6	0.731	1.000		0.907	0.144	
PF3	9540.0	1198.9	0.000	0.099	0.980	1.000	0.992	0.733
PF4	2319.0	297.0	1.000			0.580		
PF5	8913.0	1020.4	0.000	0.185	0.999	1.000	0.983	0.628
PF6	2967.0	741.8	0.918	1.000		0.733	0.044	
PF7	5230.5	933.9	0.094	0.998		0.994	0.610	
PF8	0.0	0.0						
PF9	5776.5	952.0	0.031	0.990		0.998	0.708	
PF10	1225.5	306.4	1.000			0.306		

Table 4.20 Cell configuration for minimum 95% demand coverage probability for part families at stage 2 - Three shifts case

10 Part Families	Mean Cap Req. (hr)	Std. Dev. of Cap Req (hr)	Demand Coverage Prob.			Expected Cell Utilization		
			1. Cell	2. Cell	3. Cell	1. Cell	2. Cell	3. Cell
PF1	9082.5	1172.6	0.004	0.994		1.000	0.758	
PF2	3705.0	479.6	1.000	1.000		0.617		
PF3	9540.0	1198.9	0.002	0.980		1.000	0.793	
PF4	2319.0	297.0	1.000	1.000		0.387	0.000	
PF5	8913.0	1020.4	0.002	0.999		1.000	0.740	
PF6	2967.0	741.8	1.000	1.000		0.494		
PF7	5230.5	933.9	0.795	1.000		0.849	0.111	
PF8	0.0	0.0	1.000	1.000		0.000	0.000	
PF9	5776.5	952.0	0.593	1.000		0.919	0.227	
PF10	1225.5	306.4	1.000	1.000		0.204	0.000	

Table 4.21 Cell configuration for up-to 100% and minimum 95% demand coverage probabilities for part families at stage 3

10 Part Families	Mean Cap Req. (hr)	Std. Dev. of Cap Req (hr)	Demand Coverage Probability				Expected Cell Utilization			
			Cell 1	Cell 2	Cell 3	Cell 4	Cell 1	Cell 2	Cell 3	Cell 4
PF1	3995.6	561.7	1.91E-04	0.503	1.000		1.000	0.943	0.368	
PF2	2938.0	374.8	6.17E-03	0.998			0.996	0.732		
PF3	3279.1	470.1	3.25E-03	0.937	1.000		1.000	0.815	0.044	
PF4	2404.1	284.1	7.75E-02	1.000			0.992	0.565		
PF5	3655.6	383.3	7.84E-06	0.816	1.000		1.000	0.904	0.129	
PF6	1913.5	341.1	0.600	1.000			0.908	0.224		
PF7	3289.5	414.3	9.28E-04	0.957	1.000		1.000	0.820	0.030	
PF8	3944.8	446.4	6.60E-06	0.549	0.9999	1.000	1.000	0.948	0.326	1.00E-14
PF9	3133.8	496.9	1.12E-02	0.959	1.000		1.000	0.776	0.028	
PF10	1530.6	225.3	0.981	1.000			0.766	0.010		

Table 4.21 shows demand coverage probabilities and expected cell utilization values for 10 part-family configuration for two different minimum demand coverage probabilities, up-to 100%, and 95%. As seen from the table, increasing minimum demand coverage probability from 95% to ~100% results in more cells to cover the minimum demand. For example, one cell is required for 95% demand coverage probability for PF10. If 100% demand coverage is desired, then one more cell needs to be opened.

Bold line in table shows the cutoff point between 95% minimum demand coverage probability and ~100% demand coverage probability for each part family. Highlighted numbers in the table show the cells to be opened if ~100% demand is covered. The expected cell utilizations of the cells which are opened after minimum 95% demand coverage probability are quite low in the ~100% demand coverage probability case. For example, the ECU of the first cell opened for part family 10 is 76.6%, and it covers 98.1% of the demand. However, when covering ~100% of the demand, a second cell is required and the ECU of the second cell for part family 10 is only 1%. This table shows the trade-off between covering more demand and number of cells required to cover that demand.

Similarly, lowering the minimum demand coverage probability decreases the number of cells opened to cover the demand. For example, if minimum demand coverage were chosen to be 75%, the third cell of PF3 and the third cell of PF5 would be unnecessary, since minimum demand would be covered after opening the second cells. This means that the number of cells to cover the minimum demand would be 2 less.

4.4.1 Analysis of Mathematical Model Results

The results of the mathematical model provide the cells opened for each part family, and part families assigned to each cell. Table 4.22, Table 4.23, Table 4.24 and Table 4.25, summarizes the results of mathematical model for 95% minimum demand coverage probability for stage 1, stage 2 with two shifts, stage 2 with three shifts and stage 3, respectively. Tables also provides total expected cell utilization values for the opened cells.

In stage 1, 8 dedicated, 1 shared and 1 remainder cells are opened. Total number of opened cells is 10. Maximum ECU value is 100% for cell 4, and minimum ECU value is 62.5% for cell 5.

In stage 2 with two shifts, 14 dedicated, 1 shared and 1 remainder cells are opened. Total number of opened cells is 16. Maximum ECU value is 100% for cells 2, 3, and 10, and minimum ECU value is 58% for cell 7.

In stage 2 with three shifts, 6 dedicated and 4 shared cells are opened. Total number of opened cells is 10. Maximum ECU value is 100% for cells 2, 7 and 8, and minimum ECU value is 61.8% for cell 1.

In stage 3, 15 dedicated, and 4 shared cells are opened. Total number of opened cells is 19. Maximum ECU value is 100% for many cells, and minimum ECU value is 36.8% for cell 6.

Table 4.22 Mathematical model results for minimum 95% demand coverage probability for stage 1

Part Families		**PF 1**	**PF 2**	**PF 3**	**PF 4**	**PF 5**	**PF 6**	**PF 7**	**PF 8**	**PF 9**	**PF 10**	**Total ECU (%)**	**Cell Type**
Cell(s)	**Cell numbers**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**		
Cell 1	PF4-i				1/0.738							73.8%	Ded.
Cell 2	PF3-i			1/0.868								86.8%	Ded.
Cell 3	SC-1						1/0.384				1/0.570	95.4%	SC
Cell 4	PF1-i	1/0.625										62.5%	Ded.
Cell 5	PF5-i					1/1.00						100.0%	Ded.
Cell 6	PF6-i								1/0.711			71.1%	Ded.
Cell 7	RC-1			2/0.077		2/0.684		2/.212				97.3%	RemC
Cell 8	PF2-i		1/0.800									80.0%	Ded.
Cell 9	PF7-i							1/0.932				93%	Ded.
Cell 10	PF9-i									1/0.642		64.2%	Ded.

Table 4.23 Mathematical model results for minimum 95% demand coverage probability for stage 2 for two shifts

Part Families		**PF 1**	**PF 2**	**PF 3**	**PF 4**	**PF 5**	**PF 6**	**PF 7**	**PF 8**	**PF 9**	**PF 10**	**Total Cell ECU (%)**	**Cell Types**
Cell(s)	**Cell numbers**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**		
Cell 1	PF9-i									1/0.998		99.8%	Ded.
Cell 2	PF1-i	1/1.00										100.0%	Ded.
Cell 3	PF3-i			1/1.00								100.0%	Ded.
Cell 4	PF5-ii					2/0.983						98.3%	Ded.
Cell 5	SC-1		2/0.144							2/0.708		85.2%	SC
Cell 6	PF6-ii							2/0.610				61.0%	Ded.
Cell 7	PF4-i				1/0.580							58.0%	Ded.
Cell 8	PF3-iii			3/0.733								73.3%	Ded.
Cell 9	RC-1	3/0.647					2/0.044				1/0.306	99.7%	RemC
Cell 10	PF5-i					1/1.00						100.0%	Ded.
Cell 11	PF5-iii					3/0.628						62.8%	Ded.
Cell 12	PF1-ii	2/0.984										98.4%	Ded.
Cell 13	PF2-i		1/0.907									90.7%	Ded.
Cell 14	PF3-iii			2/0.992								99.2%	Ded.
Cell 15	PF6-i						1/0.733					73.3%	Ded.
Cell 16	PF7-i							1/0.994				99.4%	Ded.

Table 4.24 Mathematical model results for minimum 95% demand coverage probability for stage 2 for three shifts

Part Families		**PF 1**	**PF 2**	**PF 3**	**PF 4**	**PF 5**	**PF 6**	**PF 7**	**PF 8**	**PF 9**	**PF 10**	**Total Cell ECU (%)**	**Cell Types**
Cell(s)	**Cell numbers**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**	**i^{th} cell/ ECU**		
Cell 1	PF2-i		1/0.618									61.8%	Ded.
Cell 2	PF1-i	1/1.00										100.0%	Ded.
Cell 3	PF9-i									1/0.919		91.9%	Ded.
Cell 4	SC-1					2/0.741					1/0.204	94.5%	SC
Cell 5	SC-2				1/0.387		1/0.495					88.2%	SC
Cell 6	SC-3			2/0.794				2/0.111				90.5%	SC
Cell 7	PF3-i			1/1.00								100.0%	Ded.
Cell 8	PF5-i					1/1.00						100.0%	Ded.
Cell 9	PF7-i							1/0.849				84.9%	Ded.
Cell 10	SC-4	2/0.758								2/0.227		98.5%	SC

Table 4.25 Mathematical model results for minimum 95% demand coverage probability for stage 3

Part Families		**PF 1**	**PF 2**	**PF 3**	**PF 4**	**PF 5**	**PF 6**	**PF 7**	**PF 8**	**PF 9**	**PF 10**	**Total ECU (%)**	**Cell Types**
Cell(s)	**Cell numbers**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**	**ith cell/ ECU**		
Cell 1	PF6-i						1/.908					90.8%	Ded.
Cell 2	PF4-i				1/.992							99.2%	Ded.
Cell 3	SC-1				2/.565				3/.326			89.1%	SC
Cell 4	PF3-ii			2/.815								81.5%	Ded.
Cell 5	SC-2		2/.732				2/.224					95.6%	SC
Cell 6	PF1-iii	3/.368										36.8%	Ded.
Cell 7	PF7-ii							2/.820				82.0%	Ded.
Cell 8	SC-3			3/.044					2/.948			99.2%	SC
Cell 9	PF1-i	1/1.00										100%	Ded.
Cell 10	PF5-ii					2/.904						90.4%	Ded.
Cell 11	PF1-ii	2/.943										94.3%	Ded.
Cell 12	PF7-i							1/1.00				100%	Ded.
Cell 13	PF5-i					1/.99999						100%	Ded.
Cell 14	PF3-i			1/.99999								100%	Ded.
Cell 15	PF2-i		1/.996									99.6%	Ded.
Cell 16	PF9-ii									2/.776		77.6%	Ded.
Cell 17	SC-4					3/.129					1/.766	89.5%	SC
Cell 18	PF8-i								1/1.00			100%	Ded.
Cell 19	PF9-i									1/1.00		100%	Ded.

Non-zero entry in row i and column j indicates expected utilization for cell i and family j. For example, the cell at the intersection of row of cell 17 and column of PF5 shows that it is the 3rd cell opened for PF5, and its expected utilization for PF5 is 12.9%. Total expected cell utilization for cell 17 is 89.5%, and the cell is a shared cell. Expected cell utilization values of dedicated cells are the values obtained from ECU tables. ECU values of shared and remainder cells are found by adding up the ECU values of all cells assigned to these cells.

Shared cell 3 of 10-PF configuration is formed by combining the third cell of PF3 and the second cell of PF8. In a classical cellular system, each of these cells would be dedicated cells of the aforementioned part families; hence each would have their own dedicated machines if separate cells were formed.

Cell 3 of PF3 needs 38 machines and expected cell utilization is 4.4%. Cell 2 of PF8 requires 34 machines and expected cell utilization is 94.8%. Total number of machines required for these two cells is 72. Layered cellular manufacturing system combines these two cells in a shared cell and reduces the number of machines drastically to 46.

The expected cell utilization of the newly formed shared cell in the layered system is 99.2%. These results are summarized in Table 4.26. By using layered system, the number of cells and machines are decreased, and a higher utilized shared cell is formed.

Table 4.26 Shared cell and dedicated cells comparison

Cell type	Part families	Utilization	required machines for dedicated cells	# of machines	total # of machines
Dedicated cells	PF 3	3/.044	10, 11, 12, 13, 15, 16, 17, 18, 19	38	
	PF 8	2/.948	10, 11, 12, 13, 14, 15, 17, 19	34	72
Shared Cell 3	PF3, PF8	0.992	10, 11, 12, 13, 14, 15, 16, 17, 18, 19	46	46

The number of machines required in a remainder cell is found by using a similar procedure. The number of machines required for each type in remainder cells is found by taking the maximum number of operators assigned to each operation among all part families. Table 4.27 shows the number of machines required in a cell that processes 4 different part families. Total number of machines in the remainder cell is 56, and total number of assigned operators to the remainder cell, i.e. cell size is 20. If dedicated cells were opened instead of a remainder cell for these 4 part families, the total number of machines would be (38+38+41+37) 154, and the number of operators assigned would be 80.

Table 4.27 Finding the total number of machines and cell size for a remainder cell

Cell type	Part family	Optimal Cell size	Op 10	Op 11	Op 12	Op 13	Op 14	Op 15	Op 16	Op 17	Op 18	Op 19	Total
Dedicated	PF1	20	0	5	6	6	5	3	5	4	1	3	38
Dedicated	PF3	20	0	5	6	6	0	4	6	7	1	3	38
Dedicated	PF5	20	2	8	7	5	4	3	7	5	0	0	41
Dedicated	PF10	20	5	5	7	0	6	4	0	5	0	5	37
Remainder	Cell 19	20	5	8	7	6	6	4	7	7	1	5	56

The mathematical model is run for 10-part family configuration for stage 1, stage 2 with two shifts, stage 2 with three shifts and stage 3. Table 4.28, Table 4.29, Table 4.30 and Table 4.31 show the part families assigned to the cells, optimal cell sizes, optimal number of operators assigned to each operation in each cell, total number of operators for each stage, and total number of machines required in cells for stage 1, stage 2 with two shifts, stage 2 with three shifts and stage 3, respectively.

The total number of machines for 10 cells of 10-part family configuration in stage 1 is 158, and the total number of machines for 16 cells of 10-part family configuration in stage 2 is 78 for two shifts and 56 for three shifts case. The number of machines in stage 2 is low because the only operation needed is one of 3 different types of plating operations, and parts can go through only one of them in stage 2. The total number of machines for 19 cells of 10-part family configuration in stage 3 is 702.

Table 4.28 Mathematical model results: number of machines in manufacturing cells for stage 1

Cells	**Part families**	**Optimal Cell size**	**Op 1**	**Op 2**	**Op 3**	**Op 4**	**Op 5**	**Op 6**	**Total # of machines**
Cell 1	4	12	0	0	3	3	3	5	14
Cell 2	3	12	4	6	0	0	0	6	16
Cell 3	6, 10	12	5	7	2	3	3	5	25
Cell 4	1	12	0	0	3	3	3	6	15
Cell 5	5	10	3	5	0	0	0	4	12
Cell 6	8	12	0	0	5	4	4	4	17
Cell 7	3, 5, 7	12	4	6	2	2	2	6	22
Cell 8	2	12	3	5	0	0	0	5	13
Cell 9	7	10	0	0	2	2	2	4	10
Cell 10	9	12	4	5	0	0	0	5	14
Total	**10 cells**	**116**	**23**	**34**	**17**	**17**	**17**	**50**	**158**

Table 4.29 Mathematical model results: number of machines in manufacturing cells for stage 2 for two shifts

Cells	**Part families**	**Optimal Cell size**	**Op 7**	**Op 8**	**Op 9**	**Total # of machines**
Cell 1	9	3	3	0	0	3
Cell 2	1	5	0	0	5	5
Cell 3	3	5	0	0	5	5
Cell 4	5	3	3	0	0	3
Cell 5	2, 9	3	3	3	0	6
Cell 6	7	3	3	3	0	6
Cell 7	4	3	3	3	0	6
Cell 8	3	5	0	0	5	5
Cell 9	1, 6, 10	5	3	3	5	11
Cell 10	5	3	3	0	0	3
Cell 11	5	3	3	0	0	3
Cell 12	1	5	0	0	5	5
Cell 13	2	3	0	3	0	3
Cell 14	3	5	0	0	5	5
Cell 15	6	3	3	0	0	3
Cell 16	7	3	3	3	0	6
Total	**16 cells**	**60**	**30**	**18**	**30**	**78**

Table 4.30 Mathematical model results: number of machines in manufacturing cells for stage 2 for three shifts

Cells	**Part families**	**Optimal Cell size**	**Op 7**	**Op 8**	**Op 9**	**Total**
Cell 1	2	3	0	3	0	3
Cell 2	1	5	0	0	5	5
Cell 3	9	3	3	0	0	3
Cell 4	5, 10	3	3	3	0	6
Cell 5	4, 6	3	3	3	0	6
Cell 6	3, 7	5	3	3	5	11
Cell 7	3	5	0	0	5	5
Cell 8	5	3	3	0	0	3
Cell 9	7	3	3	3	0	6
Cell 10	1, 9	5	3	0	5	8
Total	**10 cells**	**38**	**21**	**15**	**20**	**56**

Table 4.31 Mathematical model results: number of machines in manufacturing cells for stage 3

Cell	**Part families**	**Optimal cell size**	**Op 10**	**Op 11**	**Op 12**	**Op 13**	**Op 14**	**Op 15**	**Op 16**	**Op 17**	**Op 18**	**Op 19**	**Total # of machines**
Cell 1	3	20	0	5	6	6	0	4	6	7	1	3	38
Cell 2	9	18	0	6	5	5	2	4	2	0	1	3	28
Cell 3	4	20	3	9	6	0	5	2	5	7	4	0	41
Cell 4	3	20	0	5	6	6	0	4	6	7	1	3	38
Cell 5	6	18	2	0	6	5	2	2	3	2	1	4	27
Cell 6	8	20	3	5	5	6	5	3	0	4	0	3	34
Cell 7	8	20	3	5	5	6	5	3	0	4	0	3	34
Cell 8	7	18	2	4	0	6	0	3	4	4	0	4	27
Cell 9	10	20	5	5	7	0	6	4	0	5	0	5	37
Cell 10	4, 8	20	3	9	6	6	5	3	5	7	4	3	51
Cell 11	5	20	2	8	7	5	4	3	7	5	0	0	41
Cell 12	1	20	0	5	6	6	5	3	5	4	1	3	38
Cell 13	1	20	0	5	6	6	5	3	5	4	1	3	38
Cell 14	7	18	2	4	0	6	0	3	4	4	0	4	27
Cell 15	2	20	0	4	6	6	3	3	3	3	0	4	32
Cell 16	5	20	2	8	7	5	4	3	7	5	0	0	41
Cell 17	9	18	0	6	5	5	2	4	2	0	1	3	28
Cell 18	2, 10	20	5	5	7	6	6	4	3	5	0	5	46
Cell 19	1, 3, 5, 6	20	5	8	7	6	6	4	7	7	1	5	56
Total	**19 cells**	**370**	**37**	**106**	**103**	**97**	**65**	**62**	**74**	**84**	**16**	**58**	**702**

These tables also provide the required number of workers for each cell and each stage. In stage 1, a total of 116 operators are needed to perform the operations. The most common cells sizes are 10 and 12 operators for stage 1. In stage 2, a total of 60 workers are required for 16 cells for two shift case, and the most common cell sizes are 3 and 5. For three shift case, a total of 38 workers are required for 10 cells, and the most common cell sizes are 3 and 5 once again.

Number of cells decreased from 16 cells to 10 cells when the number of shifts increased from 2 shifts to three shifts in stage 2. In stage 3, a total of 370 operators are required for 19 cells, and the most common cell sizes are 18 and 20.

The data obtained from the mathematical model in this chapter and Chapter 3 will be used as inputs in Chapter 5.

4.5 Conclusions

In this chapter of dissertation, a mathematical model is used to design a layered cellular manufacturing system in a highly fluctuated demand environment. In classical cellular manufacturing, part families are processed in dedicated cells only, and a cell can process only one part family. However, in layered cellular manufacturing system, one cell can process more than one part family, and a part family can be processed in many cells. In both designs, cells are assumed to be independent, i.e., cells cover all of the operations needed for the product. Cells processing two part families are called shared cells, and cells processing more than two part families are called remainder cells.

Mathematical model aims to minimize the number of cells opened for the cellular system, hence provides number of machines data for each part family configuration. In order capture the performance of the system with cell utilization values, simulation models are developed for the system designed by using the mathematical model in Chapter 5. The system is fine tuned in order to approximate the cell utilization values of the simulation models to those of mathematical model.

Shifting bottleneck machines for each cell instead of using a static bottleneck machine are used in this section. Machine duplication is introduced to layered cellular manufacturing system by using the heuristic procedure developed and the mathematical model used in the previous section. Double/triple shifts are also introduced where the demand requires opening too many cells, which makes the cellular system more cost effective considering the reduction in space and number of machines required.

5 MANUFACTURING SYSTEM DESIGN MODELING

The results of the mathematical model show which cells are opened and which coverage segment of the each part family is assigned to those opened cells, but the results do not give any information about the operational aspects of the system. Since a new cellular manufacturing system is designed based on the results of the mathematical model, the behavior and performance of that system need to be analyzed. Simulation models replicates the system designed without actually investing on machines and equipment. It allows assessing the effects of changes in input parameters on the designed system over a period of time.

Stochastic parameters such as probabilistic demand and processing times can be used in the simulation models. Using probabilistic values leads to a more realistic system. The most important factor that shows the quality of the simulation models is their accuracy in representing the actual system to be simulated. Simulation models that do not resemble the actual system do not provide accurate information to decision makers.

In this chapter, simulation models are developed for the cellular manufacturing systems designed with the mathematical model in Chapter 4. The mean and standard deviation of highly fluctuating demand data is used as input to the simulation models. Other inputs for the simulation, such as number of cells, part families assigned to cells, machines that form the cells and the type of cells are obtained from the mathematical model results.

The entire demand for all of the product families are processed in one manufacturing plant in the single stage manufacturing system. Similarly, for the multi-stage manufacturing, each stage is considered to take place at a different plant. In other words, it is assumed that three plants are opened for three stages.

The simulation models are mainly used for two purposes here; 1) to compare the proposed cellular designs using performance measures, and 2) to fine tune the operational parameters of the systems, so that theoretical expected cell utilization values determined based on mathematical model can be obtained on the shop floor.

The steps for developing the simulation models for single stage and multi-stage cellular manufacturing system are explained in detail in the following sections. Since, multi-stage manufacturing system consists of three manufacturing stages, simulation models are developed for each stage, except for stage 2.

Figure 5.1 shows the product flow and logic of the entire simulation models developed. It is assumed that no setup is required for the products. Each product arrives at the system with an arrival distribution. Products are grouped in product families first, then they are sent to respective cells to be processed using a decision rule. Products leave the system after they are processed in the cells.

The models are developed in Arena simulation software. Simulation models are run for 8 hours per day, 5 days per week and 50 weeks per year, which is 2000 hours for one shift cases. For two shift cases, number of hours worked is considered as 16 hours per day, hence 4000 hours per year. For three shift cases, number of hours worked is considered as 24 hours per day, hence 6000 hours per year.

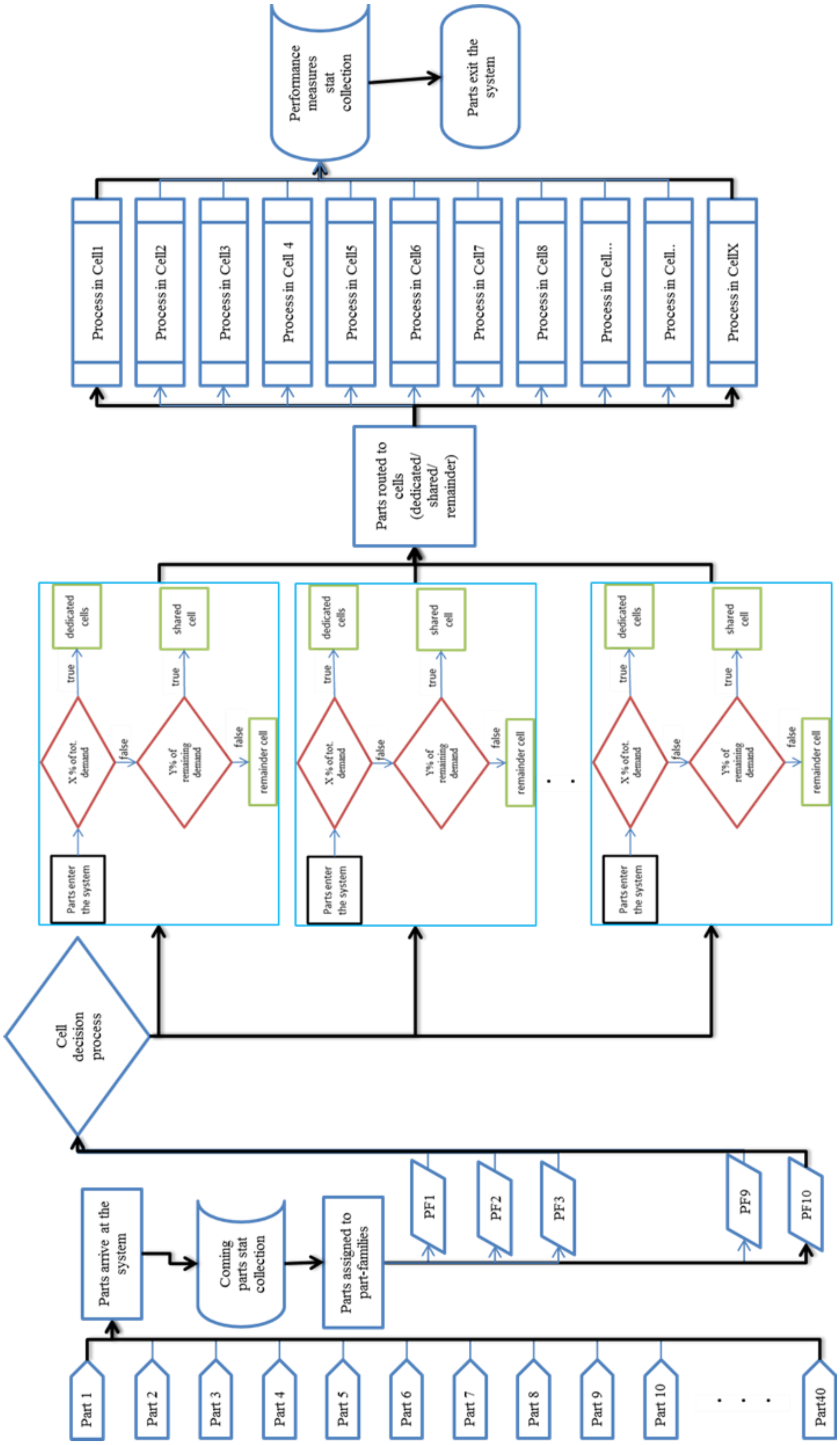


Figure 5.1 Flow of parts in the proposed simulation model

Since the simulation model of cellular system is empty at the initial status, the parts flow faster and utilization values are less than a working system. A warm-up period is required to clear the statistics and to have a steady system flow. A warm-up period analysis is performed for the simulation model developed, which is described later in this chapter. Total simulation run time is the total of warm-up period and annual operation time, which depends on number of shifts worked per day.

The simulation models developed for single stage and multi-stage manufacturing have three main sub-sections: 1) product arrival, 2) cell assignment, and 3) cell process. Cell process sub models are as many as the number of cells opened for the manufacturing system.

Figure 5.2 shows the product arrival, cell assignment and cell process sub-sections for the simulation model of stage of multi-stage manufacturing. As shown in the model, there are 16 cell process sub-models since there are 16 cells in the cellular manufacturing system designed for stage 1. Any of these cells can be dedicated, shared or remainder cells. Products exit the system after cell process sub-models.

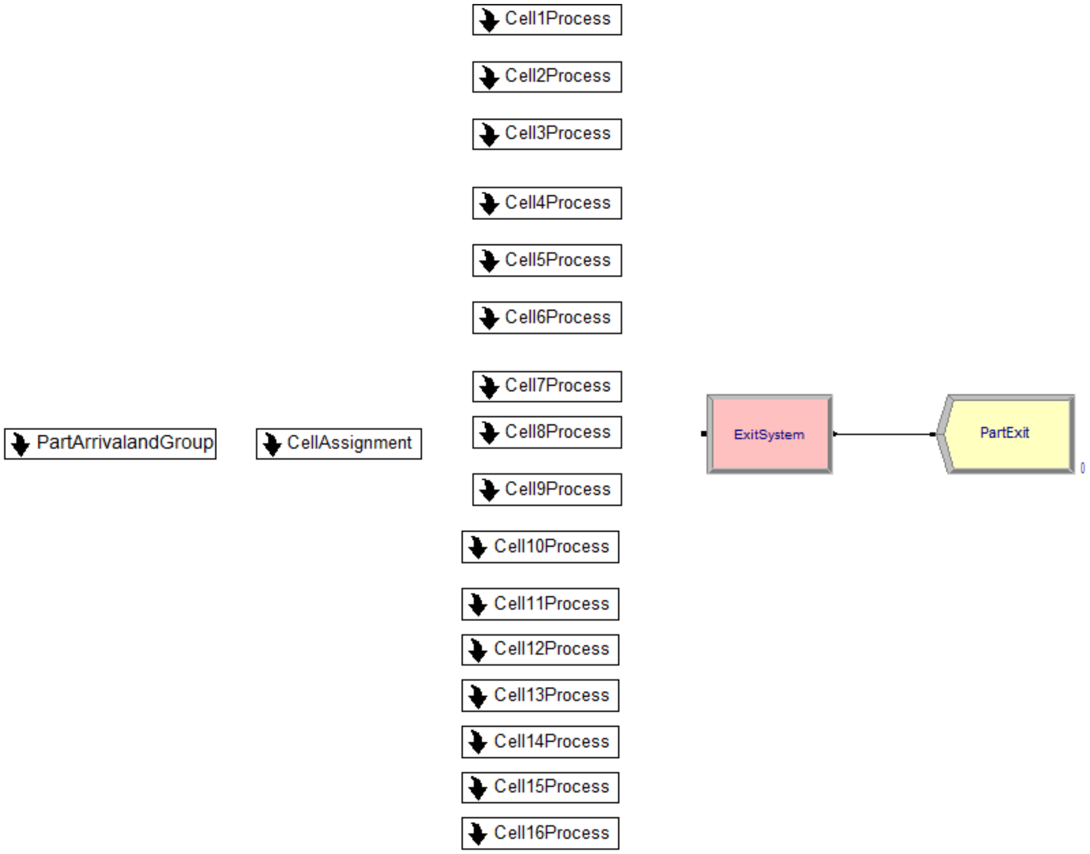


Figure 5.2 Simulation model for the manufacturing system at stage 1

5.1 Product Arrival and Product Family Assignment

The entities in Arena simulation software represent products in the models developed in this dissertation. There are 40 products in the single stage and multi-stage manufacturing systems designed. Figure 5.3 shows products arriving in the system and then being assigned to product families using a decide module.

Products arrive at the system with an arrival distribution using their mean demand and standard deviation. The methodology used to obtain the arrival distributions is explained in input data analysis section later in this chapter. Then these products are assigned to part families formed in Chapter 3.

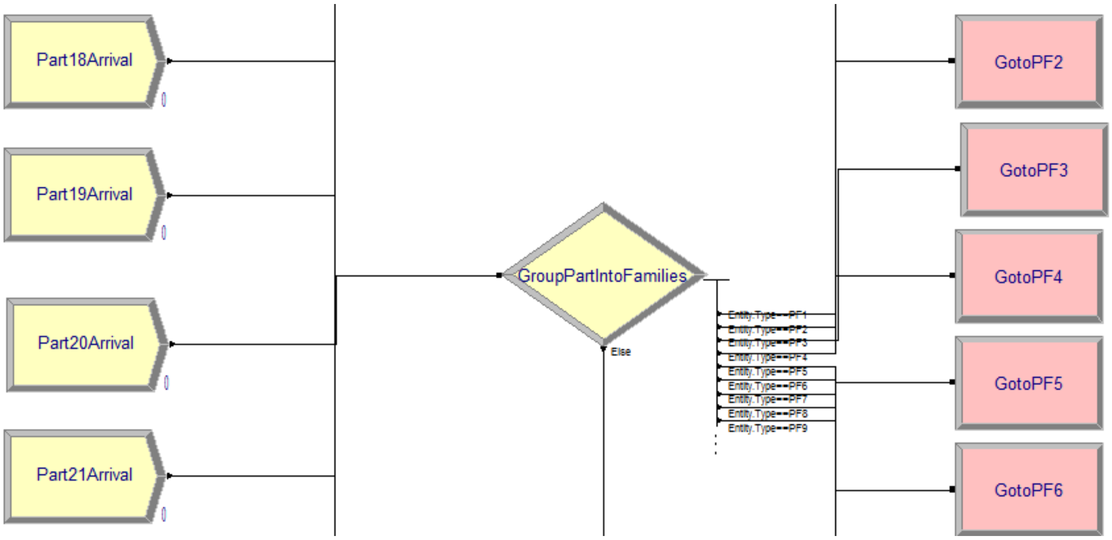
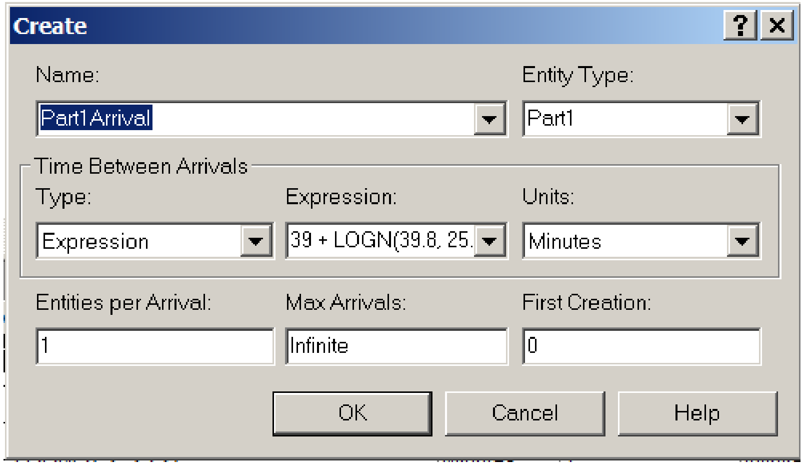


Figure 5.3 Product arrival and assignment to product families in simulation models

The arrival distributions are used in the “Expression” section of “Time Between Arrivals” part of the Create module in the Arena model. Figure 5.4 shows the arrival distribution and other parameters used in the Create module of Product 1 in the Arena model that is developed for stage 1 of multi-stage manufacturing system. Entities per Arrival shows the number of products arrive at the system at once according to the arrival distribution. Max Arrivals is infinite, i.e., there is no limit on the number of products arriving to the system. First creation is at time 0, i.e., the first product enters at system as soon as the model runs.



Create

Name: Part1 Arrival

Entity Type: Part1

Time Between Arrivals

Type: Expression

Expression: 39 + LOGN(39.8, 25.

Units: Minutes

Entities per Arrival: 1

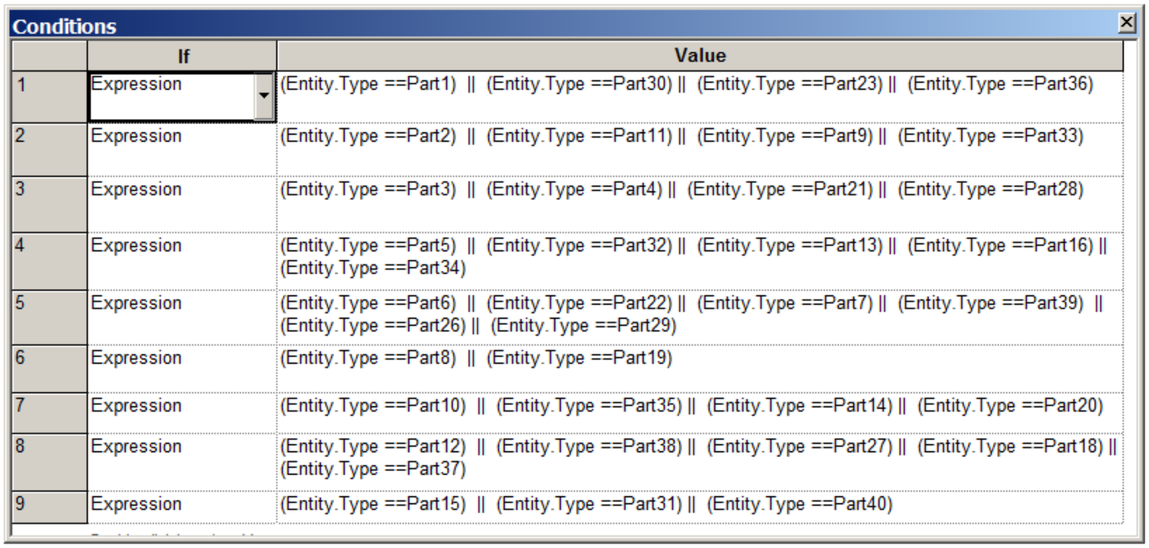
Max Arrivals: Infinite

First Creation: 0

Figure 5.4 Create module for Product 1 in the Arena model developed for stage 1

After products enter in the system, they are assigned to product families using a decide module. For each product family, an expression which has all of the products in the product family is created. Then these products are sent to respective product families with route modules.

Figure 5.5 shows an example of the decide modules used to assign products to product families in the simulation models. The first expression states that if the product entering the system is Part 1, Part 30, Part 23 or Part 36, it goes to product family 1. Similarly, other expressions direct the parts to respective product families using the same logic.



	If	Value
1	Expression	(Entity.Type ==Part1) || (Entity.Type ==Part30) || (Entity.Type ==Part23) || (Entity.Type ==Part36)
2	Expression	(Entity.Type ==Part2) || (Entity.Type ==Part11) || (Entity.Type ==Part9) || (Entity.Type ==Part33)
3	Expression	(Entity.Type ==Part3) || (Entity.Type ==Part4) || (Entity.Type ==Part21) || (Entity.Type ==Part28)
4	Expression	(Entity.Type ==Part5) || (Entity.Type ==Part32) || (Entity.Type ==Part13) || (Entity.Type ==Part16) || (Entity.Type ==Part34)
5	Expression	(Entity.Type ==Part6) || (Entity.Type ==Part22) || (Entity.Type ==Part7) || (Entity.Type ==Part39) || (Entity.Type ==Part26) || (Entity.Type ==Part29)
6	Expression	(Entity.Type ==Part8) || (Entity.Type ==Part19)
7	Expression	(Entity.Type ==Part10) || (Entity.Type ==Part35) || (Entity.Type ==Part14) || (Entity.Type ==Part20)
8	Expression	(Entity.Type ==Part12) || (Entity.Type ==Part38) || (Entity.Type ==Part27) || (Entity.Type ==Part18) || (Entity.Type ==Part37)
9	Expression	(Entity.Type ==Part15) || (Entity.Type ==Part31) || (Entity.Type ==Part40)

Figure 5.5 Decide module expressions for product assignment to product families

5.2 Decision Making Process for Parts Entering the System

After the parts are assigned to part families, they are transferred to the cells to be processed. Since each part family can be processed in more than one cell, a decision needs to be made before transferring the parts to the cells. For example, in the simulation model built for 10-part family configuration, part-family 3 requires two dedicated cells, Cell 14 and Cell 4, and a shared cell, Cell 8. When any part from part family 3 enters in the system, any of these three cells is a candidate cell for this part. Expected cell utilization values for those part families are used as initial parameters in order to make this decision. When a part from part-family 3 enters the system, a certain percent of the demand of the part family is directed to Cell 14. The remaining portion of the demand is directed to the other dedicated cell, cell 4, and the shared cell, cell 8. Another decision needs to be made before transferring remaining portion of the demand of the parts to these cells. A certain percent of the demand is directed to Cell 4, and Cell 8 processes the rest of the demand. Figure 5.6 shows this decision making process.

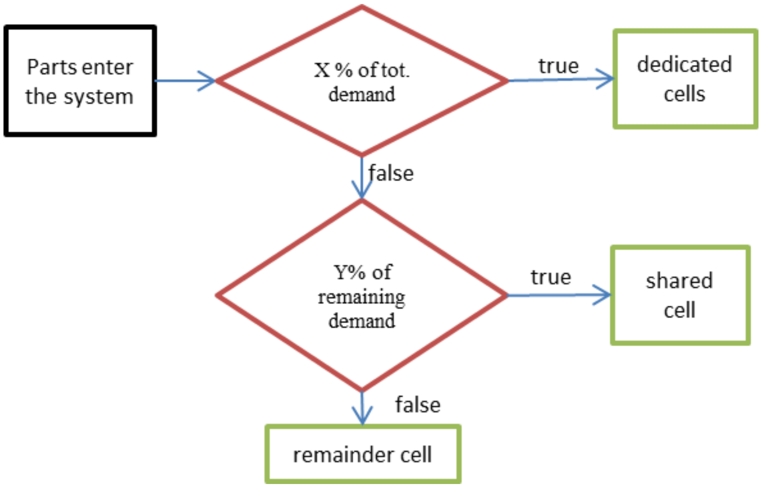


Figure 5.6 General decision making process for parts entering the system

The real situation is, however, more complex. If the cell processes only one part-family, i.e., the cell is a dedicated cell, and the manufacturing system consists of dedicated cells only, the modified initial utilization percentages may produce close utilization values to the theoretical utilization values obtained from the mathematical model results. But, in a layered cellular manufacturing system, multiple cells may be assigned to each part family, and multiple part families may be processed in each cell. Parts from many different part families, not from a single part family, arrive at decision points continuously. Since each part has a different process order, hence different cells to go, a decision needs to be made for each part separately. If three parts from different part families come to a certain cell, parts are directed with their part family's percentages to their respective cells. Figure 5.7 shows this procedure for three part families in the simulation model developed for stage 1 of multi-stage manufacturing. Product family 5 is processed in two cells, cell 5 and cell 7. When a product of product family 5 enters in the system, the decision module “Dec5For5n7” directs the product to these cells based on percent utilization. Similar procedure is followed for product family 7 which is processed in cells 9 and 7. Product family 6 is processed in cell 3 only, hence does not require a decision module.

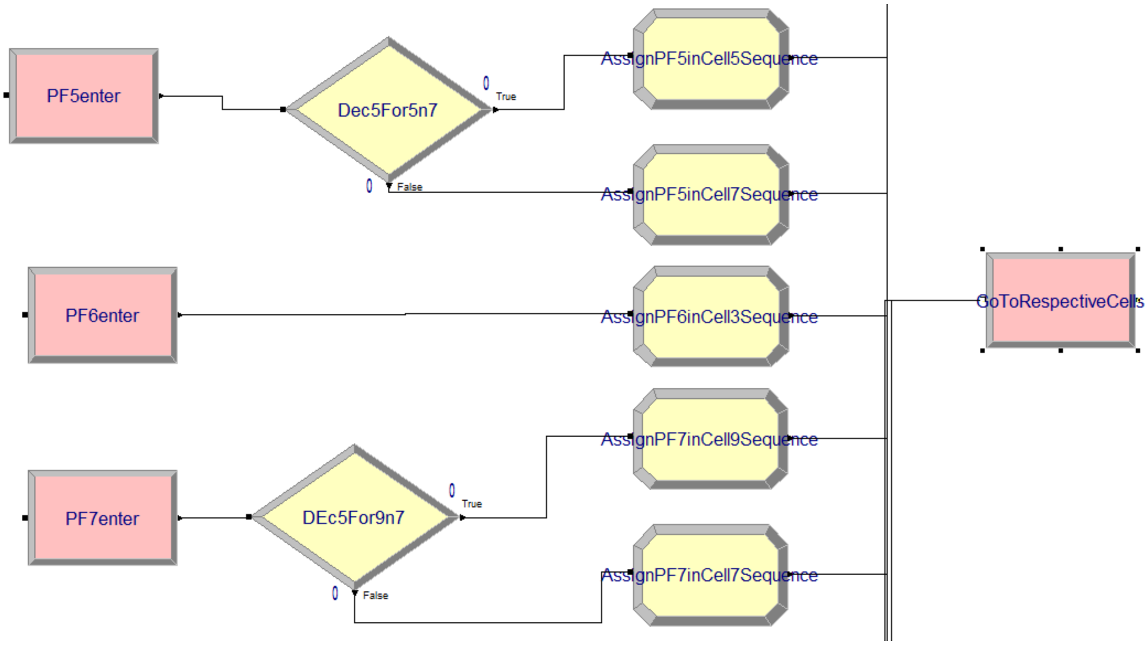
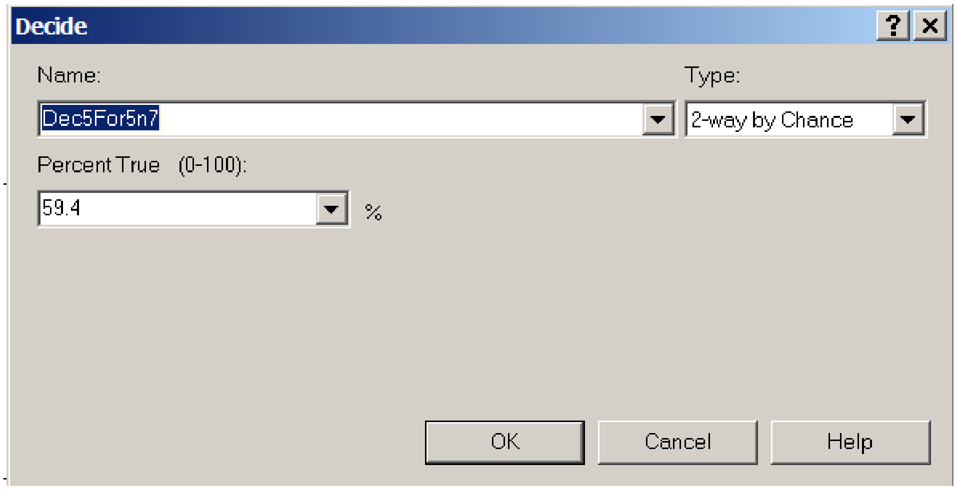


Figure 5.7 Assigning product families to cells in Arena simulation model

The goal is to approximate the cell utilization values retrieved from the results produced by the simulation models to the theoretical expected cell utilizations calculated from mathematical model results. This is achieved by altering the percent of the demand to be processed in cells at the decision points where a part family requires more than one cell, which is achieved using decide modules. Figure 5.8 shows a decide module example that directs the 59.4% of the demand to the respective cell, which is cell 5 in this case.



Name: Dec5For5n7

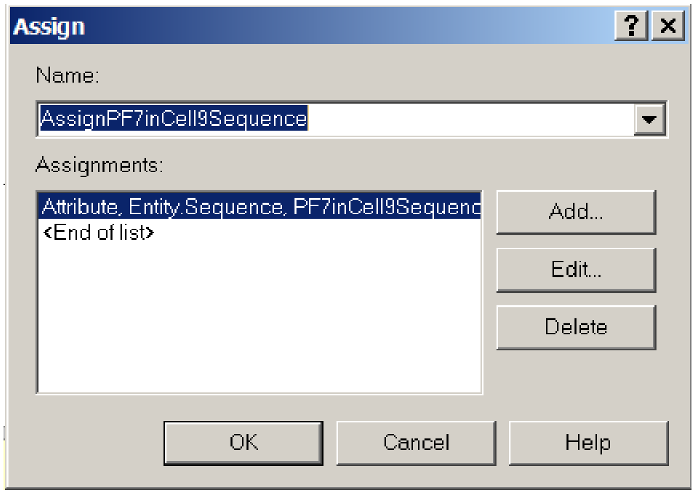
Type: 2-way by Chance

Percent True (0-100): 59.4 %

Figure 5.8 Directing products to cells by decide modules in Arena simulation models

Initially, ECU values are used as percentages to direct the parts to the appropriate cells, and then these values are altered to obtain approximate cell utilization values close to the theoretical ECU values. Each part family may need shared and remainder cells which process two or more part families. This means that increasing or decreasing the percentages results in changes in more than one cell, sometimes in a large part of the entire system. This sensitivity of the other cells to changes in the percentages of the demand does not always allow exactly replicating the utilization values to the expected cell utilizations calculated from mathematical model results.

After the product families are directed with certain percentage of demands to the cells, a sequence is assigned to transfer the products to the designated cells. A sequence determines the order of required machines to finish the product in the respective cells. Every product has its own machine sequence in each cell it is processed. For example, if a product is processed in three different cells, a sequence is created for each cell for that product in the simulation model. These sequences show the order of operations/machines in cells and the processing times of the products at machines. Figure 5.9 shows the Assign module used to assign sequences to the product families. Here, product family 7 is assigned its operation sequence in cell 9.



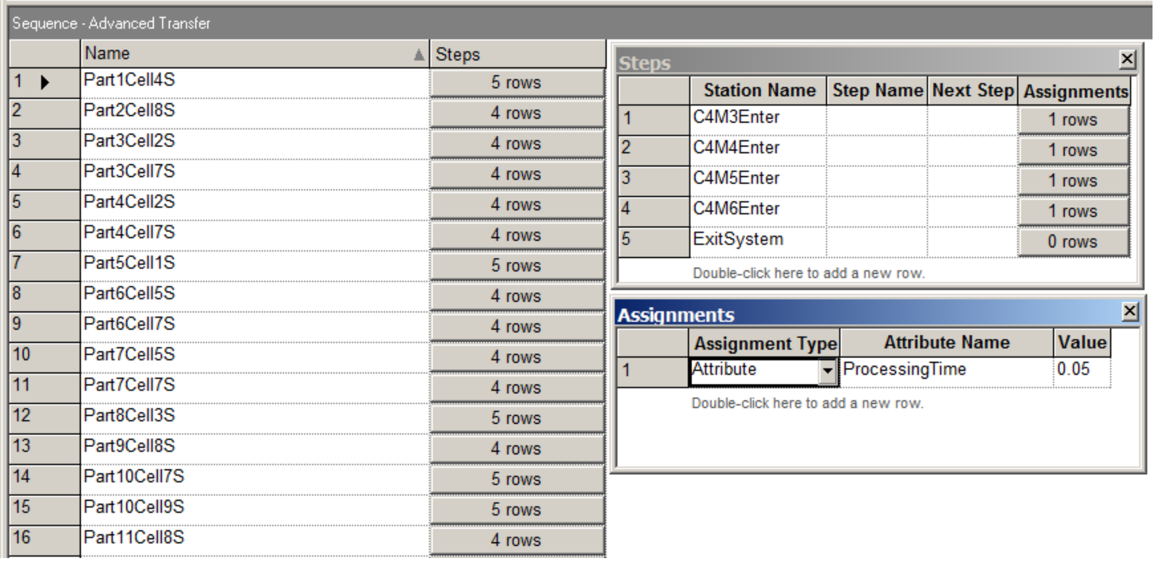
Name:
AssignPF7inCell9Sequence

Assignments:
Attribute, Entity.Sequence, PF7inCell9Sequenc
<End of list>

Figure 5.9 Assign module to assign sequences to product families

Figure 5.10 shows part of the sequences created in the simulation model of stage 1 of multi-stage manufacturing. Here, Part1 is processed in one cell: Cell 4. The right upper side of the figure shows the sequence of operations for Part1 in Cell 4. The right lower side of the figure shows that the processing time of Part1 in Machine 3 of Cell 4 is

0.05 minute. After assigning sequences to products, the entities are routed to the cells to be processed.



Sequence - Advanced Transfer

	Name	Steps
1	Part1Cell4S	5 rows
2	Part2Cell8S	4 rows
3	Part3Cell2S	4 rows
4	Part3Cell7S	4 rows
5	Part4Cell2S	4 rows
6	Part4Cell7S	4 rows
7	Part5Cell1S	5 rows
8	Part6Cell5S	4 rows
9	Part6Cell7S	4 rows
10	Part7Cell5S	4 rows
11	Part7Cell7S	4 rows
12	Part8Cell3S	5 rows
13	Part9Cell8S	4 rows
14	Part10Cell7S	5 rows
15	Part10Cell9S	5 rows
16	Part11Cell8S	4 rows

Steps

	Station Name	Step Name	Next Step	Assignments
1	C4M3Enter			1 rows
2	C4M4Enter			1 rows
3	C4M5Enter			1 rows
4	C4M6Enter			1 rows
5	ExitSystem			0 rows

Double-click here to add a new row.

Assignments

	Assignment Type	Attribute Name	Value
1	Attribute	ProcessingTime	0.05

Double-click here to add a new row.

Figure 5.10 Product family sequences in spreadsheet view of Sequence module

5.3 Cell Process Stage

Figure 5.11 shows Cell Process sub-model for Cell 1 in the simulation model. Each simulation model has these sub models as many as the number of cells in the manufacturing system.

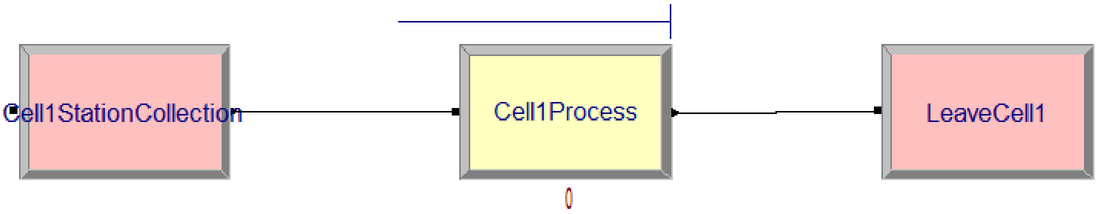
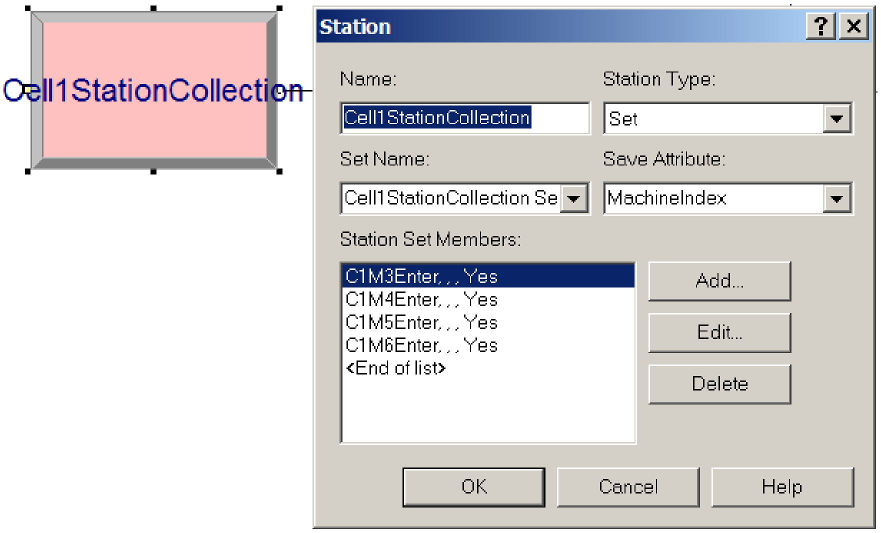


Figure 5.11 Cell process phase for Cell 1 in the simulation models developed

Products go through the machines listed in the operation sequences which are defined in cells. Each cell is developed in the ability to process an entire product family.

Cell process phase consists of three modules; Station module, Process module, and Route module. After the sequences are assigned to products with assign module in the previous stage, the products are sent to Cell1StationCollection station. Figure 5.12 shows the station module for Cell 1 and the machines found in the Cell 1 can be seen at Station Set Members section of the module. There are four machines in cell 1, namely machines 3, 4, 5 and 6, as listed in the Station Set Members section. Products entering cell 1 are processed with these machines according to their sequences in cell 1.



Name: Cell1StationCollection

Station Type: Set

Set Name: Cell1StationCollection Se

Save Attribute: MachineIndex

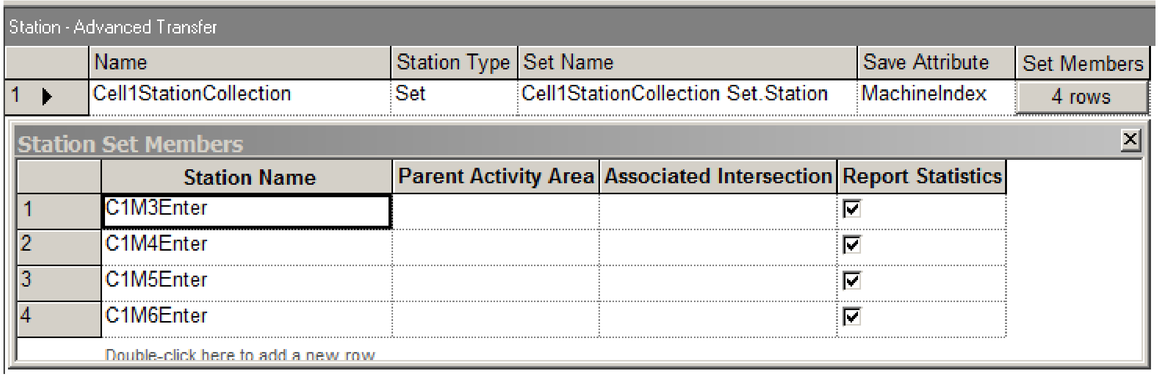
Station Set Members:

C1M3Enter, , , Yes
C1M4Enter, , , Yes
C1M5Enter, , , Yes
C1M6Enter, , , Yes
<End of list>

Figure 5.12 Station module in the cell process stage

The station type of this Station module, “Set”, allows saving attributes like “MachineIndex”. The MachineIndex attribute lists the names of the machines found in the cell as resources to use to process the products. Figure 5.13 presents the members of

Cell 1 in the simulation model developed for stage 1 of multi-stage manufacturing system. As seen from the figure, there are 16 cells in the manufacturing system. Cell 1 set has 4 machines defined in the Cell1StationCollection Set.



Station - Advanced Transfer

	Name	Station Type	Set Name	Save Attribute	Set Members
1 ▶	Cell1StationCollection	Set	Cell1StationCollection Set.Station	MachineIndex	4 rows

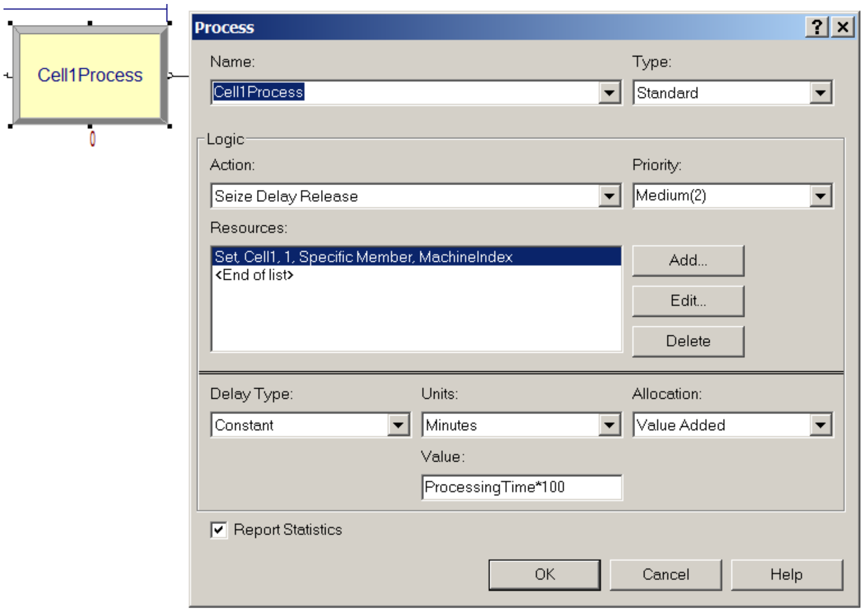
Station Set Members

	Station Name	Parent Activity Area	Associated Intersection	Report Statistics
1	C1M3Enter			☑
2	C1M4Enter			☑
3	C1M5Enter			☑
4	C1M6Enter			☑

Double-click here to add a new row

Figure 5.13 Machines defined in the Station module of cell process stage

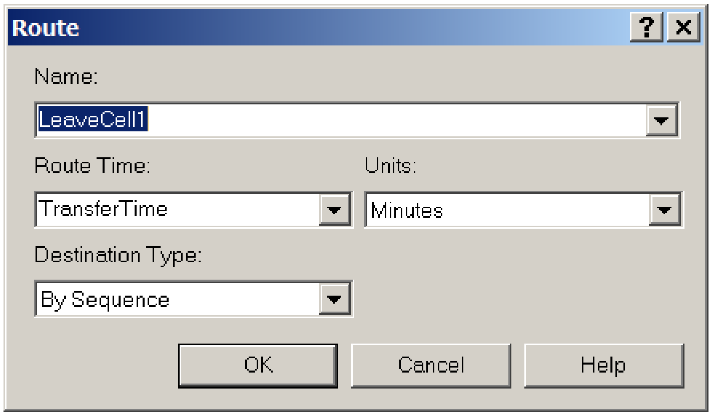
Products move to the Process module after leaving Station module. In the process module, assigned machine seizes the product, delays the part for the processing time of the product at that machine, and releases the product when the processing time is over. The product is transferred to the next station to be processed in another machine. The products are processed by a machine that is selected using Specific Member rule form the MachineIndex set. No priority is given to any product in the models. The processing times are constant, i.e, they are deterministic and they do not follow any distribution. Figure 5.14 shows the process module of Cell 1 from the simulation model developed for stage 1.



Name: Cell1Process
Type: Standard
Action: Seize Delay Release
Priority: Medium(2)
Resources:
Set, Cell1, 1, Specific Member, MachineIndex
<End of list>
Delay Type: Constant
Units: Minutes
Allocation: Value Added
Value: ProcessingTime*100
☑ Report Statistics

Figure 5.14 Process module of a simulation model

The products are sent to ExitSystem station via LeaveCellX route from cell process sub-models as shown in Figure 5.15.



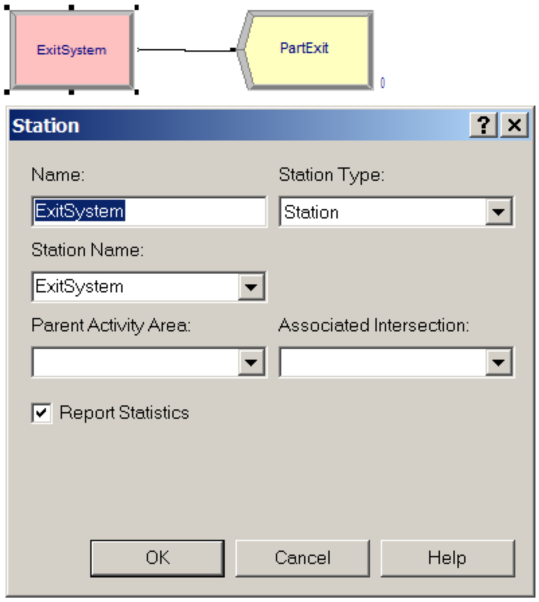
Name: LeaveCell1
Route Time: TransferTime
Units: Minutes
Destination Type: By Sequence

Figure 5.15 LeaveCell route module

5.4 Disposal of Products from the System

The products are channeled to ExitSystem station before disposal to gather statistics about the entities leaving the system. A PartExit dispose module follows the ExitSystem station module. These two elements are presented in Figure 5.16.

These statistics are used to evaluate the performance of the manufacturing systems designed with respect to desired performance measures. This is the last module before the products are disposed from the simulation model.



Station

Name: ExitSystem

Station Type: Station

Station Name: ExitSystem

Parent Activity Area:

Associated Intersection:

☑ Report Statistics

Figure 5.16 Disposal of entities from simulation models

5.5 Input Data Analysis with Arena Input Analyzer

Using the weekly demand for unit inter-arrival rates causes simulation run-time and memory problems for the computers. Therefore, a different unit arrival approach, where a unit in the Arena Simulation software represents 100 products, is used to resolve this issue. The weekly product demand for each product is divided by 100 to obtain the transformed quantities. Unit processing times at the cell process modules are multiplied by 100 in order to keep the total processing time of the products same in the model. Table 5.1 shows the original and transformed demand values for all products.

Table 5.1 Original and transformed demand values for all products

Products	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Original demand values	3300	4300	3400	3600	4900	3700	4200	3800	3800	4600
Transformed demand values	33	43	34	36	49	37	42	38	38	46

Products	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
Original demand values	2900	4900	4000	4100	3300	2600	3700	3700	4600	4400
Transformed demand values	29	49	40	41	33	26	37	37	46	44

Products	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30
Original demand values	3200	4300	4100	4300	3600	3800	4700	3300	3700	4500
Transformed demand values	32	43	41	43	36	38	47	33	37	45

Products	P31	P32	P33	P34	P35	P36	P37	P38	P39	P40
Original demand values	4200	2900	3000	2900	5000	3700	3500	3800	3100	3000
Transformed demand values	42	29	30	29	50	37	35	38	31	30

Each product has its own mean demand and standard deviation. Products arrive at the cellular system following their own arrival distributions. In order to find the arrival distribution of the parts, first 5000 weekly demand values are generated using the products' means and standard deviations, which follow normal distribution. Second, inter-arrival rates are calculated for each product using the total number of hours available for production and generated weekly demand values. Equation 6.1 shows this calculation.

$$\text{Inter-arrival rate} = \text{Total number of hours available for production} / \text{Quantities demanded} \tag{6.1}$$

Arena Input Analyzer is used to find the best distribution that fits the inter-arrival times calculated by using the generated demand values. Out of 40 products, lognormal distribution is the best fitted distribution for 39 products. The only exception is for Product 39, which has Erlang distribution as the best fitted distribution. Even for Product 39, lognormal distribution is a good fit. Therefore, for all products, lognormal distribution is used for inter-arrival times. Appendix C shows input data analysis for product 1 using Arena Input Analyzer. Table 5.2 presents inter-arrival distributions for all parts.

5.6 Warm-up Period Analysis

A warm-up period analysis is done to avoid the effects of "empty" models on performance measures. Running a simulation model without a warm-up period is like having a manufacturing system that started to function for the first time. For example, the utilization of a resource in a simulation run without a warm-up period would be less than the utilization of that resource with a warm-up period.

Table 5.2 Arrival distributions for products

Product	Arrival distribution	Product	Arrival distribution
P1	39 + LOGN(39.8, 25.9)	P21	40 + LOGN(41.3, 26.4)
P2	30 + LOGN(30.7, 20.5)	P22	30 + LOGN(30.7, 20.5)
P3	38 + LOGN(38.6, 25.4)	P23	31 + LOGN(32.4, 20.5)
P4	35 + LOGN(37.2, 23.2)	P24	30 + LOGN(30.7, 20.5)
P5	26 + LOGN(27.1, 17.2)	P25	35 + LOGN(37.2, 23.2)
P6	35 + LOGN(35.4, 23.2)	P26	34 + LOGN(34.5, 22.5)
P7	30 + LOGN(31.9, 19.8)	P27	27 + LOGN(28.3, 17.9)
P8	34 + LOGN(34.5, 22.5)	P28	39 + LOGN(39.8, 25.9)
P9	34 + LOGN(34.5, 22.5)	P29	35 + LOGN(35.4, 23.2)
P10	28 + LOGN(28.6, 18.6)	P30	28 + LOGN(29.8, 18.6)
P11	44 + LOGN(45.7, 29.1)	P31	30 + LOGN(31.9, 19.8)
P12	26 + LOGN(27.1, 17.2)	P32	44 + LOGN(45.7, 29.1)
P13	32 + LOGN(33, 21.2)	P33	43 + LOGN(43.7, 28.5)
P14	31 + LOGN(32.4, 20.5)	P34	44 + LOGN(45.7, 29.1)
P15	39 + LOGN(39.8, 25.9)	P35	26 + LOGN(26.1, 17.3)
P16	50 + LOGN(50.5, 34.4)	P36	35 + LOGN(35.4, 23.2)
P17	35 + LOGN(35.4, 23.2)	P37	36 + LOGN(38.2, 23.8)
P18	35 + LOGN(35.4, 23.2)	P38	34 + LOGN(34.5, 22.5)
P19	28 + LOGN(28.6, 18.6)	P39	42 + LOGN(42, 28)
P20	29 + LOGN(30.1, 19.1)	P40	43 + LOGN(43.7, 28.5)

The time required for the simulation model to reach the steady state is called warm-up period. Some of the resources are not used until the system reaches steady state since the model starts with an empty system. Warm-up time is required for simulation models to show their true potential on these resources. This time needs to be determined by analyzing the statistics gathered from the model runs.

Arena set-up dialog box is used to change the replication parameters for the simulation models. Some of the parameters are number of replications, warm-up period, replication length, and time units. For warm-up period analysis, the number of replications is set to 10, warm-up period length is set to 0, replication length is set 20000 minutes, and hours per day is set to 8 hours.

The performance measures and system characteristics used to analyze the warm-up period are average machine utilizations for selected manufacturing cells. The results are plotted in order to find the points where the values reach steady states. The maximum of steady state time should be considered as the warm-up period for the entire system.

Figure 5.17 shows the time-series graph for machine utilization values of cell 1 from the simulation model of the first manufacturing stage. Machine utilization values reached the steady state at around 6000 minutes, or 100 hours. Figure 5.18 shows the plotted graph of cell 10 for average of the machine utilization values for the first manufacturing stage. Average machine utilization values reached the steady state at around 4200 minutes, 70 hours. Other cells produced similar results. The warm-up period for the model is determined as 100 hours since it is the maximum of these two minimum warm-up periods.

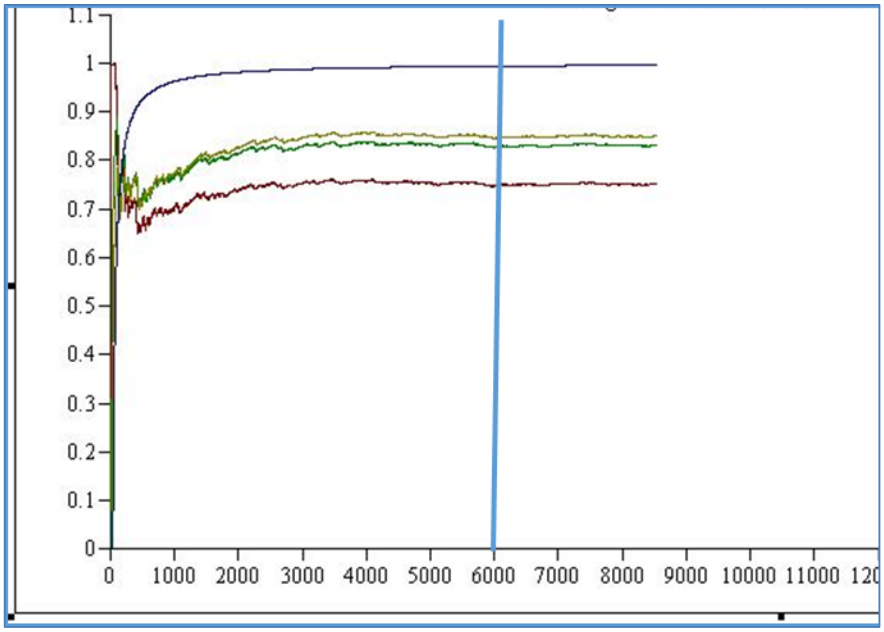


Figure 5.17 Warm-up length graph for machine utilizations of cell 1

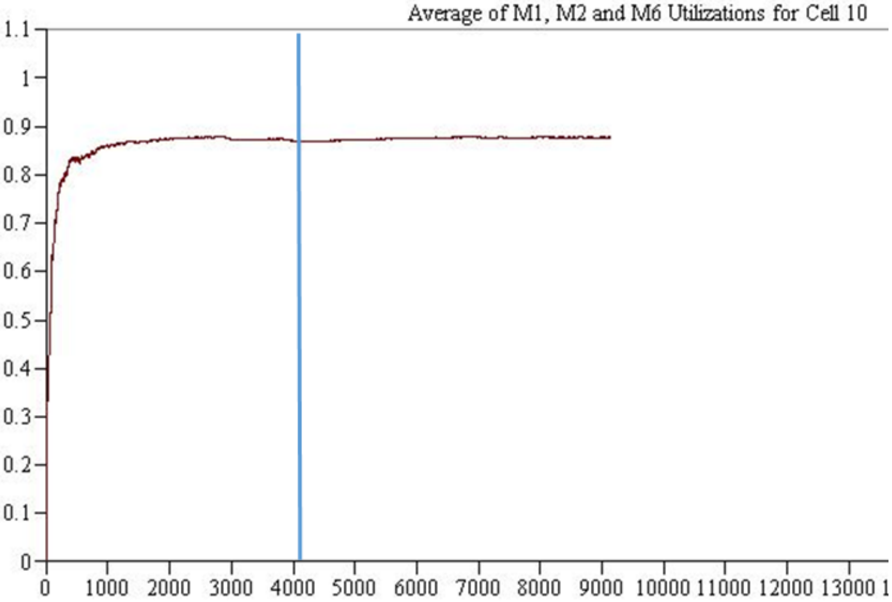


Figure 5.18 Warm-up length graph for average machine utilization of cell 10

5.7 Analysis of Simulation Results

The simulation models are developed with Arena simulation software. One year time frame is considered for experimentation, where there are 50 weeks, i.e., 250 working days and 8 hours in one day for one shift cases, and 16 hours for double shift cases. The statistics are collected on a continuous basis, i.e., end of day value of each statistics is the starting value for the following day. Queue sizes, cell and machine utilization values, average flowtime values, work-in-process inventories of the parts are the critical statistics kept for comparison purposes.

Initially, part families which can be produced in more than one cell are directed to appropriate cells using to the expected utilization values of the cells for that part family at decision points. Then these percentages are altered in order to approximate the cell utilization values from simulation model to the theoretical expected cell utilization values obtained via the mathematical model. Approximation is done by trying different values for percentages of demand, which is used as a decision tool. The probabilistic nature of the simulation models, interrelations between the cells and high number of decision points make the approximation a difficult and time consuming task.

The results of the mathematical model provide a single value for overall cell utilization for the entire system. Since shifting bottleneck concept is used while designing the cellular manufacturing systems, the bottleneck machine is different for each product. Also, some of the machines are common for most of the products in the product family. Furthermore, every part has a different arrival distribution. This may result in higher utilization of a machine different than the bottleneck machine of most parts. It might even not be a bottleneck machine for any of the products. To simulate the manufacturing system designed using the mathematical model, the utilization of the machine that is used as the bottleneck machine in the mathematical model is considered to represent the cell utilization value. This issue complicates the approximation process of theoretical utilization values to utilization values obtained from simulation results. Hence, having different utilization values is unavoidable.

Table 5.3 shows the expected cell utilization obtained from the results of the mathematical model and simulation model for stage 1. Most of the utilization values from mathematical and simulation models are either same or very close to each other except for couple cells.

Table 5.3 Cell utilizations for mathematical and simulation models for stage 1

10-part family configuration	Expected cell utilization	
Cells	Mathematical Model	Simulation Model
Cell 1	81.5%	100.0%
Cell 2	77.6%	78.9%
Cell 3	99.2%	100.0%
Cell 4	100.0%	100.0%
Cell 5	90.8%	87.7%
Cell 6	94.8%	86.5%
Cell 7	100.0%	100.0%
Cell 8	82.0%	100.0%
Cell 9	76.6%	78.4%
Cell 10	89.1%	100.0%

The means of cell utilizations for mathematical model and simulation model are 89.17% and 93.15%, respectively. The average of the absolute deviations between the expected value and the simulation model results is 6.3%, which shows that simulation models produce very close utilization values to the mathematical model utilization values. The difference between the average utilizations of cells is 3.98%.

Table 5.4 compares the expected cell utilizations from the mathematical model and simulation model utilization values for stage 3. Similar to the results of stage 1, most of the utilization values from mathematical and simulation models are close to each other except for couple cells, such as Cell 3, Cell 15 and Cell 18.

Table 5.4 Cell utilizations for mathematical and simulation models for stage 3

10-part family configuration	Expected cell utilization	
Cells	Mathematical Model	Simulation Model
Cell 1	81.5%	91.2%
Cell 2	77.6%	81.2%
Cell 3	99.2%	76.0%
Cell 4	100.0%	97.0%
Cell 5	90.8%	100.0%
Cell 6	94.8%	90.6%
Cell 7	100.0%	94.4%
Cell 8	82.0%	89.7%
Cell 9	76.6%	72.3%
Cell 10	89.1%	92.5%
Cell 11	100.0%	94.5%
Cell 12	100.0%	85.7%
Cell 13	94.3%	84.8%
Cell 14	100.0%	100.0%
Cell 15	73.2%	100.0%
Cell 16	90.4%	91.9%
Cell 17	100.0%	92.4%
Cell 18	100.0%	63.7%
Cell 19	76.6%	84.0%

The means of cell utilizations for mathematical model and simulation model are 90.85% and 88.52%, respectively. The average of the absolute deviations between the expected value and the simulation model results is 9.6%. This difference is higher that Stage 1 results. The difference between the average utilizations of cells is 2.33%. Statistical analysis is used to check if the results are significantly different than each other in the next section.

5.8 Statistical Analysis

In order to determine if there is any difference in means of utilization values of expected values and simulation model results, t-tests is used. For each stage, the normality of the data and homogeneity of the variances are checked.

First, F-test is performed is to test equality of the variances. If F value is greater than F critical value, the null hypothesis is rejected. The confidence level for all tests is 95%. According to F-test results, which is shown in Table 5.5, the F value is less than the F critical value, hence we conclude that there is not enough evidence to reject that the null hypothesis that the two utilization variances are equal at the 0.05 significance level.

Table 5.5 F-Test Two-Sample for Variances for stage 1 results

	Variable 1	*Variable 2*
Mean	0.931524	0.891707011
Variance	0.008605967	0.00857998
Observations	10	10
df	9	9
F	1.003028773	
P(F<=f) one-tail	0.498239766	
F Critical one-tail	3.178893104	

Minitab Software is used to check the normality of utilization values from mathematical and simulation models using probability plots. Figure 5.19 shows that the utilization data from the mathematical model meets the normality assumption. However, Figure 5.20 shows that the utilization data from the simulation data does not meet the normality assumption.

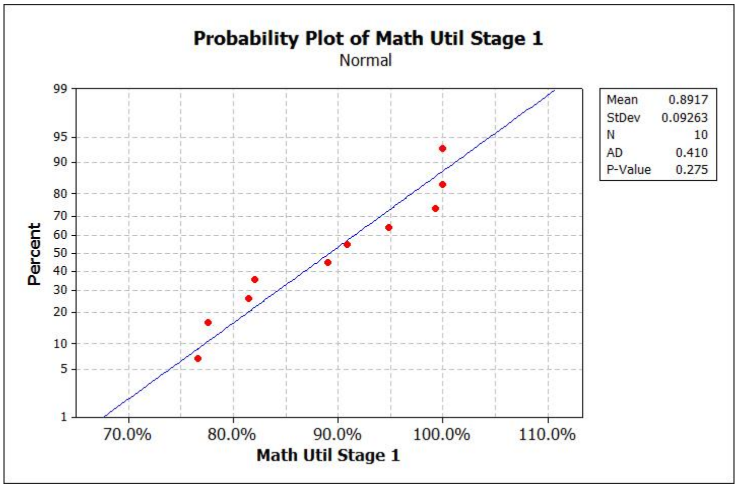


Figure 5.19 Normality plot for utilization values from math model – Stage 1

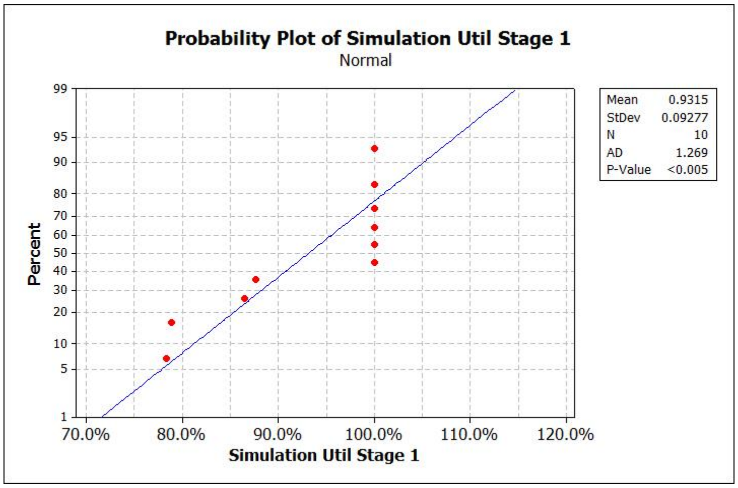
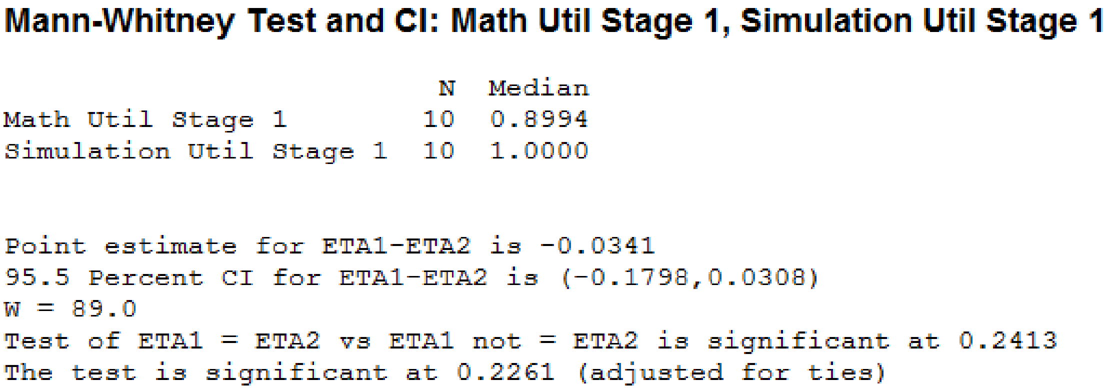


Figure 5.20 Normality plot for utilization values from simulation model – Stage 1

Hence, a non-parametric test, Mann Whitney U Test is required to test the medians of these two data sets. Figure 5.21 presents the Minitab output for stage 1 utilization values. A Mann-Whitney U test was run on 20 values to determine if there were differences in utilization values between mathematical and simulation model results using Minitab software. Median utilization score for simulation results (1.00) and mathematical model results (0.8994) was not statistically significantly different, p = 0.2261. It can concluded that simulation model produced utilization values similar to the ECU values from mathematical model for stage 1.



```
Mann-Whitney Test and CI: Math Util Stage 1, Simulation Util Stage 1

                         N  Median
Math Util Stage 1       10  0.8994
Simulation Util Stage 1 10  1.0000


Point estimate for ETA1-ETA2 is -0.0341
95.5 Percent CI for ETA1-ETA2 is (-0.1798,0.0308)
W = 89.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.2413
The test is significant at 0.2261 (adjusted for ties)
```

Figure 5.21 Mann-Whittney U test results for stage 1 utilization data

Homogeneity of variances is checked for Stage 3 utilization values as well. Table 5.6 presents the F-test results for Stage 3, which shows that there is no significant difference between the variances of two variables, hence it can be assumed that variances are equal.

Table 5.6 F-Test Two-Sample for Variances for stage 3 results

	Variable 1	*Variable 2*
Mean	0.90852163	0.885222105
Variance	0.009712804	0.009597304
Observations	19	19
df	18	18
F	1.012034645	
P(F<=f) one-tail	0.490016704	
F Critical one-tail	2.217197134	

The normality of utilization values from mathematical and simulation models for Stage 3 are checked using probability plots. Figure 5.22 shows that the utilization data from the mathematical model does not meet the normality assumption. However, Figure 5.23 shows that the utilization data from the simulation data meets the normality assumption.

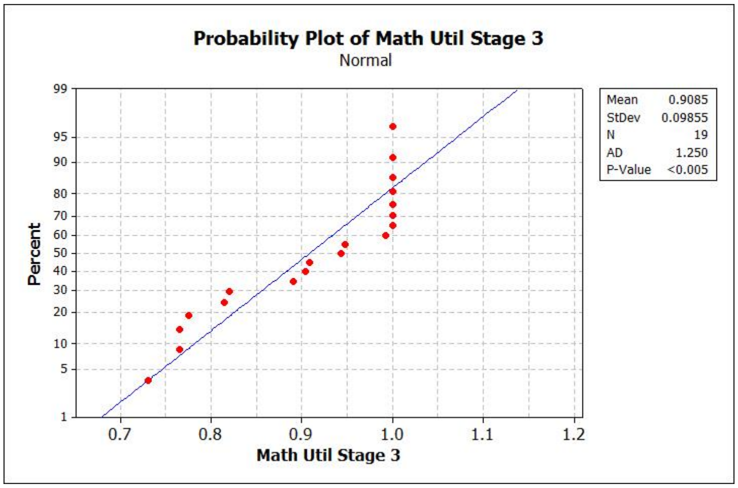


Figure 5.22 Normality plot for utilization values from mathematical model – Stage 3

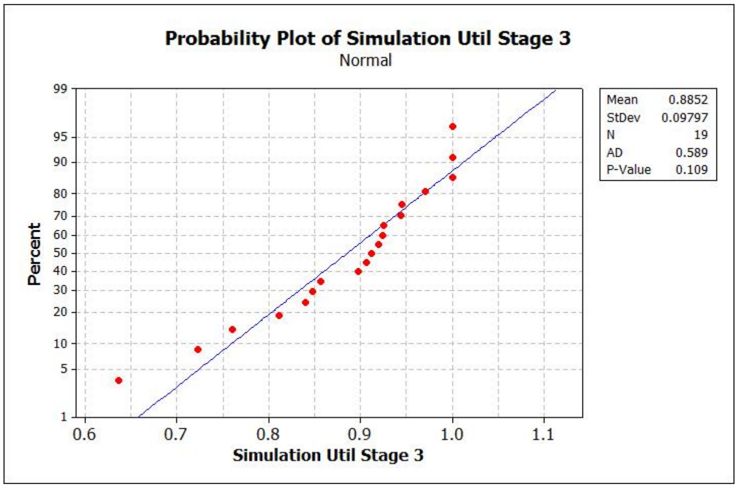
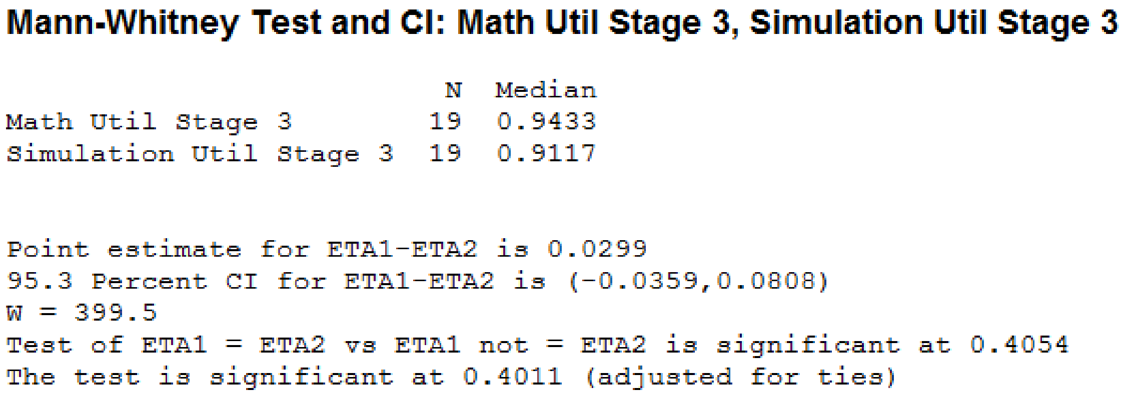


Figure 5.23 Normality plot for utilization values from simulation model – Stage 3

Similarly, since normality assumption is not met, a non-parametric test, Mann Whitney U Test is used to test the medians of these two data sets. Figure 5.24 presents the Minitab output for stage 3 for this test. The Mann-Whitney U test was run on 38 values to determine if there were differences in utilization values between mathematical and simulation model results. Median utilization score for simulation results (0.9117) and mathematical model results (0.9433) was not statistically significantly different, $p = 0.4011$. It can concluded that simulation model produced utilization values similar to the ECU values obtained from mathematical model results for stage 3.



Mann-Whitney Test and CI: Math Util Stage 3, Simulation Util Stage 3

```
                          N  Median
Math Util Stage 3        19  0.9433
Simulation Util Stage 3  19  0.9117


Point estimate for ETA1-ETA2 is 0.0299
95.3 Percent CI for ETA1-ETA2 is (-0.0359,0.0808)
W = 399.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.4054
The test is significant at 0.4011 (adjusted for ties)
```

Figure 5.24 Mann-Whittney U test results for stage 3 utilization data

5.9 Conclusions

In this chapter, simulation models are developed in order to validate the results of the manufacturing systems designed using the mathematical model in Chapter 3 and 4. The modules are explained in detail along with the input parameters of the model, such as part arrival distributions, part families, processing times, etc.

Arena simulation software is used to develop the models. Simulation models are run for 2000 hours/year. A warm-up period analysis is performed to find the minimum warm-up time to clear the statistics and to have a steady system flow for the simulation models developed. This time is added to the total simulation run time.

The difference between the cell utilization values of the mathematical model and simulation models are either same or very close to each other. The statistical tests show that there is no significant difference between the medians of two utilization data sets at 95% confidence level. This shows that the simulation models developed validate the manufacturing systems designed using the mathematical model.

6 INTEGRATED SUPPLY CHAIN NETWORK AND MANUFACTURING SYSTEM DESIGN

Supply chain integration is inherently complicated because of the number of components and variables in the system. The objective of supply chain integration is to minimize the cost or maximize the profit of the entire system by coordinating the operations of the members of the supply chain at all stages (Li & Wang, 2007). Integration among SCN members is essential as a local optimal decision of a member of the SCN may incur unpredictable losses for the other members.

In this chapter, a capacitated plant location and resource allocation model is proposed to determine the locations of the plants out of candidate plants and to allocate the cells to these opened plants. Hence, the proposed model simultaneously designs the supply chain network by determining the locations of plants, and the manufacturing systems of the plants by assigning various manufacturing cells to these opened plants. The inputs for the mathematical model are obtained from the layered cellular manufacturing system proposed in Chapter 4, from the results of the mathematical model for optimal manpower allocation, and from the heuristic procedure for optimal cell size determination in Chapter 3. Thus, Chapters 3 and 4 are incorporated in Chapter 6.

The rest of this chapter is organized as follows. Section 6.1 briefly explains the research motivation in supply chain network and manufacturing system design integration field. Section 6.2 describes the manufacturing system studied. In the following sections, the methodology followed in calculating various factors are discussed. The methodology in finding varying transportation costs are explained in Section 6.3. Section 6.4 presents the echelon inventory costs in the supply chain network design. Sections 6.5, 6.6, 6.7, 6.8, and 6.9 describe the approaches used to incorporate investment costs, labor costs, machine procurement costs, cell installment costs, and machine setup costs, respectively. The proposed mathematical model is explained in Section 6.10. The results of the proposed mathematical model are presented in Section 6.11. Section 6.12 discusses the conclusions of this chapter.

6.1 Introduction and Research Motivation

The model used in this chapter is developed based on the study of Huang and Süer (2012). Their model considered production cost as a combination of labor and machine costs where the production costs are calculated roughly by using the number of machines in cells. Furthermore, the model considers one machine from each machine type, and assumes that the number of operators is exactly the same as the number of machines in cells, which is not a realistic assumption for some manufacturing environments.

In this chapter, labor and machine costs are considered separately instead of combining them into a single cost factor. Optimal cell sizes are determined separately by using a mathematical model and a heuristic procedure developed in Chapter 3. Number of machines and number of machine setups required for each cell are found by using the results of the mathematical model developed in Chapter 4. Furthermore, machine setup costs, cell installment costs, inventory carrying costs, varying transportation costs, machine duplication and multiple shifts are considered in the manufacturing system. Dedicated cells and shared/remainder cells are defined and tracked separately in the supply chain design. Hence, this dissertation integrates the results of Chapters 3 and 4 into Chapter 6 and presents an integrated solution to the supply chain network design. To the best of the author's knowledge, integrated supply chain network and manufacturing system design is not studied in the literature in detail considering the factors below. The features in italic text are introduced to the model in this study.

- Processing similarities among parts
- Processing times of the operations
- Part families assigned to cells
- Demand for products
- Investment cost
- Optimal number of operators assigned to each operation and each cell
- Labor cost using individual optimal cell size
- Number of machines from each machine type required in each cell for the optimal cell size
- Varying transportation costs
- In-transit inventory carrying costs
- Cell installment costs
- Individual machine cost for each machine type
- Machine setup cost
- Minimum capacity utilizations

- Cell types in layered cellular design
- Multiple shifts
- Shifting bottleneck machines in cells

6.2 Description of the System Studied

A global fashion jewelry supply chain which involves a multi-stage manufacturing system all over the world is considered in this dissertation. There are seven candidate locations for the plants. Three of them are close to the market, North America, in order to take advantage of shorter transportation distances, hence lower transportation costs, three of them are in Asian countries where the company can benefit from lower labor rates. One of them is in eastern Mediterranean region where the location is relatively closer to the market and labor costs are relatively more expensive than Asian countries.

The potential locations of the plants are Shanghai (China-CHN), Veracruz (Mexico-MEX), Manila (Philippines-PHL), Mumbai (India-IND), Mersin (Turkey-TUR), San Juan (Puerto Rico-PRI) and Santo Domingo (Dominican Republic-DOM). The locations of the plants on the world map are shown in Figure 6.1. The markers do not necessarily represent the exact locations of the candidate plants on the map. North American warehouse and the ports used in east and west cost of USA are also illustrated on the map.

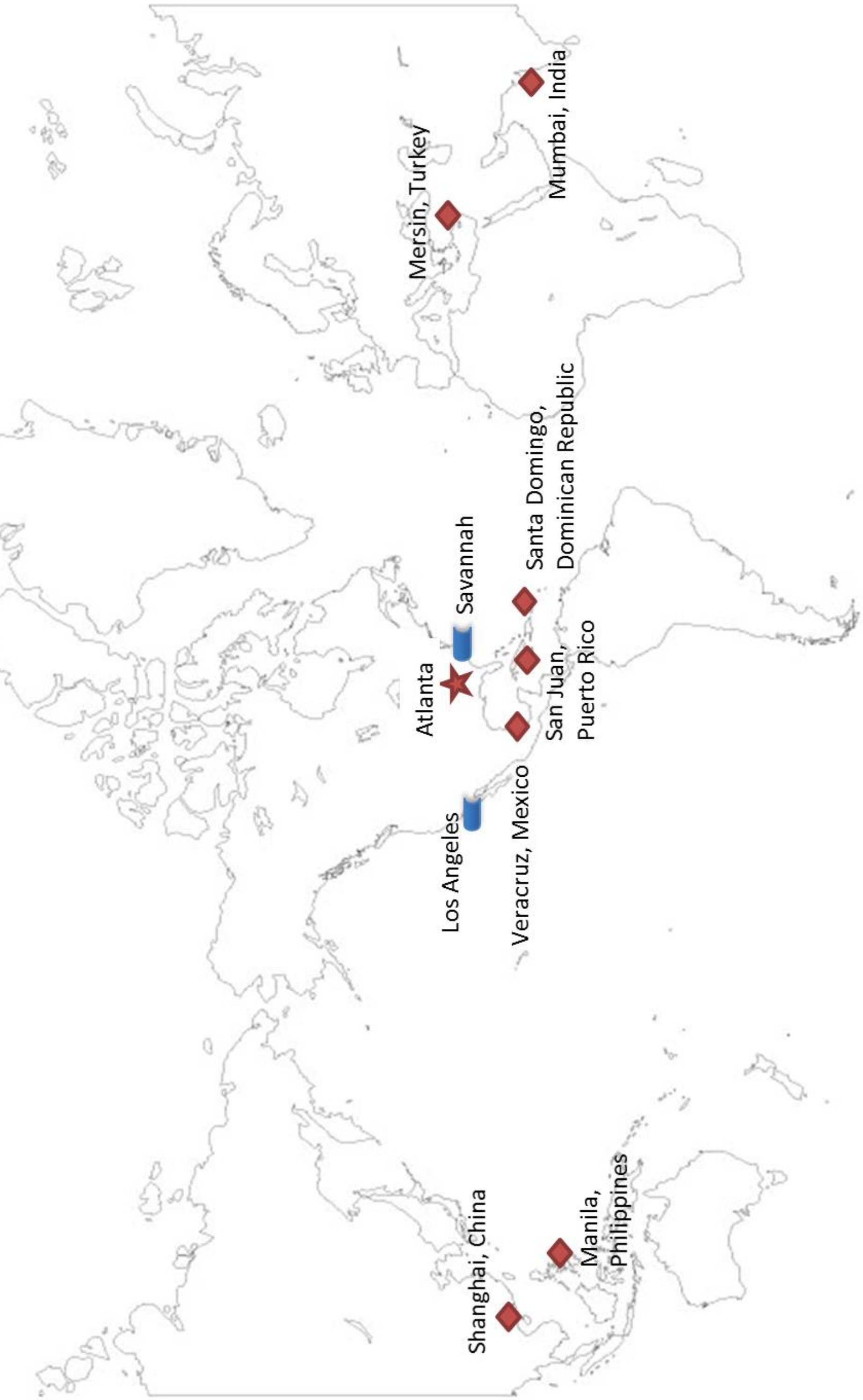


Figure 6.1 Locations of candidate plants, ports and the warehouse

There are a couple of assumptions made while determining plant capacities. The number of operations required for stage 3 is greater than the other stages, hence they require more space. Therefore it is assumed that the investment costs are higher than stages 1 and 2. Since the size of the plating machines are bigger than other machines, it is assumed that the first and the second stage operations require similar space size. The investment costs are rough estimates and these parameters can be varied.

Number of cell restrictions was determined considering realistic values observed in most industrial settings. However, these are just parameters and can be varied based on the desire to study other possible scenarios.

It is assumed that not all of the operations can be done at all of the plant locations in order to mimic the global supply chains more realistically. Companies tend to keep their critical processes in certain plants to avoid low quality and industrial espionage. In some cases this is limited by the workforce availability, availability and consistency of energy sources, access to raw materials, infrastructure, etc. Intellectual property theft costs the US economy at least 250 billion dollars and 750,000 jobs every year according to US Department of Commerce (Friel, 2006). Toyota produces some of the auto components in Japan and ships them to the US for final assembly. Similarly, here, it is assumed that the fashion jewelry company does not allow certain stages to take place in some countries because of similar considerations.

Table 6.1 presents the number of manufacturing cells that can be allocated to candidate plant locations. At stage 1, the total capacity is 30, the total cell capacity at stage 2 is 35, and at stage 3, it is 45. The total manufacturing cell capacity for all of the manufacturing stages and plants is 110.

Table 6.1 Cell capacities of the candidate plants

Cell capacities	Puerto Rico	Dom. Republic	Mexico	Turkey	India	China	Philippines	Total
Stage 1	5	5	5	5	0	10	0	30
stage 2	5	5	5	10	0	0	10	35
Stage 3	5	10	5	0	5	10	10	45
Total	15	20	15	15	5	20	20	110

6.2.1 Minimum Capacity Allocations for Certain Plants

It may be desired by the jewelry company to keep a certain plant open in order to develop and produce the prototypes, or to have a plant to be used in the case of disruptions in other plants. The desired minimum capacity allocation values are certain percentages of the available capacities for each stage in the plants. The model can be forced to use all or any percentage of the capacity of the desired main plant by using these values. Here, one of the plants is preselected to be opened and to have a minimum percent capacity allocation value. Here, the capacity of a plant is considered the number of manufacturing cells that can be opened in a plant. Hence, percent capacity allocation value is the ratio of opened cells in the plant to the available cell capacity of the plant.

In order to avoid low percent capacity allocations for every opened plant in the supply chain network, it is also possible to have a minimum percent capacity allocation value for the opened plants. In this case, the model decides which plants to open based on these usage values along with other constraints.

6.2.2 Manufacturing Cells

There are 10 part families to be produced in 38 dedicated cells, and 7 shared and remainder cells in seven candidate plants. A total of 45 manufacturing cells are required. The number of cells to be allocated to seven candidate plants is 10, 16, and 19 for stages 1, 2, and 3, respectively.

Table 6.2 provides the types of the cells and their expected utilizations for producing the corresponding part families of stage 1. Stage 1 requires 8 dedicated cells, 1 shared and 1 remainder cell. The manufacturing cells at stage 1 work for one shift. Total expected utilizations are also provided in the table. Cell 4 has the lowest ECU with 62.5%, and cell 5 has the highest ECU with 100%.

Table 6.2 Cell types, part families and expected utilization of cells at stage 1

# of shifts	**Cells**	**Part families**			**Expected cell utilizations**			**Total ECU**	**Cell type**
1	1	4			73.8%			73.8%	dedicated
1	2	3			86.8%			87%	dedicated
1	3	6	10		38.4%	57.0%		95%	shared
1	4	1			62.5%			62.5%	dedicated
1	5	5			100%			100.0%	dedicated
1	6	8			71.1%			71.1%	dedicated
1	7	3	5	7	7.7%	68.4%	21.2%	97.3%	remainder
1	8	2			80.0%			80.0%	dedicated
1	9	7			93.2%			93.2%	dedicated
1	10	9			64.2%			64%	dedicated

Table 6.3 provides the types of the cells and their expected utilizations for producing the corresponding part families. Stage 2 two-shift case requires 14 dedicated cells, 1 shared and 1 remainder cells. The manufacturing cells at stage 2 two-shift case

work for two shifts per day. Total expected utilizations are also provided in the table. Cell 7 has the lowest ECU with 58%, and cells 2, 3 and 10 have the highest ECU with 100%.

Stage 2 three-shift case requires 6 dedicated cells and 4 shared cells. The manufacturing cells at stage 2 three-shift case work for three shifts per day. Total expected utilizations are also provided in the table. Cell 1 has the lowest ECU with 61.7%, and cells 2, 3 and 10 have the highest ECU with 100%.

Table 6.3 Cell types, part families and expected utilization of cells at stage 2

# of shifts	Cells	Part families			Expected cell utilizations			Total ECU	Cell type
2	1	9			99.8%			99.8%	dedicated
2	2	1			100%			100%	dedicated
2	3	3			100%			100%	dedicated
2	4	5			98.3%			98.3%	dedicated
2	5	2	9		14.4%	70.8%		85.2%	shared
2	6	7			61.0%			61.0%	dedicated
2	7	4			58.0%			58.0%	dedicated
2	8	3			73.3%			73.3%	dedicated
2	9	1	6	10	64.7%	4.4%	30.6%	99.7%	remainder
2	10	5			100%			100%	dedicated
2	11	5			62.8%			62.8%	dedicated
2	12	1			98.4%			98.4%	dedicated
2	13	2			90.7%			90.7%	dedicated
2	14	3			99.2%			99.2%	dedicated
2	15	6			73.3%			73.3%	dedicated
2	16	7			99.4%			99.4%	dedicated
3	1	2			61.7%			61.7%	dedicated
3	2	1			100%			100%	dedicated
3	3	9			91.9%			91.9%	dedicated
3	4	5	10		74.0%	20.4%		94.5%	shared
3	5	4	6		38.7%	49.4%		88.1%	shared
3	6	3	7		79.3%	11.1%		90.5%	shared
3	7	3			100%			100%	dedicated
3	8	5			100%			100%	dedicated
3	9	7			84.9%			84.9%	dedicated
3	10	1	9		75.8%	22.7%		98.5%	shared

Table 6.4 provides the types of the cells and their expected utilizations for producing the corresponding part families. Stage 3 requires 16 dedicated, 2 shared and 1 remainder cells. The manufacturing cells at stage 3 work for one shift per day. Total expected utilizations are also provided in the table. Cell 15 has the lowest ECU with 73.2%, and cells 4, 7, 11, 12, 14, 17 and 18 have the highest ECU with 100%.

Table 6.4 Cell types, part families and expected utilization of cells at stage 3

# of shifts	**Cells**	**Part families**				**Expected cell utilizations**				**Total ECU**	**Cell type**
1	1	3				81.5%				81.5%	dedicated
1	2	9				77.6%				77.6%	dedicated
1	3	4				99.2%				99.2%	dedicated
1	4	3				100%				100%	dedicated
1	5	6				90.8%				90.8%	dedicated
1	6	8				94.8%				94.8%	dedicated
1	7	8				100%				100%	dedicated
1	8	7				82.0%				82.0%	dedicated
1	9	10				76.6%				76.6%	dedicated
1	10	4	8			56.5%	32.6%			89.1%	shared
1	11	5				100%				100%	dedicated
1	12	1				100%				100%	dedicated
1	13	1				94.3%				94.3%	dedicated
1	14	7				100%				100%	dedicated
1	15	2				73.2%				73.2%	dedicated
1	16	5				90.4%				90.4%	dedicated
1	17	9				100%				100%	dedicated
1	18	2	10			99.0%	1.0%			100%	shared
1	19	1	3	5	6	36.8%	4.4%	12.9%	22.4%	76.5%	remainder

6.3 Transportation Costs

In the global supply chain network considered in this dissertation, the manufacturing is finished in three stages. Plants with these manufacturing stages are located in various countries and continents. In the first stage, raw materials and components are processed until plating operations. Second stage is consisted of only plating operations. Operations following the plating operations including packaging operation are finished in the third stage. Then the finished products are shipped to North America warehouse to be distributed to the retailers. Intermodal containers are considered in order to handle the freight easily during transportation mode changes. Using intermodal containers results in less damage and loss of products, less cargo handling, and more secure and faster transportation. Due to cost effectiveness, maritime transportation is considered for transporting semi-finished and finished products between continents.

6.3.1 Varying Transportation Costs

Using a single value as unit transportation cost for all of semi-finished or finished products among all of the stages is not realistic. The way products are shipped from stage 1 to stage 2 is different than the way they are shipped from stage 2 to stage 3. Plating operations are expensive and parts that go through plating operations should be treated more gently to protect the surfaces of the plated parts. From stage 1 to stage 2, hundreds/thousands of products can be put and shipped in a box as bulk. However, plated products may require smaller box sizes to handle them more diligently. Finished products, which are packed, and sometimes combined with other products, weigh more, require more delicate handling and occupy significantly more space than unfinished parts. In order to account these differences, varying unit transportation costs are used in the model.

Carrying semi-finished products within the same plant also requires resources, which is not taken into consideration while calculating the transportation costs. Inner-plant transportation costs, of course, are insignificant when they are compared to inter-plant transportation costs.

6.3.2 Unit Weights after Each Stage

Fashion jewelry items are generally light in weight, and small in size. The weight of the products starts from couple grams and can go up to couple hundred grams. As stated before, plating increases the weight of the items since the surface is covered with a thin layer of metal. There is no standard for the thickness or fineness of plating. The thickness of plating is usually measured with microns, mils or micro-inches. As many different metals are used for plating in fashion jewelry industry, and the variety of the products and thickness of plates are huge, and it is not possible to use a standard total weight for plating jobs of all part families in this dissertation.

In order to obtain the total mass of plating metal required for a plating job, desired thickness of the plate, and the area to be plated need to be known. For example, for a bracelet with a surface area of 7,000 square millimeters, desired plating thickness of 1 mils (0.001 inches) silver, the weight of silver required for plating is 1.87 grams. The calculations are done using the coating thickness calculator of National Metal Finishing Resource Center's (NMFRC) website (NMFRC, 2015).

It is assumed that the extra weight caused by the plating operations is around 1-2% of the product depending on the material used to produce and plate the product.

Packaging plated products with smaller boxes is assumed to add another 5% to unit weight of each product. Furthermore, the weights and the sizes of the parts in the same part families are considered to be similar for the sake of simplicity in calculations. Unit weights of the fashion jewelry products are generated based on values obtained from websites of various fashion jewelry manufacturers. Please note that PF8 does not require plating operations. The average weights and sizes of the semi-finished and finished products are presented in Table 6.5.

Table 6.5 Average weights of items after each manufacturing stage for all product families

	After stage 1	After stage 2		After stage 3 - Finished product		
Product family	Unit Weight (lbs)	Unit Weight (lbs)	Boxed weight (lbs)	Unit Weight (lbs)	package weight (lbs)	Total weight (lbs)
PF 1	0.020	0.0202	0.0208	0.045	0.128	0.173
PF 2	0.150	0.1515	0.1560	0.334	0.370	0.704
PF 3	0.250	0.2525	0.2601	0.557	0.198	0.754
PF 4	0.040	0.0404	0.0416	0.089	0.123	0.212
PF 5	0.080	0.0808	0.0832	0.178	0.100	0.278
PF 6	0.120	0.1224	0.1261	0.270	0.110	0.380
PF 7	0.125	0.1275	0.1313	0.281	0.058	0.339
PF 8	0.060	0.0600	0.0618	0.132	0.060	0.192
PF 9	0.180	0.1836	0.1891	0.405	0.070	0.475
PF 10	0.100	0.1020	0.1051	0.225	0.018	0.243

6.3.3 Shipping with Containers

In maritime transportation, the transportation capacities of the container ships are described by the twenty-foot equivalent unit (TEU). This is a standard-sized metal box with 20-foot (almost 6.1 meters) length which can be transferred between different modes of transportation, such as trucks, trains, and container ships. There are other standard container sizes, such as 40 ft., 48 ft. etc., as well. As the intermodal container size, 40 ft. containers are considered in this dissertation.

A standard 40 ft. intermodal container's dimensions, volume and payload capacities are shown in Table 6.6. Data is retrieved from the website of World Shipping Council. (World Shipping Council, n.d.). Please keep in mind that the interior dimensions, tare weights and payloads of the 40' standard containers slightly change from manufacturer to manufacturer.

Table 6.6 40 ft. container dimensions and data

40' Standard Container (40'x8'x8'6")	
Interior Length	39' 6" (12.032m)
Interior Width	7' 8" (2.350m)
Interior Height	7' 10" (2.392m)
Cubic capacity	2,390 cu ft (67 cbm.)
Tare weight	8,820 lbs (4,000 kg)
Payload	58,380 lbs (26,480 kg)

Shipping charges are calculated mostly by using the gross weight of the cargos in kilograms or pounds. As this makes carrying light weight and large size cargo less profitable, more and more companies are adopting a new way to calculate the carrying costs. For example, FedEx announced that they would apply dimensional weight pricing to all shipments, air and ground alike, starting from June 2014. ("FedEx Announces Pricing Changes," 2014). Similar approaches are adopted by other international sea and air cargo carriers as well. Dimensional weight is an estimated weight found by using the length, width and height of the cargo. Dimensional weight is calculated with the formula below.

$$\text{Dimensional weight} = (\text{length} \times \text{width} \times \text{height}) / (\text{dimensional factor}) \quad (6.1)$$

Since each carrier uses its own dimensional factor, dimensional weight of the same package may differ from carrier to carrier, and from country to country. Given that many countries are considered as potential plant locations in this dissertation, instead of using dimensional weight, container volumes and maximum payloads are considered while calculating the transportation costs.

Semi-finished products are transported in bulks, therefore the payload of the containers are used to calculate the transportation costs among manufacturing stages. However, since the finished products are packed and transported in packages, the physical dimensions of standard product boxes should be taken into consideration. Here, whether sizes or weights of the products will be used to calculate the costs of transportation from stage 3 to the market needs to be decided. The sizes and weights of the boxes used for fashion jewelry are numerous and depend on the type and size of fashion jewelry.

It is assumed that the average box sizes for the products that belong to the same product families are the same. The fashion jewelry types, weights of the box sizes, number of boxes in a case, case weights, and unit weights of the boxes are provided in Table 6.7 ("Jewelry Boxes and Displays," n.d.). The dimensions of the jewelry boxes are also given in the table.

Table 6.7 Dimensions of fashion jewelry boxes

Product family	Box type	# of boxes/ case	Case weight (lbs)	Unit weight (lbs)	Length (inch)	Width (inch)	Height (inch)
PF 1	ring	12	1.54	0.1283	1.875	2.125	1.5
PF 2	bracelet/watch	6	2.22	0.3700	8	2	1.125
PF 3	pendant/earring	12	2.37	0.1975	2.625	2.625	1.375
PF 4	earring	12	1.48	0.1233	1.875	2.125	0.5
PF 5	bracelet	50	5	0.1000	9.75	1.875	1.125
PF 6	earrings/necklace	100	11	0.1100	7	5	1.25
PF 7	wide bracelet	100	5.8	0.0580	3.5	3.5	1.875
PF 8	necklace	100	6	0.0600	5.5	3.5	1
PF 9	bracelet	100	7	0.0700	3.5	3.5	0.875
PF 10	earring	100	1.8	0.0180	2.5	1.625	0.8

Table 6.8 shows the average volumes and average weights of the products for each product family. The average volumes of each product family are simply found by multiplying the dimensions of the boxes. The average weights of the product families are found by adding the average weights of boxes to the average weights of finished products.

Weekly demand data is used to calculate the weight and volume of product batches. Then the ratios of the volumes of product family batches to the volume of the standard container are calculated to find the percent of the space that product family occupies in a container. Similarly, the ratios of the weights of product family batches to the maximum payload capacity of the standard container are calculated to find the percent of the weight that product family needs in a container. Then these two percentages are compared with each other. Having a higher percentage means that using that measure is required for that product family.

Table 6.8 Volume-Weight analysis for finished product transportation

Product family	Average volume (cu ft)	Batch volume (cu ft)	Percent volume (batch v./ container v.)	Average unit weight (lbs)	Batch weight (lbs)	Percent weight (batch w./ container w.)	Weekly demand
PF 1	0.003459	80.9	3.39%	0.1687	3,948.36	6.76%	23400
PF 2	0.010417	218.8	9.15%	0.5518	11,587.80	19.85%	21000
PF 3	0.005483	111.0	4.65%	0.3086	6,249.15	10.70%	20250
PF 4	0.001153	29.9	1.25%	0.1738	4,510.98	7.73%	25950
PF 5	0.011902	407.0	17.03%	0.3020	10,328.40	17.69%	34200
PF 6	0.025318	315.2	13.19%	0.2324	2,893.38	4.96%	12450
PF 7	0.013292	360.9	15.10%	0.2416	6,559.44	11.24%	27150
PF 8	0.011140	344.2	14.40%	0.1200	3,708.00	6.35%	30900
PF 9	0.006203	96.8	4.05%	0.1720	2,683.20	4.60%	15600
PF 10	0.001881	32.7	1.37%	0.1200	2,088.00	3.58%	17400
Total		1,997.49	**83.58%**		54,556.71	**93.45%**	

The results show that using seven out of ten product families requires using payload capacities of the containers, and the rest three product families requires using volume of the containers. When the total capacity requirements for volume and maximum payload are compared, using maximum payload capacity is a better and less costly option. Therefore, in this dissertation, payload capacities of the containers are used to calculate the transportation costs.

6.3.4 Semi-finished and Finished Product Costs

In order to calculate freight insurance and pipeline inventory carrying costs, values of semi-finished and finished products need to be determined. After each stage, products go through various operations and their values increase. Therefore, values of products after stage 2 would be higher than the values of products after stage 1. The values of finished products are much higher since they are ready to be sold in market.

Even though the amount of money spent for the same products in different countries are different, to simplify the calculations, it is assumed that the values of the products are independent of the plants, and labor and investment costs in the countries where plants are located. It is also assumed that the values of the semi-finished products after stage 1 and stage 2 are correlated with the weights of the products. The values of finished products after stage 3 are determined considering the market prices of fashion jewelry items. Table 6.9 shows the values of part families after each stage which are used in inventory carrying cost and freight insurance cost calculations.

Table 6.9 Values of semi-finished and finished products after manufacturing stages

		Values after each stage ($)		
Part family	Unit weight (lbs)	After stage 1	After stage 2	After stage 3
PF 1	0.040	0.40	1.00	2.40
PF 2	0.180	1.80	4.50	10.80
PF 3	0.110	1.10	2.75	6.60
PF 4	0.050	0.50	1.25	3.00
PF 5	0.200	2.00	5.00	12.00
PF 6	0.120	1.20	3.00	7.20
PF 7	0.180	1.80	4.50	10.80
PF 8	0.060	0.60	1.50	3.60
PF 9	0.100	1.00	2.50	6.00
PF 10	0.100	1.00	2.50	6.00
Average	0.114	1.14	2.85	6.84
Per pound	1.000	10.00	25.00	60.00

6.3.5 Freight Insurance Costs

In order to increase the likelihood that the products are transported among manufacturing stages and to the market intact and undamaged, freights need to be insured via insurance companies. Hiring good logistic partners, investing in technology to track and monitor the products can decrease the freight losses or damages, thus decrease the insurance costs. Transportation insurance costs are calculated based on several factors such as transportation mode, type of commodity, value of commodity, desired level of protection, etc.(Ruriani, 2012).

According to Freight Insurance Center, basic coverage freight insurance rates for general merchandise category are 0.87% and 0.81% for international ocean and air transportations, respectively. Table 6.10 shows the insurance rates for international and domestic (US) transportations (“Freight Insurance Rates,” n.d.).

Table 6.10 Basic coverage freight insurance rates (Freight Insurance Center, 2015)

	Transportation mode		
Shipment type	Land	Ocean	Air
International	N/A	0.87	0.81
Domestic	0.55	0.66	0.60

The insurance rates are 0.25% lower if total loss coverage is selected instead of basic coverage. There are many other options offered in the freight insurance industry, and the cost of the freight insurance depends on purchaser's choices.

Table 6.11 shows international unit insurance costs of part families. For the sake of simplicity, it is assumed that international rates do not change from route to route, or the changes in the rates are insignificant. However, for the domestic freights, two different insurance coverage policies are considered. Since the distance and transportation time from Savannah is a lot lower than those from Los Angeles, it is assumed that products shipped from Port of Los Angeles are insured under basic coverage, and products shipped from Port of Savannah are insured under total loss coverage, which have \$0.55 and \$0.30 insurance rates for every \$100 product value, respectively.

After stage 3, there are two different insurance costs; one for international insurance for ocean freights from plants to ports of Savannah and Los Angeles, and the other for domestic shipping from the ports to the warehouse. Hence, total unit insurance costs are found by adding international and domestic insurance costs.

Table 6.11 Unit insurance costs for part families after each stage

Part family	After stage 1 International	After stage 2 International	After stage 3 International	After stage 3 - From Savannah	After stage 3 - From LA
PF 1	0.003480	0.008700	0.020880	0.007200	0.013200
PF 2	0.015660	0.039150	0.093960	0.032400	0.059400
PF 3	0.009570	0.023925	0.057420	0.019800	0.036300
PF 4	0.004350	0.010875	0.026100	0.009000	0.016500
PF 5	0.017400	0.043500	0.104400	0.036000	0.066000
PF 6	0.010440	0.026100	0.062640	0.021600	0.039600
PF 7	0.015660	0.039150	0.093960	0.032400	0.059400
PF 8	0.005220	0.013050	0.031320	0.010800	0.019800
PF 9	0.008700	0.021750	0.052200	0.018000	0.033000
PF 10	0.008700	0.021750	0.052200	0.018000	0.033000

Since after every stage, the value of the semi-finished products and products increase, insurance costs of the products shipped increase as well. This causes higher transportation costs as the products go through various manufacturing stages. For example for a batch of 10,000 PF1 products, insurance costs for transportation from stage 1 to stage 2 is $34,8. It increases to $87 from stage 2 to stage 3. For the finished products, the insurance cost is $208.8. Domestic costs depend on which port is used as the receiving port.

6.3.6 Transportation Routes among Plants

Semi-finished products are transported among plants using intermodal containers. Maritime transportation is the cheapest mode of transportation among continents since air transportation, the only other option, is way more expensive than maritime transportation.

Potential plants are located in various countries which are on different continents. Three of them are island states, and most of them have long distances among them. Table 6.12 presents the maritime distances among the ports of the potential plant locations. Maximum distance is between Veracruz, Mexico and Shanghai, China plants. Shortest distance is between San Juan, Puerto Rico, and San Santo Domingo, Dominican Republic plants.

Table 6.12 Maritime transportation distances among plants (days)

Distance (miles)	Shanghai, CHN	Veracruz, MEX	Manila, PHL	Mumbai, IND	Mersin, TUR	San Juan, PRI	Santo Domingo, DOM
Shanghai	0	11429	1290	5299	8674	10903	10688
Veracruz	11429	0	12416	11251	7803	2023	1807
Manila	1290	12416	0	4331	7706	11890	11675
Mumbai	5299	11251	4331	0	3917	9635	9836
Mersin	8674	7803	7706	3917	0	6187	6389
San Juan	10903	2023	11890	9635	6187	0	265
Santo Domingo	10688	1807	11675	9836	6389	265	0

In this dissertation, time and distance values for all sea routes among ports are acquired via SeaRates.com (“Transit Time, Distance calculator & Port to port distances,” n.d.). Freight rates are obtained from World Freight Rate (“World Freight Rates Freight Calculator,” n.d.) Please keep in mind that these market rates change daily and these rates are average rates. Appendix D provides the ranges among the candidate plant locations and from these locations to Port of Savannah and Port of Los Angeles.

Table 6.13 presents the maritime transportation times among the ports of the potential plant locations. Maximum transportation time is between Veracruz, Mexico and Manila, Philippines plants. Shortest distance is transportation time San Juan, Puerto Rico, and San Santo Domingo, Dominican Republic plants.

Table 6.13 Maritime transportation time among plants (days)

Time (days)	Shanghai, CHN	Veracruz, MEX	Manila, PHL	Mumbai, IND	Mersin, TUR	San Juan, PRI	Santo Domingo, DOM
Shanghai	0	29.5	3.3	13.7	22.4	28.2	27.6
Veracruz	29.5	0	32.1	29.1	20.2	5.2	4.6
Manila	3.3	32.1	0	11.2	19.9	30.7	30.2
Mumbai	13.7	29.1	11.2	0	10.1	24.9	25.4
Mersin	22.4	20.2	19.9	10.1	0	16	16.5
San Juan	28.2	5.2	30.7	24.9	16	0	0.7
Santo Domingo	27.6	4.6	30.2	25.4	16.5	0.7	0

Transportation times and distances between the plants and Ports of Los Angeles and Savannah are presented in Table 6.14. Port of Savannah is the closer port to Mexico, India, Turkey, Puerto Rico and Dominican Republic plants. Port of Los Angeles is closer to China and Philippines plants than Port of Savannah. Transportation times follow a similar trend with distances.

Table 6.14 Transportation times and distances from plants to US ports

Plants/US ports	Distance (miles) Los Angeles	Distance (miles) Savannah	Time (days) Los Angeles	Time (days) Savannah
Shanghai, China	**6581**	11571	**17**	29.9
Veracruz, Mexico	5089	**1649**	13.1	**4.3**
Manila, Philippines	**7515**	12558	**19.4**	32.5
Mumbai, India	11626	**9970**	30	**25.8**
Mersin, Turkey	10687	**6523**	27.6	**16.8**
San Juan, Puerto Rico	4563	**1394**	11.8	**3.6**
Santo Domingo, Dominican Rep.	4348	**1428**	11.2	**3.7**

Ocean freight rates among plant locations for a 40 ft. container are presented in Table 6.15. These are the market rates obtained from World Freight Rates ("World Freight Rates Freight Calculator," n.d.).

Table 6.15 Ocean freight rates among plants

Average ocean freight rates ($)	Shanghai CHN	Veracruz MEX	Manila PHL	Mumbai IND	Mersin TUR	San Juan PRI	Santo Domingo DOM
Shanghai	0	3204	1359	1713	2094	2992	3026
Veracruz	1996	0	4139	2450	4512	1173	1190
Manila	1359	2749	0	1856	2334	3856	3894
Mumbai	2162	2455	2317	0	1585	4674	4691
Mersin	1376	4992	1697	1161	0	5611	5673
San Juan	3510	1717	4321	2682	4138	0	892
Santo Domingo	3530	1730	4340	2694	4151	892	0

Due to dynamic market conditions, the rates for reciprocal directions are not same. For example, the cost of transporting a 40 ft. container from Veracruz, Mexico to Shanghai, China is $1,996. However, the cost of transportation for the opposite direction, from Shanghai to Veracruz is $3,204. Almost all of the reciprocal routes have different freight rates. The cheapest rate is obtained for the routes between Puerto Rico and Dominican Republic. Most expensive route is from Turkey to Mexico.

Ocean freight rates from plants to Port of Savannah and Port of Los Angeles are presented in Table 6.16. These values change on a daily basis according to market conditions. Also, different websites quote different rates for the same route.

Table 6.16 Ocean freight rates from plants to Ports of Savannah and Los Angeles

Average ocean freight rates ($)	Savannah, GA	Los Angeles, CA
Shanghai	3127	2932
Veracruz	1472	1780
Manila	4057	4115
Mumbai	3674	4162
Mersin	4511	5211
San Juan	642	3096
Santo Domingo	655	2915

These costs are partially consistent with the values reported by United Nations Conference on Trade and Development (UNCTAD, 2014). According to this report, ocean freight rates in 2013 from Shanghai to the east coast and the west coast of US is on the average $3,290 and $2,033, respectively.

Unit ocean freight costs among plants from stage 1 to stage 2 are presented in Table 6.17. Similarly, costs from stage 2 to stage 3 are presented in Table 6.18. Table

6.19 shows the unit ocean freight costs for finished products from plants to east coast and west coast ports. The values are in US dollars.

Table 6.17 PF1 unit ocean freight costs among plants from stage 1 to stage 2 ($)

Stage 1 PF1	Shanghai	Veracruz	Manila	Mumbai	Mersin	San Juan	Santo Domingo
Shanghai	0	0.002195	0.000931	0.001174	0.001435	0.002050	0.002073
Veracruz	0.001368	0	0.002836	0.001679	0.003091	0.000804	0.000815
Manila	0.000931	0.001884	0	0.001272	0.001599	0.002642	0.002668
Mumbai	0.001481	0.001682	0.001588	0	0.001086	0.003202	0.003214
Mersin	0.000943	0.003420	0.001163	0.000795	0	0.003844	0.003887
San Juan	0.002405	0.001176	0.002961	0.001838	0.002835	0	0.000611
Santo Domingo	0.002419	0.001185	0.002974	0.001846	0.002844	0.000611	0

Table 6.18 PF1 unit ocean freight costs among plants from stage 2 to stage 3 ($)

Stage 2 PF1	Shanghai	Veracruz	Manila	Mumbai	Mersin	San Juan	Santo Domingo
Shanghai	0	0.002328	0.000987	0.001245	0.001522	0.002174	0.002199
Veracruz	0.001450	0	0.003007	0.001780	0.003279	0.000852	0.000865
Manila	0.000987	0.001997	0	0.001349	0.001696	0.002802	0.002829
Mumbai	0.001571	0.001784	0.001684	0	0.001152	0.003396	0.003409
Mersin	0.001000	0.003627	0.001233	0.000844	0	0.004077	0.004122
San Juan	0.002550	0.001248	0.003140	0.001949	0.003007	0	0.000648
Santo Domingo	0.002565	0.001257	0.003154	0.001958	0.003016	0.000648	0

Table 6.19 PF1 unit ocean freight cost from plants to North American ports ($)

Stage 3 PF1	Savannah	Los Angeles
Shanghai	0.009038	0.008474
Veracruz	0.004254	0.005145
Manila	0.011726	0.011893
Mumbai	0.010619	0.012029
Mersin	0.013038	0.015061
San Juan	0.001856	0.008948
Santo Domingo	0.001893	0.008425

With these rates, carrying a batch of 10,000 PF1 products between Shanghai to San Juan costs $20.5 from stage 1 to stage 2, and $21.74 from stage 2 to stage 3. Transporting the same batch as finished products from Shanghai to Port of Savannah and Port of Los Angeles costs $90.38 and $84.25 respectively.

Freight insurance costs are another cost factor in ocean and ground transportation. These costs should be reflected in transportation costs as well. Values of the transported goods are one of the important factors to determine insurance costs. Total of ocean freight and insurance costs among plants from stage 1 to stage 2 is presented in Table 6.20. Total costs from stage 2 to stage 3 are presented in Table 6.21. Table 6.22 shows the total of ocean freight and insurance costs for finished products from plants to the receiving ports in North America. With these total cost rates, costs carrying a batch of 10,000 PF1 products between Shanghai to San Juan increased to $55.3 from $20.5 from stage 1 to stage 2, and increased to $108.74 from $21.74 from stage 2 to stage 3. Transporting the same batch as finished products from Shanghai to Port of Savannah and Port of Los Angeles costs $299.18 and $293.54, respectively.

Table 6.20 PF1 total of unit ocean freight and insurance costs among plants from stage 1 to stage 2 ($)

Stage 1 PF1	Shanghai	Veracruz	Manila	Mumbai	Mersin	San Juan	Santo Domingo
Shanghai	0	0.005675	0.004411	0.004654	0.004915	0.005530	0.005553
Veracruz	0.004848	0	0.006316	0.005159	0.006571	0.004284	0.004295
Manila	0.004411	0.005364	0	0.004752	0.005079	0.006122	0.006148
Mumbai	0.004961	0.005162	0.005068	0	0.004566	0.006682	0.006694
Mersin	0.004423	0.006900	0.004643	0.004275	0	0.007324	0.007367
San Juan	0.005885	0.004656	0.006441	0.005318	0.006315	0	0.004091
Santo Domingo	0.005899	0.004665	0.006454	0.005326	0.006324	0.004091	0

Table 6.21 PF1 total of unit ocean freight and insurance costs among plants from stage 2 to stage 3 ($)

Stage 2 PF1	Shanghai	Veracruz	Manila	Mumbai	Mersin	San Juan	Santo Domingo
Shanghai	0	0.011028	0.009687	0.009945	0.010222	0.010874	0.010899
Veracruz	0.010150	0	0.011707	0.010480	0.011979	0.009552	0.009565
Manila	0.009687	0.010697	0	0.010049	0.010396	0.011502	0.011529
Mumbai	0.010271	0.010484	0.010384	0	0.009852	0.012096	0.012109
Mersin	0.009700	0.012327	0.009933	0.009544	0	0.012777	0.012822
San Juan	0.011250	0.009948	0.011840	0.010649	0.011707	0	0.009348
Santo Domingo	0.011265	0.009957	0.011854	0.010658	0.011716	0.009348	0

Table 6.22 PF1 total of unit ocean freight and insurance cost from plants to North American ports ($)

Stage 3 PF1	Savannah	Los Angeles
Shanghai	0.029918	0.029354
Veracruz	0.025134	0.026025
Manila	0.032606	0.032773
Mumbai	0.031499	0.032909
Mersin	0.033918	0.035941
San Juan	0.022736	0.029828
Santo Domingo	0.022773	0.029305

6.3.7 Shipments of Finished Products to the North American Ports

Since land transportation is not possible between most of the plant locations to the warehouse in North America, only maritime and air transportation modes can be used. As stated before, maritime transportation is the only logical mode of transportation among countries because of its cost effectiveness over air transportation. Air freight carriers charge per kilogram or pound. According to Tanger (2007), even though almost 40% of the value of all of the world trade was carried by air transportation in 2006, this made only 1% of the total weight of the world trade. Products which are carried via air usually have the one or more of the following properties: expensive and lightweight, perishable, requires high security, and time-sensitive.

Air transportation is the most expensive way of shipping products from one country to another. UPS charges 9.73$ per pound from US to China, and it costs $9,730 to ship 1,000 lbs. cargo (“UPS Express Air Freight,” 2015). However, according to the international trade website, alibaba.com, Chinese logistics companies' air freight costs from China to US ranges between two and five dollars per kilogram (“The World’s Leading Platform for Global Trade,” n.d.). In order to have a better price estimate, nine international air freight carrier companies were contacted and asked to give an estimate to carry a fashion jewelry pallet that is 1,000 pounds in weight and 120cm x 120cm x 125cm in size from Shanghai International Airport, China, to Atlanta International Airport, USA. The prices range between 2.6 and 4.8 dollars per kilogram. Some companies charge customs and documentation fee on shipping costs. The minimum quotation is 1,180.4 dollars, and the maximum quotation amount is 2,179.2 dollars. Table 6.23 shows these shipping quotations for various carriers from Shanghai to Atlanta.

Table 6.23 Shipping cost quotations by air from Shanghai, China to Atlanta, US

Shipping Company	Rate ($/kg)	Weight (kg)	Shipping cost ($)	Customs& handling costs	Total costs ($)
Seabay International	4.5	454	2,043.0	0	2,043.0
Sinotech Logistics	3.95	454	1,793.3	0	1,793.3
Cooperate Logistics	3.65	454	1,657.1	100	1,757.1
Shenzhen Kingstar Shipping	4.8	454	2,179.2	90	2,269.2
Shenzhen Top Way Int. Forwarding	2.6	454	1,180.4	95	1,275.4
Shenzhen Global Interlink Logistics	2.75	454	1,248.5	0	1,248.5
Guangzhou Hongdex Int. Logistics	4.5	454	2,043.0	0	2,043.0
Ever Triumph Logistics Limited	3.45	454	1,566.3	0	1,566.3

Even if the lowest estimate of air transportation is considered, maritime transportation is still many times cheaper than air transportation. Hence, maritime transportation is used to ship products from plants to the receiving ports in North America.

6.3.8 Shipments of Finished Products from the US Ports to Atlanta Warehouse

Intermodal containers are used to transport finished products from plants to the market. This enables using multiple modes of transportation including maritime, air, road, and rail transportation.

Rodrigue, Comtois, and Slack (2013) studied the relations between transportation cost, distance and transportation mode selection. Each transportation mode has its own cost function according to the distance between the source and the destination. Cost functions of road, rail and maritime transportation modes are represented by C1, C2 and C3 in Figure 6.2. For shorter distances, road transportation is more profitable than other modes of transportation. After distance D1, rail transportation becomes more profitable than road transportation. After distance D2, maritime transportation is the most profitable mode of transportation. The authors did not consider air transportation due its high costs. The authors reported that in the USA, the breakeven distance for road and rail transportation is between 500 and 750 km, or 310 and 466 miles. The breakeven distance between rail and maritime transportations is 1500 km or 932 miles (Rodrigue *et al.*, 2013). The transportation mode selection of maritime transportation between continents is also supported by this research. However, the only available modes of transportation are air and maritime transportations among continents.

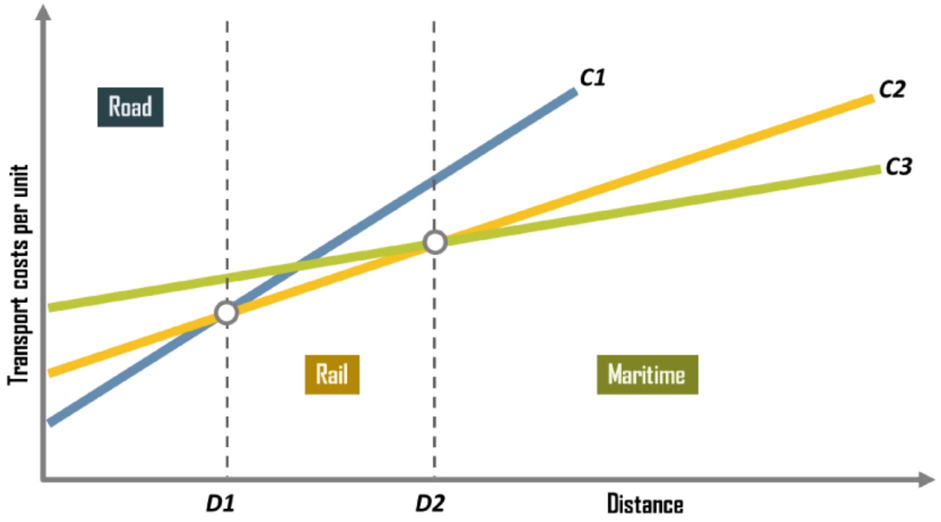


Figure 6.2 Transportation mode choice by considering distance & cost
(Rodrigue *et al.*, 2013)

Rodrigue *et al.*, (2013) reported that the cost of transportation via railroad is 2.7 cents per ton-mile, while it is 5 cents per ton-mile for trucking. These cost figures are not realistic since fuel costs increased dramatically since this research was conducted.

A more recent study by Austin (2015) for Congressional Budget Office gives more realistic and updated costs for road and rail transportation in the US. Table 6.24 shows average shipping rates in cents per ton-mile for various service freight service types. The numbers in parenthesis are standard deviations of shipping rates. Intermodal transportation costs, which is used in this dissertation, follow a normal distribution with a mean of 17.4 cents per ton-mile and a standard deviation of 4.2 cents per ton-mile.

Table 6.24 Average shipping rates in cents per ton-mile (adapted from Austin, 2015)

Service Type	Truck	Rail
Carload/Truckload	14.6 (3.4)	4.7 (2.3)
Bulk	13.6 (1.4)	3.5 (1.2)
Intermodal	17.4 (4.2)	5.6 (2.2)
Auto Transport	13.8 (2.4)	9.6 (4.3)
Total	15.6 (3.9)	5.1 (2.5)

There are multiple routes available from each plant location to the warehouse. The products can be shipped to either Port of Savannah at east coast, or to Port of Los Angeles at west coast. In any case, after the products reach ports, they can be shipped via road, rail or air transportation. Since air transportation is not an option due to its high costs, it is eliminated.

Table 6.25 presents the available modes of transportation between the ports and the warehouse. The distance between Port of Savannah and Atlanta is 250 miles which is less than 500 km. Therefore, road transportation is used to transport products from the port to the warehouse.

Table 6.25 Transportation mode selection from ports to warehouse

Port	Available modes of transportation	Road distance to Atlanta	Rail distance to Atlanta
Savannah	Road, rail, air	248 miles	167 miles
Los Angeles	Road, rail, air, maritime	2173 miles	2601 miles

Freight can be transported using all of the four possible modes of transportation from Port of Los Angeles to Atlanta. Air transportation is eliminated due to its high costs. The road distance between the warehouse and Port of Los Angeles is 2173 miles, which is more than even D2 distance, requires using maritime transportation between Los

Angeles and Atlanta. Maritime transportation adds unnecessary layers of complexity to the logistics. If maritime is used, the products which are shipped to Los Angeles via maritime will need to be loaded on to ships again, shipped to Port of Savannah, and then carried to Atlanta via rail or road transportation. Thus, maritime transportation choice is eliminated as well. The last two options are rail and road transportation.

Railway transportation from Port of Los Angeles to Atlanta requires using two different railway companies: BNSF and CSX. BNSF brings the freight to Birmingham, AL, and CSX takes over the freight from there and carries to Atlanta, GA. Table 5.24 shows the railway distances and transportation times from Los Angeles, CA to Atlanta, GA. The data distance data is obtained from BNSF Railway's website. Appendix E shows the average transportation time from Los Angeles, CA to Birmingham, AL with respect to departure days of the week. Average transportation time between these locations is used here. Transportation times from Los Angeles, CA to Birmingham, AL is retrieved from BNSF, and it is assumed that CSX offers similar service speed from Birmingham, AL to Atlanta, GA, and transportation time is calculated accordingly.

Table 6.26 Route distances and transportation times from Los Angeles to Atlanta

Carrier	Route	Distance (miles)	Time (hr)	Time (days)	Cost ($)
BNSF	Los Angeles, CA to Birmingham, AL	2363	304.70	12.7	3504.0
CSX	Birmingham, AL to Atlanta, GA	238	30.69	1.28	352.9
Rail Total	Los Angeles, CA to Atlanta, GA	2601	335.39	13.97	**3857.0**
Road	Los Angeles, CA to Atlanta, GA	2192	120.00	4.5	**10099.7**

Shortest road distance from Los Angeles to Atlanta is 2192 miles. In order to find the estimated shipping time, an online shipping quote website is used and freight companies quoted 4 to 5 business days to ship freight from Los Angeles to Atlanta. The cost of road transportation is reported to be on average 17.4 cents per ton mile for intermodal freights (Austin, 2015). Estimated cost is found by multiplying average shipping rate in cents per ton-mile with the distance.

Road transportation cost for one 40-ft container from Los Angeles to Atlanta is found by multiplying the distance, the cost per ton mile in dollars, and the capacity of one container in tones. The result is 0.174 x 2192 x 26.48 = $10,099.7

In order to check the validity of this estimation using 0.174 cents per ton-mile, the quotations made by the freight companies are used. FreightCenter website does not allow getting quotes for more than 15,000 pounds. Therefore, estimated prices for one 40-ft container, which is around 58,378 pounds, are found using the quotes made for this amount. Table 6.27 shows the quotes of the first six quotes from freight companies.

Table 6.27 Quote results and estimated prices for Los Angeles-Atlanta from FreightCenter (“FreightCenter.com,” n.d.)

#	Freight Company	Transit Time (business days)	Price ($/15000 lbs)	Estimated Price ($/1 container)
1	Clear Lane Freight Lane	5	2090.96	8137.8
2	Central Transport	5	2788.05	10850.8
3	Roadrunner Transportation	5	3050.63	11872.7
4	SAIA Motor Freight	4	4147.88	16143.1
5	YRC Freight	4	4296.16	16720.2
6	R+L Carriers	4	4540.89	17672.7
	Average	4.5	3485.8	**13566.2**

The minimum estimated price is $8,137.8, and the average estimated price of the first six cheapest transportation companies is $13,566.2. The 0.174 cents per ton-mile cost seems reasonable. Transportation times in days and estimated prices for a container are also presented in the table. See Appendix E for quotes from other freight companies.

The distance from Port of Savannah to Atlanta is about 250 miles for road transportation, and 167 miles for rail transportation. CSX charges $1,869 for box cars, and $2,801 for flat cars for this route. Price range varies according to shipping dates and types of rail cars. In any case, rail transportation is not cost efficient for this short distance. Therefore, road transportation is selected for this route. Table 6.28 shows transportation distances, times, and costs for rail and road transportation modes from Port of Savannah to Atlanta. One 40ft container takes 26.48 tons and the distance between the port and the warehouse is 250 miles. Then the cost of transportation is calculated as follows:

Road transportation cost for one 40-ft container from Savannah to Atlanta is found by multiplying the distance, the cost per ton mile in dollars, and the capacity of one container in tones. The result is 0.174 x 250 x 26.48 = $1,151.9.

Table 6.28 Railway and road distances and transportation times from Port of Savannah to Atlanta

Mode	Route	Distance (miles)	Time (hr)	Time (days)	Estimated Cost ($)
Rail	Savannah to Atlanta	167	-	1	1,869
Road	Savannah to Atlanta	250	3.5	0.15	1151.9

6.3.9 Potential Route Options from US Ports to Atlanta Warehouse

When the products are ready to ship from plants after stage 3, the two options to receive the products are Port of Savannah and Port of Los Angeles. After the products arrive at these ports, they can be shipped via either rail or road transportation to the warehouse in North America. Each of them has different costs and estimated transportation times.

Table 6.29 shows domestic freight costs for a 40 ft container from Port of Los Angeles and Port of Savannah to Atlanta warehouse for rail and road transportation options. It also presents the time required for each option. It is assumed that the times that the containers wait to be shipped at the ports are insignificant.

Table 6.29 Costs and times of potential modes of transportation from the US ports to the warehouse

Ports	Mode of transportation	Freight cost ($/40'container)	Time (days)
Port of Los Angeles	Rail	3857	13.97
	Road	10099.7	4.5
Port of Savannah	Rail	1869	1
	Road	1151.9	0.15

Unit freight costs of each part family from ports to Atlanta warehouse for rail and road transportation options are shown in Table 6.30. Calculations are made assuming that the containers are fully loaded up to their maximum payloads.

Insurance costs are added to domestic unit freight costs in Table 6.31 for all part families. Due to huge difference between the transportation times, two different insurance rates are used for products shipped from Port of Savannah and Port of Los Angeles. It is assumed that products shipped from Los Angeles and Savannah are insured for \$0.55 and \$0.30 for every \$100 product value, respectively.

Table 6.30 Unit domestic freight costs from ports to the warehouse (\$/unit)

Routes	**PF1**	**PF2**	**PF3**	**PF4**	**PF5**	**PF6**	**PF7**	**PF8**	**PF9**	**PF10**
LA Rail	0.011148	0.036456	0.020388	0.011485	0.019952	0.015354	0.015962	0.007928	0.011364	0.007928
LA Road	0.029191	0.095461	0.053388	0.030073	0.052246	0.040205	0.041797	0.020760	0.029756	0.020760
Savannah Rail	0.005402	0.017666	0.009880	0.005565	0.009668	0.007440	0.007735	0.003842	0.005506	0.003842
Savannah Road	0.003329	0.010888	0.006089	0.003430	0.005959	0.004586	0.004767	0.002368	0.003394	0.002368

Table 6.31 PF1 total of domestic freight and insurance costs from the US ports to Atlanta warehouse (\$)

Routes	**PF1**	**PF2**	**PF3**	**PF4**	**PF5**	**PF6**	**PF7**	**PF8**	**PF9**	**PF10**
LA Rail	0.012076	0.039491	0.022086	0.012441	0.021613	0.016632	0.017291	0.008588	0.012310	0.008588
LA Road	0.030119	0.098496	0.055085	0.031029	0.053907	0.041483	0.043125	0.021420	0.030702	0.021420
Savannah Rail	0.005908	0.019321	0.010805	0.006087	0.010574	0.008137	0.008459	0.004202	0.006022	0.004202
Savannah Road	0.003835	0.012543	0.007015	0.003951	0.006865	0.005283	0.005492	0.002728	0.003910	0.002728

Table 6.32 presents unit transportation costs of PF1 for all route options from stage 3 to the warehouse. This cost is a combination of ocean freight cost and international insurance costs from stage 3 to ports of Savannah and Los Angeles, and domestic freight costs and domestic insurance costs from ports to the warehouse. Unit transportation costs from Port of Los Angeles to Atlanta via road transportation are the

highest costs among all options. The lowest costs are the ones from Port of Savannah via road transportation. Transportation costs for other part families are calculated in the same way.

Table 6.32 Unit transportation costs of PF1 after stage 3 to Atlanta warehouse

PF1	LA Rail	LA Road	Savannah Rail	Savannah Road
Shanghai	0.041430	0.059473	0.035826	0.033753
Veracruz	0.038100	0.056143	0.031043	0.028970
Manila	0.044849	0.062892	0.038514	0.036441
Mumbai	0.044985	0.063028	0.037407	0.035334
Mersin	0.048017	0.066060	0.039826	0.037753
San Juan	0.041904	0.059947	0.028644	0.026571
Santo Domingo	0.041381	0.059424	0.028681	0.026609

These cost values are used as inputs in the supply chain network design mathematical model.

6.4 In-transit Inventory Carrying Costs

Inventory holding costs constitute an important part of supply chain operating costs; therefore reducing inventory holding costs has always been one of the goals in supply chain management. Inventory decisions are considered as tactical decisions which involve determination of the optimal stocking points of the products and development of effective inventory policies for these stocking points. These decisions get more difficult in multi-echelon multi-facility supply chain networks. The pressure to decrease the inventory costs forces the companies to build more effective inventory policies that reduce the inventory levels to a minimum. The typical decisions to be made in an inventory system are the frequency of replenishment, order size, reorder point, safety stock and performance level targeted.

The integration among various facilities and tiers across the supply chain network affects the profitability of each tier. Major companies such as Toyota require sharing all critical information about manufacturing and inventory from their suppliers. Integration among manufacturers, manufacturers and suppliers, manufacturers and distribution centers, and among distribution centers allows coordinated decision making for the entire supply chain (Meixell & Gargeya, 2005).

The objective of an effective inventory management in any tier of a supply chain network is to minimize the sum of ordering and procurement cost, holding and carrying cost, and shortage cost by determining the optimal reorder points and order quantities for each product. Supply chain costs are closely related to the design of supply chain network, and increase as leadtime and distance increase. However, finding an optimal inventory policy for an echelon does not mean that it improves the profitability of the entire supply chain. The optimal inventory policy that maximizes the profit of a supply chain may be way different than each echelon. The reasons for not having an optimal common inventory policy for the entire supply chains vary for each network (Cachon, 2001). First, each echelon may not have enough information about the other echelons. Second, even if they have information, they may not have the capability to develop an optimal policy for the entire supply chain. Third, each echelon, even if they belong to the same company, tries to maximize its own profitability.

The inventory between stages is called echelon inventory. This is the inventory between the manufacturing stages and its final customer. Supply chains have inventory at every part of the chain. In a two stage supply chain, the manufacturer carries raw material inventory, WIP and finished product inventory. When products are shipped, they become in-transit inventory. After they arrive at ports or rail ramps and wait for the customer, the inventory is called waiting-to-ship inventory. Figure 6.3 shows where inventory is carried throughout a multi-stage supply chain. Other than WIP in the plants; trucks, ships and trains have in-transit inventory. Ports and rail ramps have waiting-to-be-unloaded or waiting-to-be-shipped inventory. As the lead times and waiting times increase at these locations, echelon inventory of the supply chain, thus the inventory carrying cost increases. Please keep in mind that these products need to have freight insurances as well.

In multi-stage supply chains where multiple modes of transportations are used, the cost of carrying inventory through supply chain is one of the most important cost factors. Therefore, before deciding for a location of a plant in a multi-stage supply chain, inventory carrying costs have to be considered in the decision making process. Hence, in this dissertation, inventory costs are incorporated in the plant location and manufacturing system design decisions. WIP inventory is not considered here.

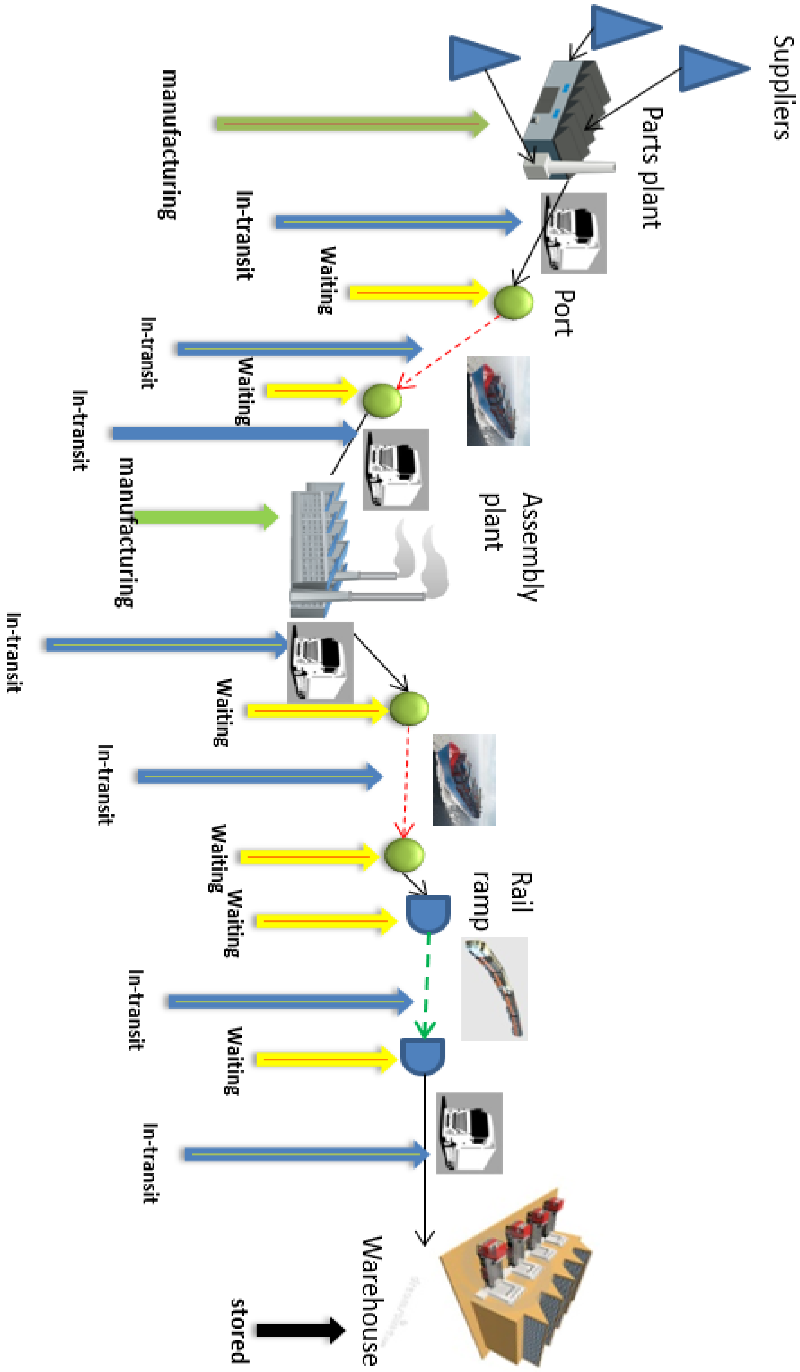


Figure 6.3 Inventory throughout a multi-stage supply chain network

Inventory carrying costs are calculated using cost of capital, value of products and time spent by the products for transportation. Cost of capital is 7.09% for apparel industry as of January 2015 according to Damodaran from Stern School of Business at New York University (Damodaran, 2015). The values of products increase as the product goes through manufacturing stages. Transportation time is the time product leaves the manufacturing facility at one manufacturing stage to the time it arrives to the next manufacturing stage or to the market. It is assumed that all products are produced in one week regardless of their assigned amounts to the cells since manufacturing schedules of the products are not known ahead of time, and the data available is weekly demand and production capacities of the cells. Weekly inventory carrying costs are calculated using Equation (6.2) as shown below.

In-transit Weekly Inventory Carrying Cost = Transportation Quantity x Product Value x Transportation Time x Cost of Capital (6.2)

Transportation time is defined in days and cost of capital is defined annually, therefore they need to be defined in weekly terms. Weekly costs of capital and transportation times are converted to weekly terms using Equation (6.3) and Equation (6.4), respectively.

Weekly Cost of Capital = Annual Cost of Capital / 52 = 7.09/52 = 0.13635% (6.3)

Transportation Time in Weeks = Transportation time in days / 7 (6.4)

Table 6.33 shows transportation time among potential manufacturing facilities in weeks.

Table 6.33 Transportation time in weeks among plants

Time (weeks)	Shanghai, China	Veracruz, Mexico	Manila, Philippines	Mumbai, India	Mersin, Turkey	San Juan, Puerto Rico	Santo Domingo, Dominican Rep.
Shanghai	0.00000	4.21429	0.47143	1.95714	3.20000	4.02857	3.94286
Veracruz	4.21429	0.00000	4.58571	4.15714	2.88571	0.74286	0.65714
Manila	0.47143	4.58571	0.00000	1.60000	2.84286	4.38571	4.31429
Mumbai	1.95714	4.15714	1.60000	0.00000	1.44286	3.55714	3.62857
Mersin	3.20000	2.88571	2.84286	1.44286	0.00000	2.28571	2.35714
San Juan	4.02857	0.74286	4.38571	3.55714	2.28571	0.00000	0.10000
Santo Domingo	3.94286	0.65714	4.31429	3.62857	2.35714	0.10000	0.00000

6.5 Investment Costs

There are many factors that affect investment costs in a country. Taxes, regulations, land costs, labor costs, construction costs, utility costs, customs, security, incentives are some of the factors that have to be taken into account while doing investment. These costs differ from country to country, region to region in a country, city to city in a region, even district to district in the same city.

In this dissertation, investment cost includes the land and construction costs. This cost is not proportional to the number of cells opened in a plant. Cell installment costs and machine costs are covered separately, and depend on the number of cells opened in a plant, and the number of machines required for all of the cells opened.

The weekly investment cost for Puerto Rico is obtained from the study of Süer and Huang (2012). It is assumed that the investment costs increases by the consumer price index every year in USA. According to The World Bank (TheWorldBank, 2015), consumer price indices for 2011 and 2014 are 103.2 and 108.6, respectively. Table 6.34 shows investment costs for all stages for Puerto Rico after consumer price index is taken into account.

Table 6.34 Updated investment costs for Puerto Rico

Years	Consumer price index	Stage 1 cost ($)	Stage 2 cost ($)	Stage 3 cost ($)
2011	103.2	30,000	30,000	30,000
2014	108.6	31,570	31,570	63,140

In order to find the other countries' investment costs compared to the United States, comparative price level indices which are obtained from The Organisation for Economic Co-operation and Development (OECD) and The World Bank are used. Comparative price level indices are found by taking the ratio of purchasing power parities to the market exchange rates (OECD, 2015). Comparative price level allows comparing the cost of goods and services in other countries with the cost of same goods and services in USA. This index basically tells the amount of money in dollars needed to buy one US dollar's worth of goods and services as compared to the USA (TheWorldBank, 2015). When the price level index of a country is 0.5, it means buying a bundle of products in that country is half of the cost of buying the same bundle of products in USA. It is assumed that investment costs for a manufacturing stage for that country is also 50% cheaper than USA. Table 6.35 presents comparative price level indices for other countries and their corresponding investment costs. Price level indices for USA, Turkey, Mexico, China and India are retrieved from OECD database, and price level indices for Dominican Republic and Philippines are retrieved from The World Bank database. Please note that these investment costs do not include machine procurement and cell installment costs.

Table 6.35 Investment costs of manufacturing stages for potential plant locations

Countries	Comparative price level index	Investment costs		
		Stage 1 cost ($)	Stage 2 cost ($)	Stage 3 cost ($)
Puerto Rico (USA)	1.01	31,570	31,570	63,140
Dominican Republic	0.50	15,629	15,629	31,257
Mexico	0.61	19,067	19,067	38,134
Turkey	0.55	17,191	17,191	N/A
India	0.29	N/A	N/A	18,129
China	0.60	18,754	N/A	37,509
Philippines	0.40	N/A	12,503	25,006

6.6 Labor Costs

Potential plants are located in various countries and continents. The locations close to the North American market, labor costs are relatively higher than the rest of the countries. Manufacturing wages data for Puerto Rico, Mexico, India, China and Philippines are retrieved from The Conference Board website (“The Conference Board International Labor Comparisons,” 2014). Manufacturing wages for Turkey is obtained from Trading Economics website (“Turkey Gross Wages in Manufacturing Index,” 2015). Table 6.36 shows hourly and weekly manufacturing wages for the potential countries of manufacturing facilities.

Table 6.36 Weekly manufacturing wages for potential plants

2013 wages	Hourly wages ($)	weekly wages ($)
Puerto Rico	23.42	936.8
Dominican Republic	2.58	103.2
Mexico	6.13	245.2
Turkey	6.84	273.6
India	1.46	58.4
China	1.98	79.2
Philippines	1.85	74

Manufacturing wage information for Dominican Republic is obtained a report from KPMG (KPMG, 2013) and International Labour Organization database (ILO) (ILO, n.d.). According to ILO, a manufacturing worker's monthly net wage was 15,033.4 and yearly salary was 180,400.8 Dominican Pesos (DOP) in 2013. KPMG reports that employees earning less than 290,243 DOPs are exempt from income tax. But employers and employees have to pay health insurance, disability insurance, and labor risks insurance. This makes almost 21% of the wages. This brings annual cost of a manufacturing worker to the employer 219,294.7 DOPs. When this amount is converted to US dollars, weekly wage is found as $130,2.

Even though working hours in these countries are not the same, it is assumed that workers work 40 hours a week in every potential plant location.

6.7 Machine Costs

Fashion jewelry machines are generally small and inexpensive machines except for plating machines. Plating machines are quite expensive and the prices of these machines range depending on the technology and automation they have.

In order to have a better estimate of the costs of the machines used in fashion jewelry manufacturing, most up-to-date prices are searched at a popular international trade website, alibaba.com. Each machine has a wide range of prices depending on the technology used and capacity. The prices shown in Table 6.37 are neither the cheapest nor the most expensive ones provided on the website.

Table 6.37 Procurement costs and weekly costs of fashion jewelry manufacturing machines

Op#	Operation	Price ($)	Weekly cost ($)	Op#	Operation	Price ($)	Weekly cost ($)
1	Finding	4,000	16	11	Welding/ Soldering	4,000	16
2	Deburring	3,750	15	12	Linking	5,000	20
3	Casting	2,000	8	13	Stone setting	10,000	40
4	Degating	2,500	10	14	Enameling	5,000	20
5	Tumbling	5,000	20	15	Finishing	2,000	8
6	Buffing	2,000	8	16	Oven	2,000	8
7	Chain plating	104,000	416	17	Carding and packaging	5,000	20
8	Barrel Plating	60,000	240	18	Inspection	500	2
9	Manual plating	40,000	160	19	Combination	500	2
10	Dying/Frosting	4,000	16				

No machine is used for inspection and combination operations. Since some tools may be required for these operations, costs are also assigned for these tools. It is assumed that regardless of its location, all of the plants use the same machines, and they acquire the machines with same prices.

It is assumed that the useful lives of the machines are 5 years, their values are depreciated steadily, and the plants are working 50 weeks per year. Weekly costs are found using the equation below:

$$\text{Weekly cost} = (\text{Machine cost} / 5 \text{ years}) / 50 \text{ weeks} \tag{6.5}$$

Number of machines from each type of machine required for dedicated, shared and remainder cells is determined in Chapter 4. For dedicated cells, first, number of machines to process each product of the product family to be produced in the cell is found. Then, the maximum values among all products are taken as the required number of machines for that part family, hence for the dedicated cell. For shared and remainder cells, the same procedure is followed for each product family, then the maximum of the required number of machines for each product family is used as the number of machines for the shared or remainder cell. Table 6.38 shows the number of machines required for a dedicated cell that processes PF 8 at stage 3.

Table 6.38 Number of machines from each machine type for PF8 at stage 3

Parts	Op.10	Op.11	Op.12	Op.13	Op.14	Op.15	Op.16	Op.17	Op.18	Op.19
Part 12	3	5	-	5	-	3	-	4	-	-
Part 18	2	-	5	5	3	2	-	3	-	-
Part 27	2	-	-	6	5	3	-	4	-	-
Part 37	2	2	3	4	2	2	-	2	-	3
Part 38	2	3	5	5	-	2	-	3	-	-
Max	3	5	5	6	5	3	0	4	0	3

6.8 Cell Installment

Opening a cell incurs a cost. Since building and construction costs are covered by investment costs, it is assumed that cell installment costs consist of only labor cost. Each cell in the layered cellular manufacturing system has different cell sizes. They have different number of machines and different number of operators. Therefore, cell installment costs for these various sized cells would be different. It is assumed that setting up a machine in stages 1 and 3 in a cell for the first time requires 10 hours labor. For plating machines, this setup time is 500 labor hours. It is also assumed that this setup process is repeated for every five years for the cells in stages 1 and 3. Thus, the cell installment costs for stages 1 and 3 calculated here are divided 250 working weeks (50 weeks per year) in order to find the weekly cell installment costs. It is also assumed that cell installment process is repeated for every ten years for plating machines. The cell installment costs for stage 2 calculated are divided 500 working weeks in order to find the weekly cell installment costs. By determining cell installment costs using this methodology, bigger cells will have higher cell installment costs.

Cells at Stage 2 have one of the three plating operations: manual plating, barrel plating, and chain plating. The production lines for these operations are more complex than the ones in stages 1 and 3. Therefore, cell installment costs assigned to these production lines are considered differently from stage 1 and stage 3 machines.

Table 6.39 shows weekly setup costs for cells at all stages for every plant location.

Table 6.39 Weekly cell installment labor costs for plant locations

Cells	# of machines	Setup labor hours	Puerto Rico	Dom. Rep.	Mexico	Turkey	India	China	Philippines
			$23.42	**$2.58**	**$6.13**	**$6.84**	**$1.46**	**$1.98**	**$1.85**
1	14	140	13.1	1.4	3.4	3.8	0.8	1.1	1.0
2	16	160	15.0	1.7	3.9	4.4	0.9	1.3	1.2
3	25	250	23.4	2.6	6.1	6.8	1.5	2.0	1.9
4	15	150	14.1	1.5	3.7	4.1	0.9	1.2	1.1
5	12	120	11.2	1.2	2.9	3.3	0.7	1.0	0.9
6	17	170	15.9	1.8	4.2	4.7	1.0	1.3	1.3
7	22	220	20.6	2.3	5.4	6.0	1.3	1.7	1.6
8	13	130	12.2	1.3	3.2	3.6	0.8	1.0	1.0
9	10	100	9.4	1.0	2.5	2.7	0.6	0.8	0.7
10	14	140	13.1	1.4	3.4	3.8	0.8	1.1	1.0
11	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
12	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
13	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
14	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
15	2	1000	93.7	10.3	24.5	27.4	5.8	7.9	7.4
16	2	1000	93.7	10.3	24.5	27.4	5.8	7.9	7.4
17	2	1000	93.7	10.3	24.5	27.4	5.8	7.9	7.4
18	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
19	3	1500	140.5	15.5	36.8	41.0	8.8	11.9	11.1
20	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
21	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
22	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
23	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
24	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
25	1	500	46.8	5.2	12.3	13.7	2.9	4.0	3.7
26	2	64	6.0	0.7	1.6	1.8	0.4	0.5	0.5
27	38	380	35.6	3.9	9.3	10.4	2.2	3.0	2.8
28	28	280	26.2	2.9	6.9	7.7	1.6	2.2	2.1
29	41	410	38.4	4.2	10.1	11.2	2.4	3.2	3.0
30	38	380	35.6	3.9	9.3	10.4	2.2	3.0	2.8
31	27	270	25.3	2.8	6.6	7.4	1.6	2.1	2.0
32	34	340	31.9	3.5	8.3	9.3	2.0	2.7	2.5
33	34	340	31.9	3.5	8.3	9.3	2.0	2.7	2.5
34	27	270	25.3	2.8	6.6	7.4	1.6	2.1	2.0
35	37	370	34.7	3.8	9.1	10.1	2.2	2.9	2.7
36	51	510	47.8	5.3	12.5	14.0	3.0	4.0	3.8
37	41	410	38.4	4.2	10.1	11.2	2.4	3.2	3.0
38	38	380	35.6	3.9	9.3	10.4	2.2	3.0	2.8
39	38	380	35.6	3.9	9.3	10.4	2.2	3.0	2.8
40	27	270	25.3	2.8	6.6	7.4	1.6	2.1	2.0
41	32	320	30.0	3.3	7.8	8.8	1.9	2.5	2.4
42	41	410	38.4	4.2	10.1	11.2	2.4	3.2	3.0
43	28	280	26.2	2.9	6.9	7.7	1.6	2.2	2.1
44	46	460	43.1	4.7	11.3	12.6	2.7	3.6	3.4
45	51	510	47.8	5.3	12.5	14.0	3.0	4.0	3.8

Weekly cell installment cost is calculated by using Equation (6.6). Weekly cost for Cell 1 in Puerto Rico is calculated as follows. Cell 1 has 14 machines, thus it requires 140 hours to setup the entire cell for the first time for production. Labor rate in Puerto Rico is \$23.42 per hour.

Weekly cell installment cost = # of machines in cell x 10 x labor rate (\$/hr)/ 250 (6.6)

Weekly cell installment cost for Cell 1 = 140 hours x \$23.42 / 250 weeks = \$13.1 \$/ week

6.9 Machine Setup

Changing from one product to other or from one product family to another requires setups at machines, which is done by workers. Machine setup is required to change tools, to clean the machines, to remove finished parts, to prepare the machines for different materials etc. It is assumed that each machine setup requires one hour of labor. Since plants are located in different countries with different labor costs, machine setup costs are different as well.

In layered cellular manufacturing system, a manufacturing cell can process more than one part family. Each part family consists of many parts which require different operations, hence different machines. If the cell is a dedicated cell, it processes one part family. The number of setup required is found by adding up the number of operations required for each part in that part family. If it is a shared or remainder cell, then number of operations required for all part families are summed. Here, it is assumed that parts are processed in batches and setups are required after batch production. Table 6.40 shows the number of machine setups required for each cell at manufacturing stages. Number of setups in stage 2 is lower due to lower number of required plating operations for products.

Table 6.40 Number of machine setups required for cells at stages

Cell#	Stage 1	Stage 2	Stage 3
1	20	3	22
2	12	4	19
3	18	4	24
4	16	5	22
5	18	7	12
6	17	3	30
7	46	4	30
8	12	4	20
9	16	6	13
10	9	5	54
11		5	31
12		4	25
13		4	25
14		4	20
15		1	21
16		3	31
17			19
18			34
19			90

6.10 Mathematical Model for Plant Location and Resource Allocation

The proposed mathematical model uses the manufacturing cells found by the mathematical model developed in Chapter 4 as resources instead of production capacities of candidate plants as in classical plant location allocation models. The model allocates the cells opened in the previous chapter to the candidate plants. This allocation determines the number and type of cells that will operate in each plant, and the families to be produced in each cell. Therefore, number and location of the plants and manufacturing system of the opened plants are determined simultaneously.

The objective of the model is to minimize investment, machine procurement, labor, machine setup, cell installment, and transportation costs. Investment costs occur when a manufacturing stage is opened at plant. Transportation costs cover the shipping costs of products among plants and from plants to the market. Transportation costs include the freight shipping and insurance costs among the stages and from the stages to the warehouse. The indices, parameters, decision variables are provided along with the objective function and the constraints below.

Notation:

Indices:

i	Product family index
j	Manufacturing stage index
k	Dedicated cell index
r	Shared and remainder cell index
m	Plant index
t	Machine index

Parameters:

I	Number of product families
J	Number of manufacturing stages
K	Number of dedicated cells
R	Number of shared and remainder cells
M	Number of potential plants
T	Number of machines from each type
IR	Weekly cost of capital
U_{jk}	1, if dedicated cell k performs operations in manufacturing stage j; 0, otherwise.
U_{jr}	1, if shared/remainder cell r performs operations in manufacturing stage j; 0, otherwise.
NMT_{kt}	Number of machines from each machine type t in dedicated cell k
NMT_{rt}	Number of machines from each machine type t in shared/remainder cell r
NO_{k}	Number of workforce in dedicated cell k
NO_{r}	Number of workforce in shared/remainder cell r
NS_{k}	Number of setups in dedicated cell k
NS_{r}	Number of setups in shared/remainder cell r
EQ_{ik}	Estimated quantity of product family i produced in dedicated cell k
EQ_{ir}	Estimated quantity of product family i produced in shared/remainder cell r
PSI_{ij}	Previous stage index of stage j for product family i. 0 implies stage j is the first stage for family i or family i does not require manufacturing stage j

$MAXC_{jm}$	Available number of cells for stage j in plant m
$MINUTIL_{jm}$	Min. percent of cells to be assigned to open main plant m in stage j
$UTIL_{jm}$	Desired percent of cells to be assigned to opened plant m in stage j
IC_{jm}	Weekly equivalent investment cost for stage j in plant m
UMC_t	Unit machine cost for machine t ($/week)
OC_{jm}	Labor cost for stage j in plant m ($/week)
$CSET_{km}$	Weekly cell installment cost of dedicated cell k in plant m
$CSET_{rm}$	Weekly cell installment cost of shared/remainder cell r in plant m
PVij	Product value of PF i in stage j.
TT_{mn}	Transportation time from plant m to plant n
TTM_m	Transportation time from plant m to the market
TC_{ijmn}	Unit transportation (freight+insurance) cost of semi-finished PF i in stage j from plant m to n
TCM_{im}	Unit transportation cost of finished PF i from plant m to the **warehouse**
M	Big value

Decision variables:

X_{km}	1, if dedicated cell k is allocated to plant m; 0, otherwise
Y_{rm}	1, if shared/remainder cell r is allocated to plant m; 0, otherwise
W_{jm}	1, if stage j is opened in plant m; 0, otherwise
TQ_{ijmn}	Transportation quantity of family i from plant n to plant m for stage j

Objective Function:

Min Z = (a) MachineCost + (b) LaborCost + (c) InvestmentCost + (d)InventoryCarryingCost + (e) VaryingTransportationCost + (f)MachSetupCost + (g)CellSetupCost

$$
\begin{aligned}
Z = {} & \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{t=1}^{T}(NMT_{kt} \times UMC_t \times U_{jk} \times X_{km}) + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}(NMT_{rt} \times UMC_t \times U_{jr} \times Y_{rm}) \rightarrow (a) \\
& + \sum_{j=1}^{J}\sum_{m=1}^{M}(OC_{jm} \times (\sum_{k=1}^{K}(NO_k \times U_{jk} \times X_{km}) + \sum_{r=1}^{R}(NO_r \times U_{jr} \times Y_{rm}))) \rightarrow (b) \\
& + \sum_{j=1}^{J}\sum_{m=1}^{M}(IC_{jm} \times W_{jm}) \rightarrow (c) \\
& + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{n=1}^{M}\sum_{m=1}^{M}(TQ_{ijmn} \times TT_{mn} \times PV_{ij} \times IR) \rightarrow (d) \\
& + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{k=1}^{K}(EQ_{ik} \times TTM_m \times PV_{i3} \times X_{km} \times U_{jk} \times IR) \\
& + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{r=1}^{R}(EQ_{ir} \times TTM_m \times PV_{i3} \times Y_{rm} \times U_{jr} \times IR) \\
& + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{n=1}^{M}\sum_{m=1}^{M}(TQ_{ijmn} \times TC_{ijmn}) \rightarrow (e) \\
& + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{k=1}^{K}(EQ_{ik} \times TCM_{im} \times X_{km} \times U_{jk}) + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{r=1}^{R}(EQ_{ir} \times TCM_{im} \times Y_{rm} \times U_{jr}) \\
& + \sum_{j=1}^{J}\sum_{m=1}^{M}(OC_{jm} \times (\sum_{k=1}^{K}(NS_k \times U_{jk} \times X_{km}) + \sum_{r=1}^{R}(NS_r \times U_{jr} \times Y_{rm}))) \rightarrow (f) \\
& + \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{k=1}^{K}(CSET_{km} \times X_{km} \times U_{jk}) + \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{r=1}^{R}(CSET_{rm} \times Y_{rm} \times U_{jr}) \rightarrow (g)
\end{aligned}
\tag{6.7}
$$

Subject to:

$$\sum_{k=1}^{K}(X_{km} \times U_{jk}) + \sum_{r=1}^{R}(Y_{rm} \times U_{jr}) \leq MAXC_{jm} \quad \text{for } j = 1, \cdots, J \ \&\ m = 1, \cdots, M \tag{6.8}$$

$$\sum_{m=1}^{M} X_{km} = 1 \quad \text{for } k = 1, \cdots, K \tag{6.9}$$

$$\sum_{m=1}^{M} Y_{rm} = 1 \quad \text{for } r = 1, \cdots, R \tag{6.10}$$

$$\left. \sum_{n=1}^{M} TQ_{ijmn} = 0 \right|_{PSI_{ij}=0}$$

$$\left. \sum_{n=1}^{M} TQ_{ijmn} = \sum_{k=1}^{K}(X_{km} \times U_{jk} \times EQ_{ik}) + \sum_{r=1}^{R}(Y_{rm} \times U_{jr} \times EQ_{ir}) \right|_{PSI_{ij} \neq 0} \quad \text{for } i = 1, \cdots, I \ \& \tag{6.11}$$

$$j = 1, \cdots, J \ \&\ m = 1, \cdots, M$$

$$\left. \sum_{m=1}^{M} TQ_{ijmn} = 0 \right|_{PSI_{ij}=0}$$

$$\left. \sum_{m=1}^{M} TQ_{ijmn} = \sum_{k=1}^{K}(X_{kn} \times U_{PSI_{ij}k} \times EQ_{ik}) + \sum_{r=1}^{R}(Y_{rn} \times U_{PSI_{ij}r} \times EQ_{ir}) \right|_{PSI_{ij} \neq 0} \quad \text{for } i = 1, \cdots, I \ \& \tag{6.12}$$

$$j = 1, \cdots, J \ \&\ n = 1, \cdots, M$$

$$M \times W_{jm} \geq \sum_{k=1}^{K}(X_{km} \times U_{jk}) + \sum_{r=1}^{R}(Y_{rm} \times U_{jr}) \quad \text{for } j = 1, \cdots, J \ \&\ m = 1, \cdots, M \tag{6.13}$$

$$\sum_{k=1}^{K}(X_{km} \times U_{jk}) + \sum_{r=1}^{R}(Y_{rm} \times U_{jr}) \geq MINUTIL_{jm} \times MAXC_{jm} \quad \text{for } j = 1, \cdots, J \ \& \tag{6.14}$$

$m = 1, \cdots, M$

$$\sum_{k=1}^{K}(X_{km} \times U_{jk}) + \sum_{r=1}^{R}(Y_{rm} \times U_{jr}) \geq W_{jm} \times UTIL_{jm} \times MAXC_{jm} \quad \text{for } j = 1, \cdots, J \ \& \tag{6.15}$$

$m = 1, \cdots, M$

The objective of the model is to minimize the total cost of machine costs (a), labor costs (b), investment costs (c), inventory carrying costs (d), varying transportation costs (e), machine setup costs (f) and cell installment costs (g), as given in Equation (6.7). Equation (6.8) ensures that number of assigned cells from all types to a plant cannot exceed the maximum available capacity of that plant, i.e., the number of cells at all stages in any plant cannot be more than the maximum cell capacity of the plant. Equations (6.9) and (6.10) prevents a cell to be assigned to more than one plant. Equations (6.11) and (6.12) are transportation balance constraints which guarantees that the amounts of products received at plants are equal to the amounts of products sent from the plants. Opening a manufacturing stage in a plant requires an investment cost as stated in Equation (6.13). This constraint makes sure that if a cell in a plant is opened, then that plant in the corresponding stage is also opened. Equation (6.14) assures that a minimum percent of the number of available cells for a stage in a plant is assigned to the opened plant. The number of cells at any stage in any plant cannot be less than a certain percentage of the maximum cell capacity of the plant. This equation is used to force the model to open a main plant. Equation (6.15) assures that a desired percent of the number of available cells for a stage in a plant is assigned to the opened plant if that stage is opened in that plant.

Estimated quantity of product family *i* produced in cell k, EQ_{ik}, is calculated using Equation (6.16). The estimation is not exact, as ECU_{ik} value is the *expected* utilization of product family i in cell k. PT_{ij} is the processing time of bottleneck operation for product family i in stage j, 40 represents the weekly working hours in a cell, and 60 is used to convert the hours to minutes.

$$EQ_{ik} = 40 \times 60 \times ECU_{ik} / PT_{ij} \qquad (6.16)$$

6.11 Results of the Mathematical Model

The model is run at IBM ILOG CPLEX Optimization Studio, Version 12.4. The results of the model shows the total of investment, machine, inventory carrying and transportation costs, opened plants for each stage or opened stages at each plant, assignment of dedicated, shared and remainder cells to the opened plants, and the amount of products shipped among plants and stages.

Two shifts are considered for the second stage in the SCN designed in this chapter. A three-shift case is also studied and the results are provided in the following chapter along with other SCN scenarios. Also, it is assumed that the transportation routes from the plants to the warehouse are preselected in this SCN design. The results of alternative transportation route options are presented in the following chapter as well.

Cell installments and machine setups are not considered in this chapter. Hence, costs related to machine setups (6.7-f) and cell installments (6.7-g) in the objective function and equations (6.14) and (6.15) are omitted from the mathematical model for the experimentation in this chapter.

6.11.1 Number of Machines from Each Type of Machine

In order to calculate the machine costs, number of machines from each type is determined. Number of machines from each type in remainder cells and in dedicated cells are shown in Table 6.41 and Table 6.42, respectively. This data is obtained using the mathematical model for the optimal operator assignment and the heuristic procedure for optimal cell size determination in Chapter 3, and the mathematical model for minimization of number of cells in Chapter 4.

Table 6.41 Number of machines from each type in shared and remainder cells

Cells	**Machines at stage 1**						**stage 2**			**Machines at stage 3**									
3	5	7	2	3	3	5	0	0	0	0	0	0	0	0	0	0	0	0	0
7	4	6	2	2	2	6	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	3	9	6	6	5	3	5	7	4	3
44	0	0	0	0	0	0	0	0	0	5	5	7	6	6	4	3	5	0	5
45	0	0	0	0	0	0	0	0	0	2	8	7	6	5	4	7	7	1	4

6.11.2 Transportation Routes

The cheapest transportation options are selected as transportation routes among the plants and from the plants to the warehouse. Since each part family has different product values, hence different insurance costs, total transportation costs are different as well. Therefore, in order to find the cheapest route for each part family, total of ocean freight, ocean freight insurance, and domestic freight and freight insurance costs are found for each route alternative.

Table 6.42 Number of machines from each type in dedicated cells

	Machines at stage 1						**At stage 2**			**Machines at stage 3**									
Cells	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
1	0	0	3	3	3	5	0	0	0	0	0	0	0	0	0	0	0	0	0
2	4	6	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	3	3	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0
5	3	5	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	5	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
8	3	5	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	2	2	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0
10	4	5	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	5	6	6	0	4	6	7	1	3
28	0	0	0	0	0	0	0	0	0	0	6	5	5	2	4	2	0	1	3
29	0	0	0	0	0	0	0	0	0	3	9	6	0	5	2	5	7	4	0
30	0	0	0	0	0	0	0	0	0	0	5	6	6	0	4	6	7	1	3
31	0	0	0	0	0	0	0	0	0	2	0	6	5	2	2	3	2	1	4
32	0	0	0	0	0	0	0	0	0	3	5	5	6	5	3	0	4	0	3
33	0	0	0	0	0	0	0	0	0	3	5	5	6	5	3	0	4	0	3
34	0	0	0	0	0	0	0	0	0	2	4	0	6	0	3	4	4	0	4
35	0	0	0	0	0	0	0	0	0	5	5	7	0	6	4	0	5	0	5
37	0	0	0	0	0	0	0	0	0	2	8	7	5	4	3	7	5	0	0
38	0	0	0	0	0	0	0	0	0	0	5	6	6	5	3	5	4	1	3
39	0	0	0	0	0	0	0	0	0	0	5	6	6	5	3	5	4	1	3
40	0	0	0	0	0	0	0	0	0	2	4	0	6	0	3	4	4	0	4
41	0	0	0	0	0	0	0	0	0	0	4	6	6	3	3	3	3	0	4
42	0	0	0	0	0	0	0	0	0	2	8	7	5	4	3	7	5	0	0
43	0	0	0	0	0	0	0	0	0	0	6	5	5	2	4	2	0	1	3

The cheapest routes from all of the plants to the warehouse for all of the part families go through Port of Savannah. After the port, road transportation is selected for all of the part families.

Figure 6.4 shows the cheapest transportation routes for the finish products from the plant candidate locations to the warehouse.

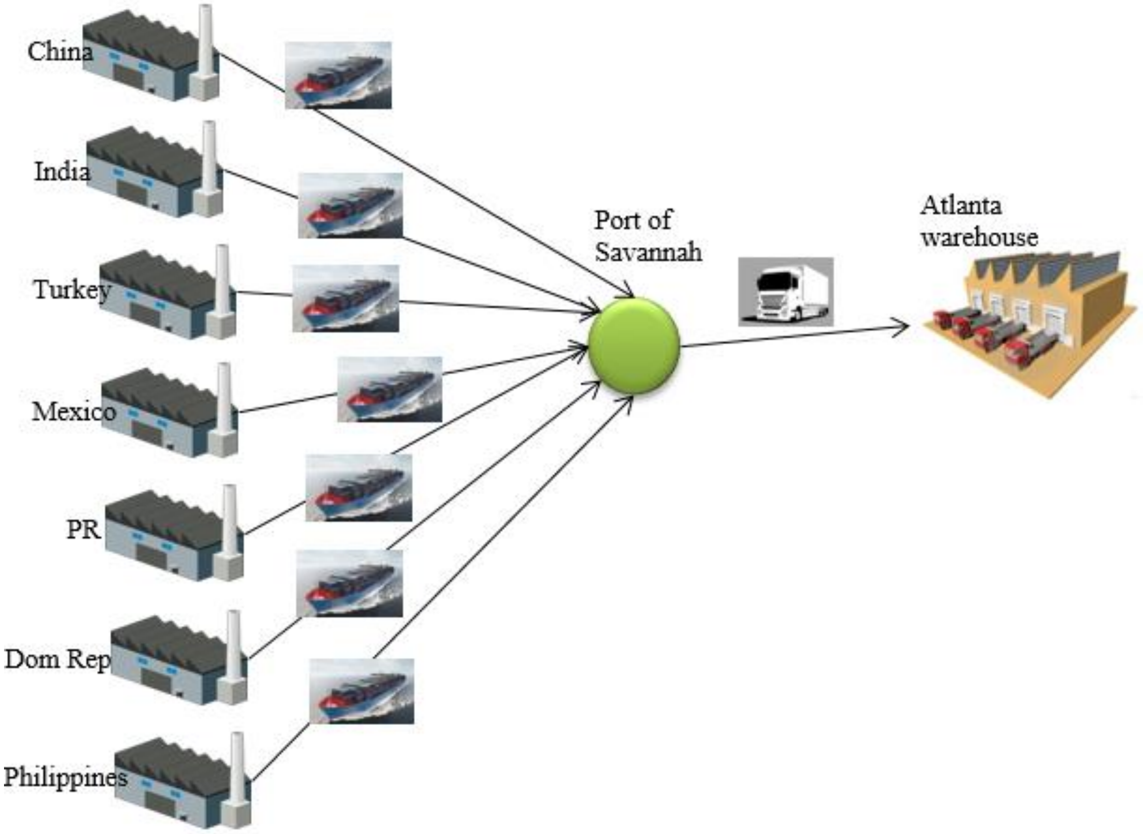


Figure 6.4 The cheapest transportation routes from plants to the warehouse

Table 6.43 shows the minimum total transportation costs per unit product of each product family from the manufacturing plants to the Atlanta warehouse. This cost includes the maritime transportation from plants to Port of Savannah, maritime insurance costs, road transportation costs from Port of Savannah to the warehouse and domestic freight insurance costs.

Transportation times from plants to the warehouse are found using the cheapest transportation routes. Table 6.44 shows the transportation times in weeks for the cheapest transportation routes.

Table 6.43 Total transportation costs from the plants to Atlanta warehouse based on the cheapest routes ($/unit)

Costs	Shanghai	Veracruz	Manila	Mumbai	Mersin	San Juan	Santo Domingo
PF1	0.033753	0.028970	0.036441	0.035334	0.037753	0.026571	0.026609
PF2	0.136059	0.120416	0.144849	0.141229	0.149140	0.112571	0.112694
PF3	0.080964	0.072216	0.085880	0.083856	0.088280	0.067828	0.067897
PF4	0.039362	0.034434	0.042132	0.040991	0.043483	0.031963	0.032002
PF5	0.127441	0.118879	0.132252	0.130270	0.134600	0.114586	0.114653
PF6	0.080371	0.073782	0.084073	0.082548	0.085880	0.070478	0.070530
PF7	0.112393	0.105544	0.116241	0.114656	0.118120	0.102109	0.102162
PF8	0.040475	0.037073	0.042387	0.041600	0.043320	0.035367	0.035394
PF9	0.065323	0.060447	0.068063	0.066934	0.069400	0.058001	0.058040
PF10	0.061355	0.057953	0.063267	0.062480	0.064200	0.056247	0.056274

Table 6.44 Transportation times based on the cheapest routes in weeks

Plants	to Savannah (weeks)	to Atlanta (weeks)	Total time (weeks)
Shanghai, China	4.2714	0.075	4.3464
Veracruz, Mexico	0.6143	0.075	0.6893
Manila, Philippines	4.6429	0.075	4.7179
Mumbai, India	3.6857	0.075	3.7607
Mersin, Turkey	2.4000	0.075	2.4750
San Juan, Puerto Rico	0.5143	0.075	0.5893
Santo Domingo, Dominican Rep.	0.5286	0.075	0.6036

6.11.3 Results: Plants Opened

The results of the plant location and resource allocation model are presented in this section. The model produces results in couple areas. It determines the plants opened for each stage, the dedicated, shared, and remainder cells assigned at each plant for each stage, and total cost incurred for the supply chain and manufacturing system design of the plants. Total cost for this supply chain network is $ 230,965.7 per week.

Table 6.45 shows the opened plants at each stage. At stage 1, The China plant is the only plant opened. At stage 2, plants in Mexico, Philippines and Dominican Republic are opened. At stage 3, China, Philippines, and India plants are opened. Plants in Turkey and Puerto Rico are not selected for any manufacturing stage. The reason for not opening plants at these locations is probably the higher labor and investment costs. China, Philippines and India locations offer lower labor and investment costs. Mexico has transportation proximity advantage.

Table 6.45 Opened plants at manufacturing stages

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	Open	0	N/A	N/A	0	0	0
Stage 2	N/A	Open	Open	N/A	0	0	Open
Stage 3	Open	0	Open	Open	N/A	0	0

The number of assigned cells to each plant is also provided in Table 6.46. Even though plant is opened in Mexico for stage 2, only 1 cell is assigned to this plant. Total number of cells opened at these locations is also provided in the table. The total number of cells opened in China, Mexico, Philippines, India, and Dominican Republic plants are 14, 1, 20, 5, and 5, respectively.

Table 6.46 Number of assigned manufacturing cells to opened plants at each stage

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.	Total
Stage 1	10	0	N/A	N/A	0	0	0	10
Stage 2	N/A	1	10	N/A	0	0	5	16
Stage 3	4	0	10	5	N/A	0	0	19
Total	14	1	20	5	0	0	5	45

Percent capacity allocation values in Table 6.47 indicate a problem in the supply chain design here. At stage 2, 20% of the Mexico plant is allocated for the cells. The China plant's capacity is allocated at 40% level at stage 3. On the other hand, the plants in Philippines and India use 100% of their capacities at stage 3, and the plants in Philippines and Dominican Republic use 100% of their capacities at stage 2. The China plant also uses 100% of its capacity for stage 1.The low labor costs and investment costs are the main reasons to select these plants over other locations.

Table 6.47 Percent capacity allocation of opened plants at each stage

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	100%	0%	N/A	N/A	0%	0%	0%
Stage 2	N/A	20%	100%	N/A	0%	0%	100%
Stage 3	40%	0%	100%	100%	N/A	0%	0%
Overall	70%	7%	100%	100%	0%	0%	25%

Assuming that these plants serve only to the company, percent capacity allocations of these plants are low. The model is modified to enforce minimum percent capacity allocation of plants at the stages they are opened in the following chapter. The results are provided in Chapter 7 along with the results of other scenarios.

Table 6.48 shows the manufacturing cells allocated to opened plants at each stage. Shared and remainder cells are shown explicitly in the table. Most opened plants have shared or remainder cells. SC stands for shared cells, and RC stands for remainder cells.

Table 6.48 Assigned cells to opened plants at each stage

Plants	Cell type	CHN	MEX	PHL	IND	TUR	PRI	DOM
Stage 1	Dedicated	1, 2, 4, 5, 6, 8, 9, 10		N/A	N/A			
	SC/RC	3, 7		N/A	N/A			
Stage 2	Dedicated	N/A		12, 13, 14, 16, 17, 20, 23, 24, 26	N/A	11, 13, 14, 25		
	SC/RC	N/A	15	19	N/A	15, 19		
Stage 3	Dedicated	27		29, 30,31,32, 34, 35, 37, 38, 39, 43	28, 33, 40, 41, 42	N/A		11, 18, 21, 22, 25
	SC/RC	36, 44, 45		12, 13, 14, 16, 17, 20, 23, 24, 26		N/A		

Table 6.49 presents the plants that produce the part families at each stage. As seen from the table, some part families are processed in more than one plant at each stage.

Table 6.49 Plants that produce each part family at each stage

Plants	stage 1	stage 2	stage 3
PF1	1	3, 7	1, 3
PF2	1	2, 3	1, 4
PF3	1	3, 7	1, 3
PF4	1	3	1, 3
PF5	1	3, 7	1, 3, 4
PF6	1	3, 7	1, 3
PF7	1	3	3, 4
PF8	1	N/A	1, 3, 4
PF9	1	2, 7	3, 4
PF10	1	3	1, 3

In the table above and in the similar tables in Chapter 7, number “1” represents China, number “2” represents Mexico, number “3” represents Philippines, number “4” represents India, number “5” represents Turkey, number “6” represents Puerto Rico, and number “7” represents Dominican Republic.

Figure 6.5 illustrates these results along with transportation relations among plants and stages.

The model produced expected results. Plants are opened at all of the available stages in China and Philippines due to lower labor and investment costs. However, when other cost factors, such as transportation and insurance costs, are considered in the design problem, other locations, such as Dominican Republic and Turkey plants are also opened. A one cell plant is opened in Mexico which indicates that even if for one cell that location is still less costly.

6.12 Conclusions

A modified plant location-resource allocation model which integrates manufacturing system and supply chain network design is proposed in this chapter. The model is improved by considering the following;

- Features of layered cellular manufacturing
- Optimal manpower levels for each operation
- Optimal cell sizes for each cell
- Individual machine costs
- In-transit inventory carrying costs

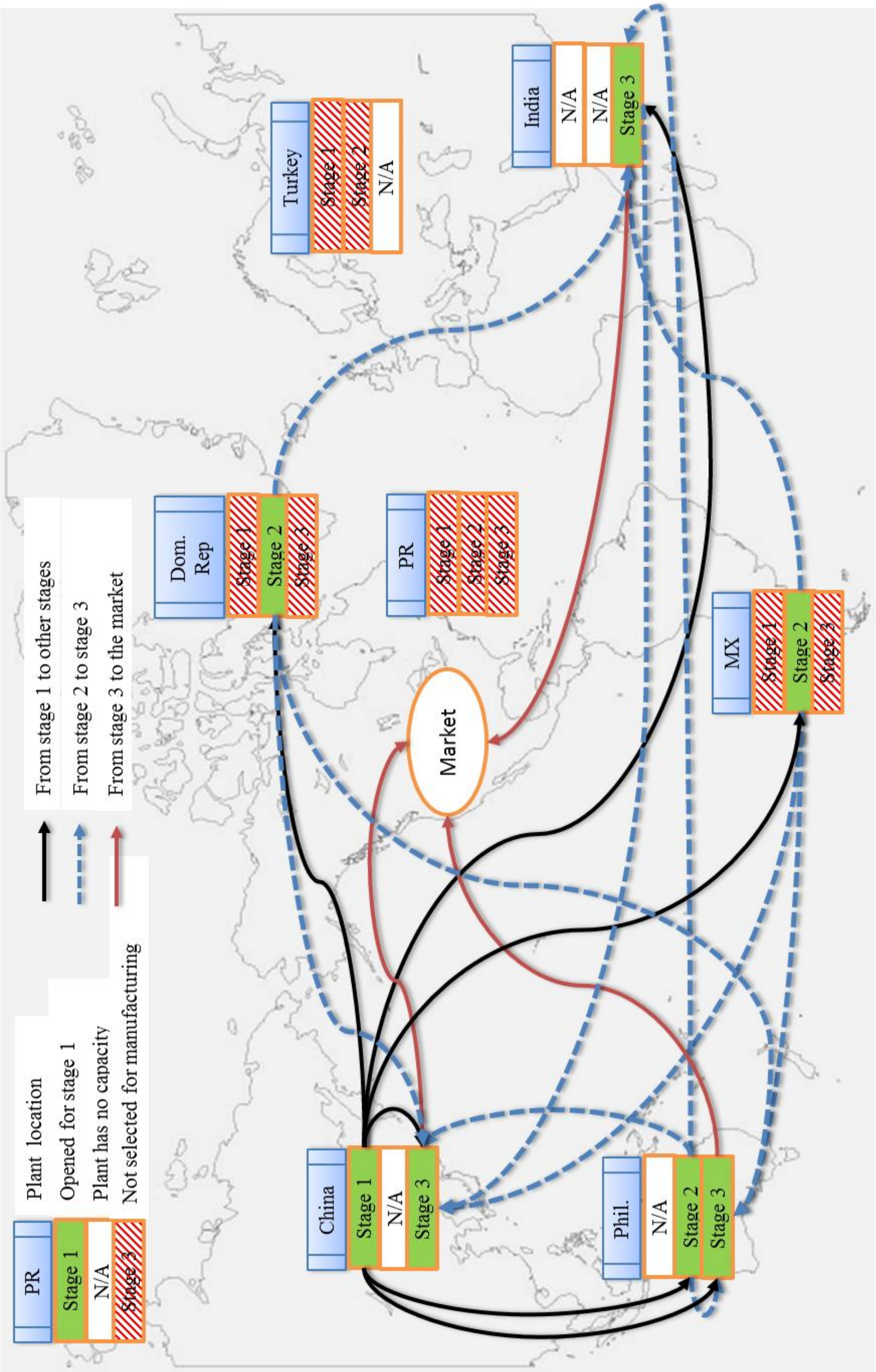


Figure 6.5 Opened plants at manufacturing stages

- Machine duplication
- Multiple shifts
- Varying transportation costs

The model is improved more by considering varying transportation costs among the stages and the market. In the model of Huang and Süer (2012) transportation costs from stage 1 to stage 2, from stage 2 to stage3, and from stage 3 to markets are assumed to be equal. However, unit transportation cost of a partially-finished product and a finished product cannot be same due to increasing weight and size for the finished products. Partially-finished products can be carried in bulk since they do not need packaging, however finished products requires more space and cannot be shipped as many amounts as partially-finished products. Also, plated parts require more attention than the non-plated parts, and this will be reflected in the costs. Therefore, transportation costs from stages to stages, and from stage 3 to market should have different values.

Echelon inventory costs are considered in the model as well. Cost of capital, value of products, and time spent by the products for transportation among stages are considered while calculating the inventory carrying costs. The longer the time takes to transport the product from one plant to another, the higher the inventory carrying costs become. Also, the value of the product affects the cost as well.

In Chapter 7, five different supply chain design scenarios are studied considering three shifts in one stage, minimum percent capacity allocation enforcement, the fastest transportation routes, machine setups, cell installments, and keeping the main plant open.

7 EXPERIMENTATION FOR VARIOUS SCENARIOS

In this chapter, different supply chain design scenarios are considered. The supply chain network model is modified for some of the scenarios. For the rest, the model is run for various factors such as numbers of shifts and transportation routes. The results of these scenarios are provided at the end of each scenario. The following scenarios are investigated.

- Scenario 1: SCN design considering minimum capacity enforcement for the selected main plant for all stages, hence forcing the model to open that plant
- Scenario 2: SCN design based on the fastest transportation routes
- Scenario 3: SCN design considering machine and cell installment costs
- Scenario 4: SCN design based on three shifts for the plants opened in the second stage
- Scenario 5: SCN design considering minimum capacities for opened plants

7.1 SCN Design Considering the Main Plant

In this scenario, one of the plants is considered as the main plant which will be kept open for design and production of new products, and as a cushion for highly fluctuating demand environment. Minimum percent capacity allocation is enforced at each stage that the plant is capable to perform operations in order to keep the plant close to home office where product design is carried out.

San Juan, Puerto Rico plant is selected as the main plant since the main plant of the fashion jewelry manufacturing company in mind in this dissertation was located in Puerto Rico.

7.1.1 Percent Capacity Allocation Values and Transportation Routes

The cheapest transportation routes are selected as the transportation routes for this scenario. This means that all of the plants send the finished products to Atlanta warehouse via Port of Savannah. Road transportation is used to transport the products from the port to the warehouse. The rest of the inputs for the model, such as labor costs, investment costs, etc., remained the same in this scenario.

The minimum percent capacity allocation of the plant is determined as 80% for all of the manufacturing stages available at this location. Any value other than zero forces the model to open a stage and to allocate cells to that stage of the plant at least at the minimum desired percent capacity allocation level. Equation (6.14) is added to the base model. This equation ensures that a minimum percent of the number of available cells for a stage in a plant is assigned to the main plant; hence that plant is opened for that stage.

7.1.2 Results for the SCN Design Based On Having the Main Plant Decision

The results of the plant location and resource allocation model with the main plant enforcement are presented in this section. The total cost for this supply chain design is $417,877.1 per week.

Table 7.1 shows the opened plants at each stage. As expected, all of the manufacturing stages are opened at San Juan, Puerto Rico location. At stage 1, The China plant is the only other plant opened besides Puerto Rico. At stage 2, plants at Philippines and Dominican Republic locations are opened besides Puerto Rico. At stage 3, Philippines and India plants are opened. Mexico and Turkey plants are not selected for any of the manufacturing stages.

Table 7.1 Opened plants at manufacturing stages for scenario 1

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	Open	0	N/A	N/A	0	Open	0
Stage 2	N/A	0	Open	N/A	0	Open	Open
Stage 3	0	0	Open	Open	N/A	Open	0

The total number of cells assigned to each plant is provided in Table 7.2. Four cells are assigned to each manufacturing stage at The Puerto Rico plant.

There are only two cells assigned to the Dominican plant. The total number of cells opened in China, Philippines, India, and Puerto Rico are 6, 20, 5, and 2, respectively.

Table 7.2 Number of assigned manufacturing cells to opened plants at each stage

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.	Total
Stage 1	6	0	N/A	N/A	0	4	0	10
Stage 2	N/A	0	10	N/A	0	4	2	16
Stage 3	0	0	10	5	N/A	4	0	19
Total	6	0	20	5	0	12	2	45

Percent capacity allocation values are provided in Table 7.3. As expected, at all of the manufacturing stages at The Puerto Rico plant, the percent capacity allocation is 80%. But the percent capacity allocation did not exceed the minimum value as well. One would expect to use the capacity of this plant 100% since the investment has been already made when the plant is opened for all manufacturing stages. The reason for not using this plant more than the enforced percent capacity allocation value is higher labor costs in Puerto Rico. Dominican plant's cell capacity is allocated at 40% level at stage 2. Plant in China uses 60% of its capacity at stage 1. These percent capacity allocations are low assuming that these plants serve only to the company. The model is modified to enforce minimum percent capacity allocation of plants at the stages they are opened. The results are provided in this chapter. Philippines and India plants use 100% of their capacities at the manufacturing stages they operate.

Table 7.3 Percent capacity allocations of opened plants at each stage for scenario 1

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	60%	0%	N/A	N/A	0%	80%	0%
Stage 2	N/A	0%	100%	N/A	0%	80%	40%
Stage 3	0%	0%	100%	100%	N/A	80%	0%
Overall	30%	0%	100%	100%	0%	80%	10%

Table 7.4 presents the dedicated, shared and remainder cells allocated to opened plants at each stage. Most of the opened plants at stages have shared or remainder cells. Puerto Rico plant has 4 opened cells at each stage. SC stands for shared cells, and RC stands for remainder cells.

Table 7.4 Assigned cells to opened plants at each stage for scenario 1

Plants	Cell type	CHN	MEX	PHL	IND	TUR	PRI	DOM
Stage 1	Dedicated	1, 2, 6, 8, 9		N/A	N/A		4, 5, 10	
	SC/RC	3		N/A	N/A		7	
Stage 2	Dedicated	N/A		12, 13, 16, 17, 18, 22, 23, 24	N/A		11, 14, 20, 26	21, 25
	SC/RC	N/A		15, 19	N/A			
Stage 3	Dedicated			29, 30, 32, 34, 35, 38, 39, 43	27, 28, 41, 42	N/A	31, 33, 37, 40	
	SC/RC			44, 45	36	N/A		

Table 7.5 presents the part families produced at each plant at manufacturing stages. Some of the part families are produced in more than one plant at each stage. Figure 7.1 shows the opened plants and transportation relations among plants and stages.

Table 7.5 Plants that produce each part family at each stage

Plants	stage 1	stage 2	stage 3
PF1	6	3	3
PF2	1	3	3, 4
PF3	1, 6	3	3, 4
PF4	1	3	3, 4
PF5	6	6, 7	3, 4, 6
PF6	1	3, 7	3, 6
PF7	1, 6	3, 6	3, 6
PF8	1	N/A	3, 4, 6
PF9	6	3, 6	3, 4
PF10	1	3	3

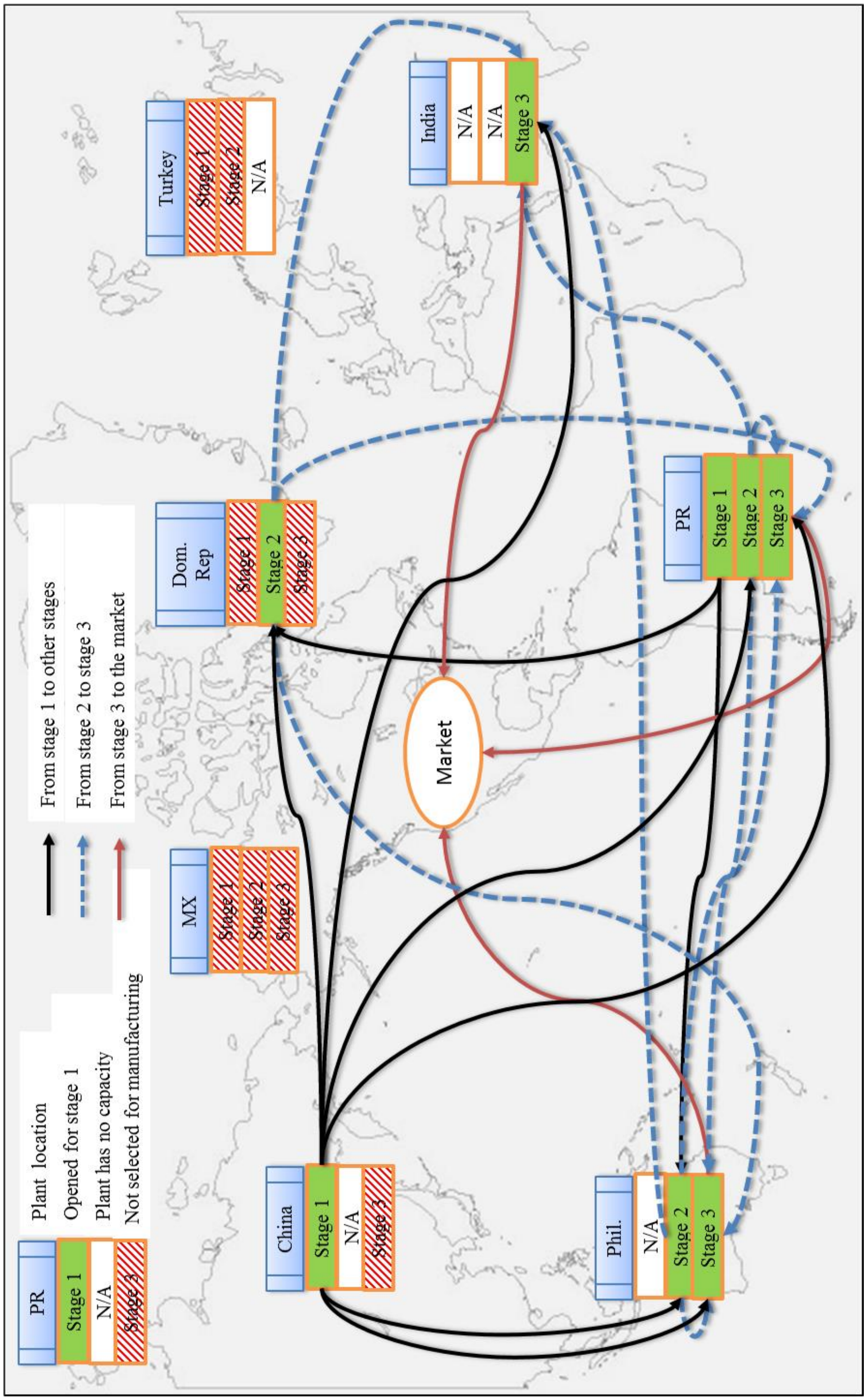


Figure 7.1 Opened plants at manufacturing stages for the mail plant scenario

7.1.3 Conclusions

When the model is forced to open the main plant at 80% percent capacity allocation level at every stage, weekly costs almost doubled. Total costs increased from \$230,965.7 to \$417,877.1 per week. Even though, the plants are opened at every stage at Puerto Rico location, the model did not use the full capacity of the plant due to higher labor costs.

The reason to select Puerto Rico to open the main plant is to mimic the fashion jewelry manufacturing company located on that island. Other locations, where skilled designers and workers are available, and which has lower labor rates can be used as the main plant to decrease the total weekly operation costs.

7.2 SCN Design Based On the Fastest Transportation Routes

The transportation routes among plants from stage 1 to stage 2, from stage 2 to stage 3, and between the plants and the market can be preselected based on decision makers' preferences or other factors such as safety, weather etc. In this section, it is assumed that the company would like to use the fastest transportation option among alternatives. Please keep in mind that air transportation is excluded from alternatives due to its high costs.

7.2.1 Transportation Routes

The fastest transportation routes are selected to transport semi-finished products among the plants and products from the plants to the warehouse. Since maritime transportation is the only option considered among plants, the speed of the transportation is determined depending on the receiving port and the transportation mode selected in the US. The finished products can enter the US via two ports; Port of Los Angeles and Port of Savannah. Railway transportation and road transportation can be used to transport the products from the ports to the warehouse. Therefore, in order to find the fastest route from plants to the warehouse, the total of maritime transportation times and domestic transportation times are found for each port and domestic transportation mode, and then the fastest one is selected.

Tables 7.6 shows the total transportation times from plants to Atlanta warehouse using Port of Los Angeles. Road transportation provides the fastest transportation from this port.

Table 7.6 Transportation times from plants to the warehouse via Port of Los Angeles

Transportation times	Maritime to Los Angeles	LA to Atlanta - Railway	LA to Atlanta - Road	Total via railway	Total via road trans.
Shanghai, CHN	17	14	4.5	31	**21.5**
Veracruz, MEX	13.1	14	4.5	27.1	**17.6**
Manila, PHL	19.4	14	4.5	33.4	**23.9**
Mumbai, IND	30	14	4.5	44	**34.5**
Mersin, TUR	27.6	14	4.5	41.6	**32.1**
San Juan, PRI	11.8	14	4.5	25.8	**16.3**
Santo Domingo, DOM	11.2	14	4.5	25.2	**15.7**

Tables 7.7 shows the total transportation times from plants to Atlanta warehouse using Port of Savannah. Road transportation provides the fastest transportation from this port as well.

Table 7.7 Transportation times from plants to the warehouse via Port of Savannah

Transportation times	Maritime to Savannah	Savannah to Atlanta - Railway	Savannah to Atlanta - Road	Total via railway	**Total via road trans.**
Shanghai, CHN	29.9	1	0.15	30.9	**30.05**
Veracruz, MEX	4.3	1	0.15	5.3	**4.45**
Manila, PHL	32.5	1	0.15	33.5	**32.65**
Mumbai, IND	25.8	1	0.15	26.8	**25.95**
Mersin, TUR	16.8	1	0.15	17.8	**16.95**
San Juan, PRI	3.6	1	0.15	4.6	**3.75**
Santo Domingo, DOM	3.7	1	0.15	4.7	**3.85**

The fastest transportation routes from China and Philippines plants to the warehouse are via Port of Los Angeles. The fastest transportation routes from Mexico, India, Turkey, Puerto Rico and Dominican Republic plants to the warehouse are via Port of Savannah. After the ports, road transportation is used for all of the plants.

Table 7.8 Comparison of ports with respect to total transportation times

Transportation times	Total time via Port of Los Angeles	Total time via Port of Savannah
Shanghai, China	**21.5**	30.05
Veracruz, Mexico	17.6	**4.45**
Manila, Philippines	**23.9**	32.65
Mumbai, India	34.5	**25.95**
Mersin, Turkey	32.1	**16.95**
San Juan, Puerto Rico	16.3	**3.75**
Santo Domingo, Dominican Rep.	15.7	**3.85**

Figure 7.2 shows the fastest transportation routes for the finished products from the candidate plant locations to the warehouse. As illustrated in the figure, maritime

transportation is used from plants to the ports, and after ports trucks are used to transport finished products to the warehouse.

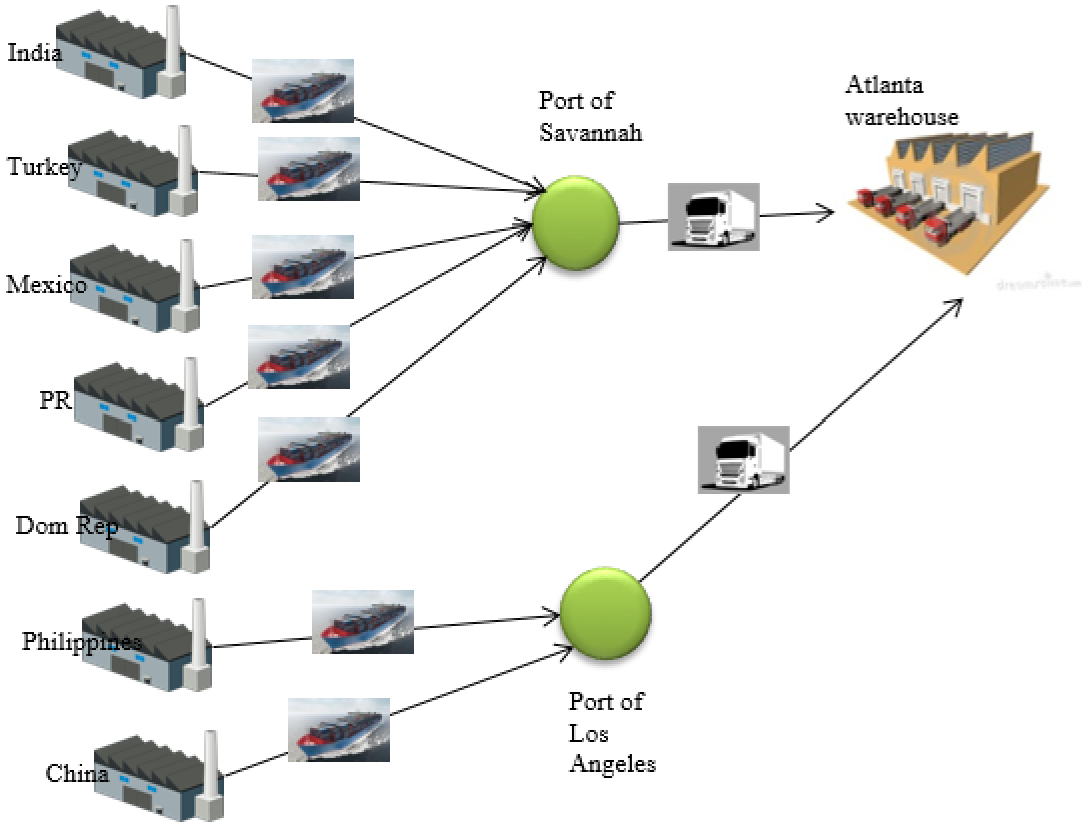


Figure 7.2 The fastest transportation routes from plants to the warehouse

The difference between this SCN design and the SCN design based on the cheapest transportation route is using LA port for the products coming from China and Philippines plants. This will yield an increase in the total transportation costs for these two locations.

7.2.2 Results of SCN Design Based On the Fastest Transportation Routes

The results of the plant location and resource allocation model based on the fastest transportation routes are presented in this section. The total cost for this supply chain design is $228,220.6 per week. This cost is very close to the design where cheapest transportation routes are used.

Table 7.9 shows the opened plants at each stage. Puerto Rico and Turkey are not selected for any of the manufacturing stages. In stage 1, The China plant is the only plant that is opened. In stage 2, Mexico, Philippines and Dominican Republic plants are opened. In stage 3, Philippines, India, and China plants are opened. These are the same plants opened for the model that is based on the cheapest transportation routes.

Table 7.9 Opened plants at manufacturing stages based on the fastest transportation routes

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	Open	0	N/A	N/A	0	0	0
Stage 2	N/A	Open	Open	N/A	0	0	Open
Stage 3	Open	0	Open	Open	N/A	0	0

The total number of cells assigned to opened plants is provided in Table 7.10. The China plant has 10 assigned cells in stage 1 and 4 cells in stage 3. A total of 20 cells are assigned to the Philippines plant, 10 cells for stage 2 and 3. Only one cell is assigned to the Mexico plant at stage 2. The total number of cells opened in both of the India and Dominican Republic plants are 5. Puerto Rico plant has no assigned cells since it was not opened for any of the stages.

Table 7.10 Number of assigned cells to plants based on the fastest transportation routes

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.	Total
Stage 1	10	0	N/A	N/A	0	0	0	10
Stage 2	N/A	1	10	N/A	0	0	5	16
Stage 3	4	0	10	5	N/A	0	0	19
Total	14	1	20	5	0	0	5	45

Percent capacity allocation values are provided in Table 7.11. Mexico plant uses 20% of its capacity at stage 2. The rest of the plants have high percent capacity allocations when stages are considered alone. Overall allocation percentages are also high for Philippines and India plants with 100% allocations for both of them. Since there is only one cell assigned to the Mexico plant, overall capacity allocation is only 7%.

Table 7.11 Percent capacity allocation of opened plants based on the fastest transportation routes

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	100%	0%	N/A	N/A	0%	0%	0%
Stage 2	N/A	20%	100%	N/A	0%	0%	100%
Stage 3	40%	0%	100%	100%	N/A	0%	0%
Overall	70%	7%	100%	100%	0%	0%	25%

Table 7.12 presents the dedicated, shared and remainder cells allocated to opened plants at each stage. Cell 15 is the only cell assigned to the Mexico plant. SC stands for shared cells, and RC stands for remainder cells. No shared or remainder cells are assigned to the Dominican and Mexico plants. Also, the plant at stage 3 in China has no shared or remainder cells as well. India plant has two shared/remainder cells and three dedicated cells assigned at stage 3.

Table 7.12 Assigned cells to opened plants based on the fastest transportation routes

Plants	Cell type	CHN	MEX	PHL	IND	TUR	PRI	DOM
Stage 1	Dedicated	1, 2, 4, 5, 6, 8, 9, 10		N/A	N/A			
	SC/RC	3, 7		N/A	N/A			
Stage 2	Dedicated	N/A	15	13, 14, 16, 17, 20, 21, 23, 24, 26	N/A			11, 12, 18, 22, 25
	SC/RC	N/A		19	N/A			
Stage 3	Dedicated	27, 33, 39, 42		29, 30, 31, 32, 35, 37, 38, 40, 43	28, 34, 41	N/A		
	SC/RC			44	36, 45	N/A		

Table 7.13 presents the part families produced at each plant at manufacturing stages 1, 2 and 3. Almost all of the part families, except for PF10, are produced in more than two plants at stage 3. All of the part families are produced in the China plant at stage 1.

Table 7.13 Plants that produce each part family at each stage

Plants	stage 1	stage 2	stage 3
PF1	1	3, 7	1, 3, 5
PF2	1	2, 3	3, 5
PF3	1	3, 7	1, 3, 5
PF4	1	3	3, 5
PF5	1	3	1, 3, 5
PF6	1	3, 7	3, 5
PF7	1	3	3, 5
PF8	1	N/A	1, 3, 5
PF9	1	2, 7	3, 5
PF10	1	3	3

Figure 7.3 shows the opened plants and transportation relations among plants and stages based on the fastest transportation routes.

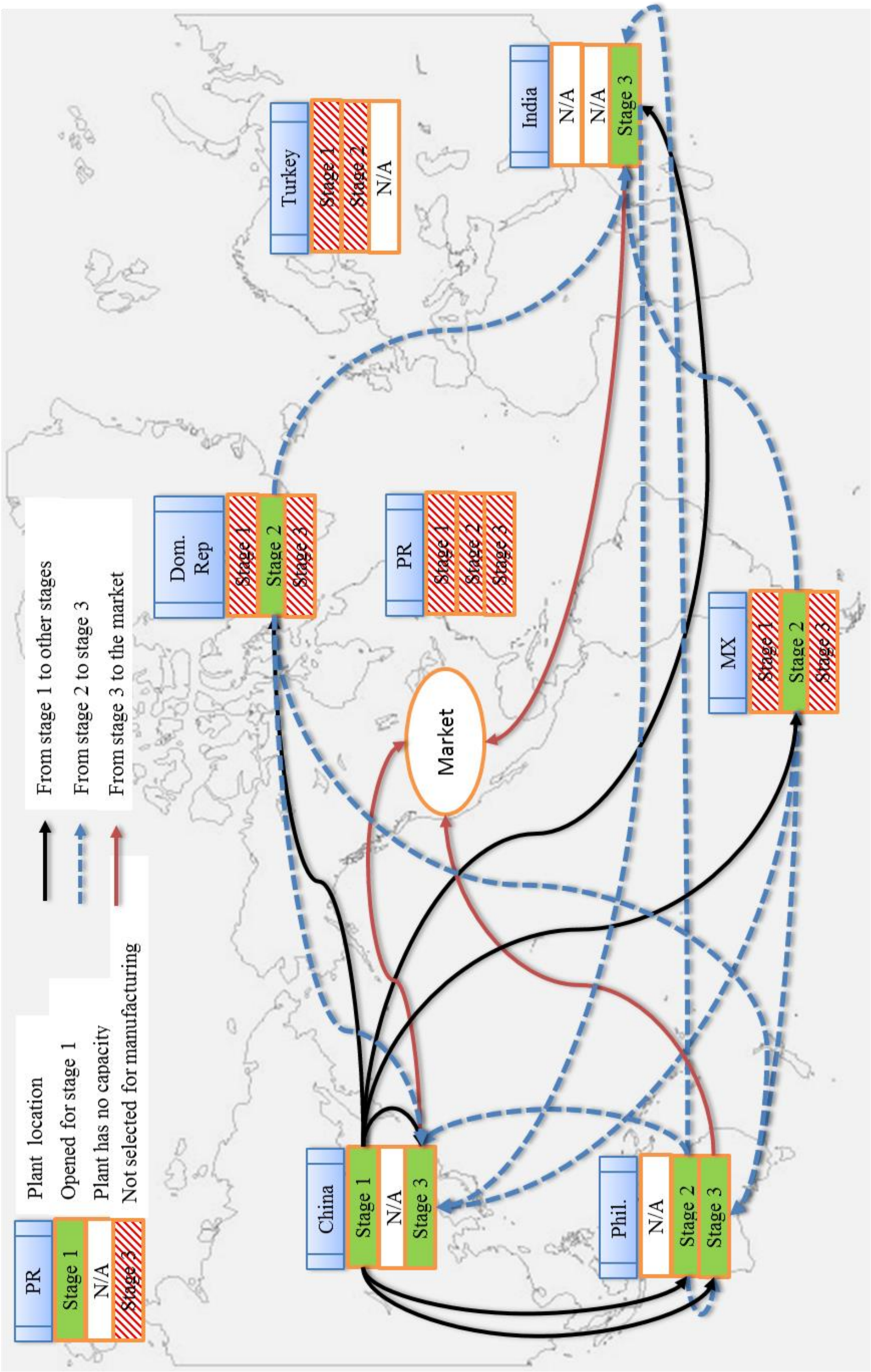


Figure 7.3 Opened plants at manufacturing stages considering the fastest transportation routes

7.2.3 Conclusions

In this section, supply chain network and manufacturing systems are designed based on the fastest transportation routes instead of the cheapest transportation routes. The same routes are used except for the products shipped from China and Philippines plants. As a result, the plants are opened at the same locations. The total weekly costs are very close as well. Hence, using faster transportation routes is a better decision since the leadtimes for the two plant locations are lower than the other alternative.

7.3 SCN Design Considering Machine Setups and Cell Installments

In this section, machine setups and cell installments are considered in the manufacturing systems designed. Machine procurement costs are covered in machine costs, and building and construction costs are covered in investment costs. Therefore, it is assumed that cell installment costs consist of labor costs only.

Setting up the same cell in different countries incurs different costs based on the labor costs in those countries. The number of machines in a cell affects the cell installment costs. Bigger cells have higher cell installment costs. Table 6.39 presents cell installment costs for each cell in every plant location.

Machine setups are required between product changes at machines. Since plants are located in different countries with different labor costs, machine setup costs for the same machines are different in each country. It is assumed that each machine requires one labor hour. Including cell installment and machine setup costs and connecting them to the labor cost in the countries where plants are located in the supply chain and manufacturing system design will make the countries with higher labor costs less attractive. Table 6.40 presents the number of machine setups required for cells at manufacturing stages.

7.3.1 Results of SCN Design Considering Machine Setups and Cell Installments

The results of the supply chain network and manufacturing system design model considering machine setup and cell installment costs are presented in this section. The total cost for this supply chain design is $ 294,555.4 per week.

The opened plants at each stage are shown in Table 7.14. Puerto Rico and Turkey are selected for none of the manufacturing stages. In stage 1, The China plant is the only selected plant to be opened. In stage 2, Mexico, Philippines and Dominican Republic plants are opened. In stage 3, China, Philippines and India plants are opened. These are the same plants opened for the initial model in Chapter 6. Hence, considering machine setup and cell installment costs does not change the locations for these parameters.

Table 7.14 Opened plants at manufacturing stages considering machine setups and cell installments

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	Open	0	N/A	N/A	0	0	0
Stage 2	N/A	Open	Open	N/A	0	0	Open
Stage 3	Open	0	Open	Open	N/A	0	0

The number of cells assigned to opened plants at each stage is provided in Table 7.15. These results are same as the results of the base model where cell installment and machine setups are not considered. Only 1 cell is assigned to the Mexico plant. The total number of cells opened in China, Mexico, Philippines, India, and Dominican Republic plants are 14, 1, 20, 5, and 5, respectively.

Table 7.15 Number of assigned cells to plants

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.	Total
Stage 1	10	0	N/A	N/A	0	0	0	10
Stage 2	N/A	1	10	N/A	0	0	5	16
Stage 3	4	0	10	5	N/A	0	0	19
Total	14	1	20	5	0	0	5	45

Table 7.16 provides capacity percent capacity allocation values. The Mexico plant uses 20% of its cell capacity at stage 2. The China plant uses 40% of its cell capacity at stage 3. The rest of the plants have 100% percent capacity allocations when stages are considered only. Overall percent capacity allocations for Philippines and India plants are 100%. Overall percent capacity allocation for China, Mexico and Dominican plants are 70%, 7% and 25%, respectively.

Table 7.16 Percent capacity allocation of opened plants considering cell installment and machine setup costs

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	100%	0%	N/A	N/A	0%	0%	0%
Stage 2	N/A	20%	100%	N/A	0%	0%	100%
Stage 3	40%	0%	100%	100%	N/A	0%	0%
Overall	70%	7%	100%	100%	0%	0%	25%

Table 7.17 presents the dedicated, shared and remainder cells assigned to opened plants at each stage. SC stands for shared cells, and RC stands for remainder cells. In stage 1, the China plant is the only opened plant, hence, all of the shared and remainder

cells are assigned to the China plant. In stage 2, all of the shared and remainder cells are assigned to the Philippines plant. In stage 3, all of the shared and remainder cells are assigned to the India plant. In all of the manufacturing stages, shared and remainder cells are assigned to plants where labor costs are relatively lower than the other opened plants. This is an expected result since labor costs gained importance in the supply chain design after including machine setup and cell installment costs in the calculations. These two operations are done by workers, and shared and remainder cells have higher number of machines and workers, hence higher cell installment and machine setup costs. When the model without cell installment and machine setups and this model is compared, the opened plants are the same, but the cells assigned to these opened plants are different.

Table 7.17 Assigned cells to opened plants considering cell installment and machine setups

Plants	Cell type	CHN	MEX	PHL	IND	TUR	PRI	DOM
Stage 1	Dedicated	1, 2, 4, 5, 6, 8, 9, 10		N/A	N/A			
	SC/RC	3, 7		N/A	N/A			
Stage 2	Dedicated	N/A	25	14, 17, 18, 20, 22, 23, 24, 26	N/A			11, 12, 13, 16, 21,
	SC/RC	N/A		15, 19	N/A			
Stage 3	Dedicated	27, 31, 33, 43		28, 29, 30, 32, 34, 35, 37, 38, 39, 41	40, 42	N/A		
	SC/RC				36, 44, 45	N/A		

Table 7.18 shows the part families produced at opened plants at manufacturing stages 1, 2 and 3. All of the part families are produced in The China plant (plant 1) in

stage 1. But most of the part families are produced in more than one plant in stage 2, and all of the part families are produced in multiple plants in stage 3.

Table 7.18 Plants that produce each part family at each stage

Plants	stage 1	stage 2	stage 3
PF1	1	3, 7	3, 4
PF2	1	3	3, 4
PF3	1	3, 7	1, 3
PF4	1	3	3, 4
PF5	1	3, 7	3, 4
PF6	1	2, 3	1, 4
PF7	1	3, 7	3, 4
PF8	1	N/A	1, 3, 4
PF9	1	3, 7	1, 3
PF10	1	3	3, 4

When the model without cell installment and machine setups and this model is compared with respect to part family assignments, some of the part families are produced at different plants when cell installments and machine setups are considered.

Figure 7.4 shows the opened plants and transportation relations among plants and stages for the SCN and manufacturing system design model considering cell installments and machine setups.

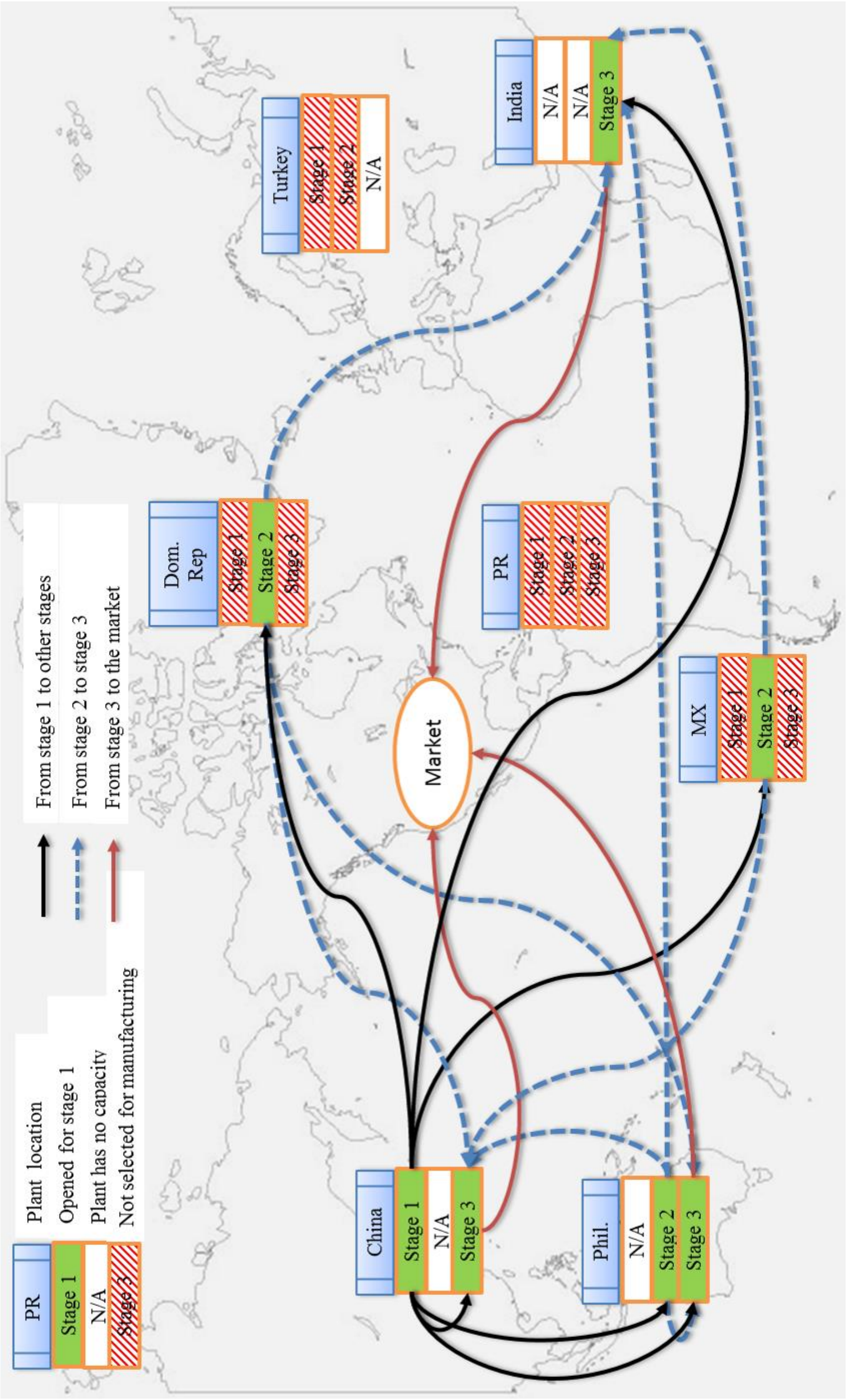


Figure 7.4 Opened plants at manufacturing stages considering cell installment and machine setups

7.3.2 Conclusions

In this section, cell installments and machines setups are considered while designing the supply chain network and manufacturing systems. The cheapest transportation routes are used. The total supply chain cost increased by almost 28% when it is compared to the initial model without machine setup and cell installment costs. Shared and remainder cells are assigned to plants where the labor costs are relatively lower than the other candidate locations. This is an expected result since both setup jobs are done by workers, and shared and remainder cells have higher number of workers than dedicated cells.

As a result, the plants are opened at the same locations. The number of cells assigned to plants remained same as well. However, plants have slightly different manufacturing cells assigned to them. Also, product families have different plants when they are compared to the scenario where cell installments and machine setups are not considered.

7.4 SCN Design Considering Three Shifts at the Second Stage

In Chapter 6, plants opened for stage 2 are assumed to work for 16 hours per day or two shifts. This required opening 16 manufacturing cells for stage 2. Since investment and machine costs for stage 2 are higher, decreasing the number of cells at stage 2 is expected to reduce the investment and machine procurement cost significantly.

The number of manufacturing cells decreases from 16 cells to 10 cells for stage 2 when the number of shifts increases from two to three at stage 2. When the number of manufacturing cells changes; number of machines from each machine type, number of workers in each cell, number of cell installments, and number of machine setups also changes. In this setting, machine and cell installments are not considered.

Tables 7.19 shows the number of machines from each machine type in each cell for all manufacturing stages in the shared and remainder cells.

Table 7.19 Number of machines from each type in shared and remainder cells

Stage	Machines at stage 1						At stage 2			Machines at stage 3									
Cell	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
3	5	7	2	3	3	5	0	0	0	0	0	0	0	0	0	0	0	0	0
7	4	6	2	2	2	6	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	3	9	6	6	5	3	5	7	4	3
38	0	0	0	0	0	0	0	0	0	5	5	7	6	6	4	3	5	0	5
39	0	0	0	0	0	0	0	0	0	2	8	7	6	5	4	7	7	1	4

Tables 7.20 shows the number of machines from each machine type in each cell for all manufacturing stages in dedicated cells.

Table 7.20 Number of machines from each type in dedicated cells

Stage	Machines at stage 1						At stage 2			Machines at stage 3									
Cells	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	0	0	3	3	3	5	0	0	0	0	0	0	0	0	0	0	0	0	0
2	4	6	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	3	3	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0
5	3	5	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	5	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
8	3	5	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	2	2	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0
10	4	5	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	5	6	6	0	4	6	7	1	3
22	0	0	0	0	0	0	0	0	0	0	6	5	5	2	4	2	0	1	3
23	0	0	0	0	0	0	0	0	0	3	9	6	0	5	2	5	7	4	0
24	0	0	0	0	0	0	0	0	0	0	5	6	6	0	4	6	7	1	3
25	0	0	0	0	0	0	0	0	0	2	0	6	5	2	2	3	2	1	4
26	0	0	0	0	0	0	0	0	0	3	5	5	6	5	3	0	4	0	3
27	0	0	0	0	0	0	0	0	0	3	5	5	6	5	3	0	4	0	3
28	0	0	0	0	0	0	0	0	0	2	4	0	6	0	3	4	4	0	4
29	0	0	0	0	0	0	0	0	0	5	5	7	0	6	4	0	5	0	5
31	0	0	0	0	0	0	0	0	0	2	8	7	5	4	3	7	5	0	0
32	0	0	0	0	0	0	0	0	0	0	5	6	6	5	3	5	4	1	3
33	0	0	0	0	0	0	0	0	0	0	5	6	6	5	3	5	4	1	3
34	0	0	0	0	0	0	0	0	0	2	4	0	6	0	3	4	4	0	4
35	0	0	0	0	0	0	0	0	0	0	4	6	6	3	3	3	3	0	4
36	0	0	0	0	0	0	0	0	0	2	8	7	5	4	3	7	5	0	0
37	0	0	0	0	0	0	0	0	0	0	6	5	5	2	4	2	0	1	3

7.4.1 Results for the SCN Design Considering Three Shifts at the Second Stage

The results of the supply chain network and manufacturing system design model considering three shifts at the second stage are presented in this section. Total cost for this supply chain design is $177,132.3 per week. Adding one more shift to stage 2 decreased the total cost significantly when the result is compared with the base SCN design where the number of shifts at stage 2 is two.

The opened plants at each stage are shown in Table 7.21. Mexico, India, Turkey, Dominican and Puerto Rico are not selected for any of the manufacturing stages. The China plant is the only plant opened in stage 1. In stage 2, only The Philippines plant is opened. In stage 3, Philippines and China plants are opened. Increasing number of shifts from two to three at stage 2 changed the number of plants opened, significantly.

Table 7.21 Opened plants at manufacturing stages considering three shifts at stage 2

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	Open	0	N/A	N/A	0	0	0
Stage 2	N/A	0	Open	N/A	0	0	0
Stage 3	Open	0	Open	0	N/A	0	0

The total number of cells assigned to opened plants is provided in Table 7.22. These results are a lot different than the ones from the initial model where two shifts are considered for stage 2. In this design, all of the manufacturing cells are shared within two plants, China and Philippines with 19 and 20 manufacturing cells, respectively. These two plants offer lower labor costs than most of the unselected candidate plants. They also have lower investment costs.

Table 7.22 Number of assigned manufacturing cells to opened plants at each stage

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.	Total
Stage 1	10	0	N/A	N/A	0	0	0	10
Stage 2	N/A	0	10	N/A	0	0	0	10
Stage 3	9	0	10	0	N/A	0	0	19
Total	19	0	20	0	0	0	0	39

Table 7.23 provides capacity percent capacity allocation values. All of the selected plants at the opened stages use 90% or more of their cell capacities. The China plant uses 100% of its capacity at stage 1, and 90% at stage 2. The Philippines plant use 100% of its cell capacities at stages 2 and 3. Overall percent capacity allocation for the Philippines plant is 100%. Overall percent capacity allocations for China plant is 95%. Plants percent capacity allocations at each opened stage and overall plant percent capacity allocation increased when the results are compared with the two shifts case.

Table 7.23 Percent capacity allocation of opened plants considering cell installment and machine setup costs

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	100%	0%	N/A	N/A	0%	0%	0%
Stage 2	N/A	0%	100%	N/A	0%	0%	0%
Stage 3	90%	0%	100%	0%	N/A	0%	0%
Overall	95%	0%	100%	0%	0%	0%	0%

Table 7.24 shows dedicated, shared and remainder cells assigned to opened plants at each manufacturing stage. SC stands for shared cells, and RC stands for remainder cells. In stage 1, all of the shared and remainder cells are assigned to the China plant. In stage 2, the Philippines plant is the only opened plant, hence all of the manufacturing

cells are assigned to the Philippines plant. In stage 3, Philippines and China plants are opened, and all of the cells are assigned to these plants.

Table 7.24 Assigned cells to opened plants considering three shifts at stage 2

Plants	Cell type	CHN	MEX	PHL	IND	TUR	PRI	DOM
Stage 1	Dedicated	1, 2, 4, 5, 6, 8, 9, 10		N/A	N/A			
	SC/RC	3, 7		N/A	N/A			
Stage 2	Dedicated	N/A		11, 12, 13, 17, 18, 19	N/A			
	SC/RC	N/A		14, 15, 16, 20	N/A			
Stage 3	Dedicated	21, 25, 27, 31, 33, 34, 37		22, 23, 24, 26, 28, 29, 32, 35, 36		N/A		
	SC/RC	30, 38		39		N/A		

Table 7.25 shows the part families produced at each stage at the opened plants. All of the part families are produced in The China plant (plant 1) in stage 1. Similarly, all of the part families are produced in the Philippines plant (plant 3) in stage 2. All of the part families are produced in two plants in stage 3.

Table 7.25 Plants that produce each part family at each stage

Plants	stage 1	stage 2	stage 3
PF1	1	3	1, 3
PF2	1	3	1, 3
PF3	1	3	1, 3
PF4	1	3	1, 3
PF5	1	3	1, 3
PF6	1	3	1, 3
PF7	1	3	1, 3
PF8	1	N/A	1, 3
PF9	1	3	1, 3
PF10	1	3	1, 3

When the three-shift design and the initial design with two shifts in stage 2 are compared with respect to part family assignments to plants, one plant produces all of the part families at stage 2 for three-shift case. At stage 3, instead of three plants for the wo-shifts case, two plants are used for production. Assignments are mostly different for stages 2 and 3.

Figure 7.5 shows the opened plants and transportation relations among plants and stages for the supply chain network and manufacturing system design model considering three shifts at stage 2.

7.4.2 Conclusions

In this section, the number shifts at stage 2 are increased from two shifts per day to three shifts per day. As a result, the number of required manufacturing cells for stage 2 decreased from 16 to 10, and the total number of manufacturing cells decreased from 45 to 39. As in the base SCN design, the cheapest transportation routes are used. Cell installment and machine setups are not considered in this model. The weekly cost for the entire supply chain decreased from 210,529.8 per week to $166,084 per week, which corresponds to about 21% reduction in total costs.

When the number of shifts increased from two to three, fewer plants are required to meet the demand. The selected plants are the ones with relatively lower labor costs. Also, these plants are geographically closer to each other and to the market as well. This will have a positive effect on transportation and insurance costs.

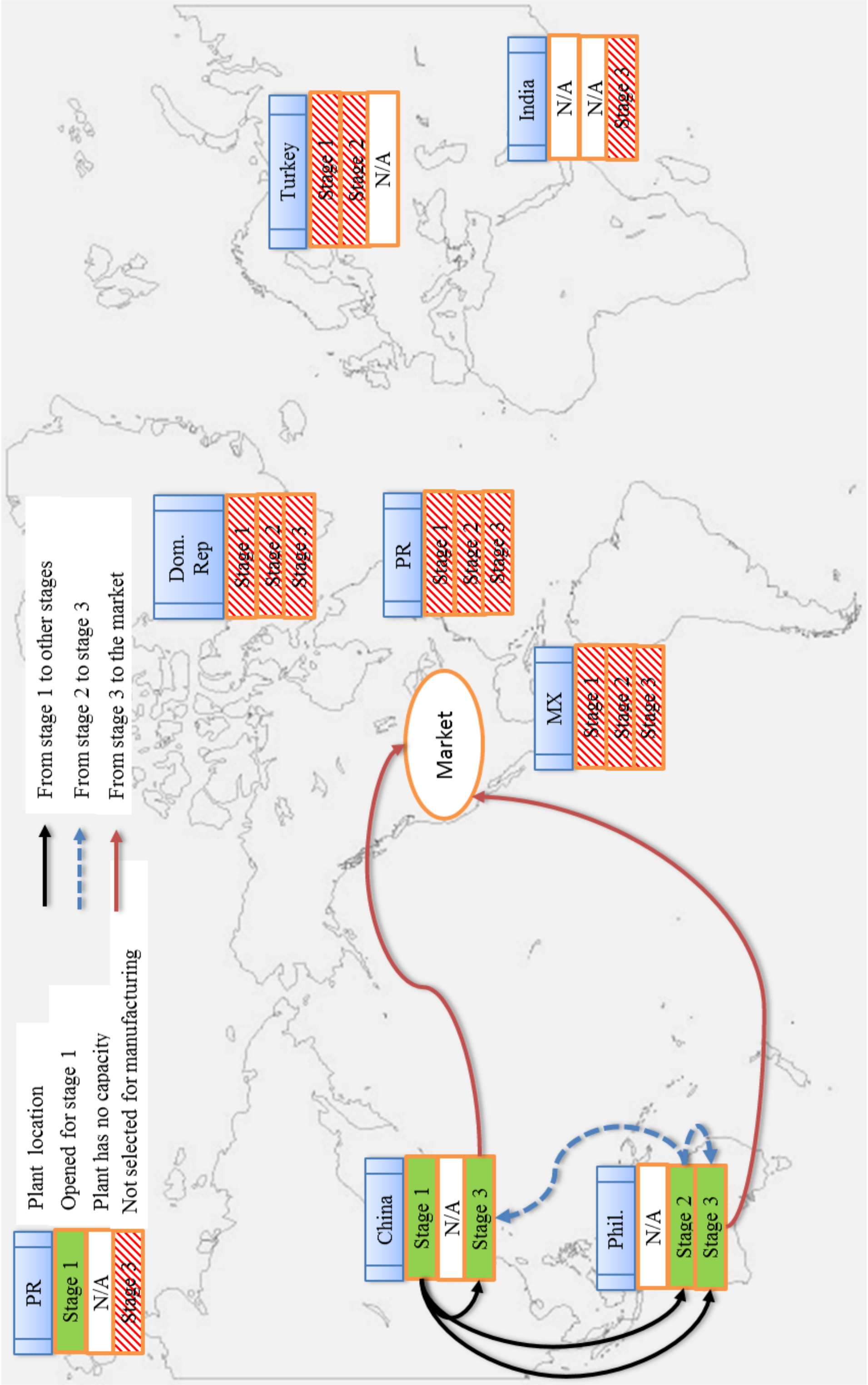


Figure 7.5 Opened plants at manufacturing stages considering three shifts at stage 2

7.5 SCN Design Considering Minimum Capacities for Opened Plants

The SCN designs considered to this point do not consider the percent capacity allocation of the plants opened except for the main plant in one scenario. While some of the opened plants are using their full cell capacities, the rest of the opened plants generally are using way less than their full cell capacities. In this section, if a plant is opened at any manufacturing stage, the model will force it to have a minimum percent capacity allocation.

This minimum percent capacity allocation enforcement seems similar to the main plant enforcement case but it is quite different. In the main plant enforcement case, one of the plants is determined as the main plant and the model is forced to open that plant with a minimum percent capacity allocation. In this section, the model is not forced to open any plant, instead, if the plant is opened, a minimum percent capacity allocation is required to that opened plant. Equation (6.15) is used to assign these minimum percent capacity allocations to the plants.

The minimum percent capacity allocation value for this design is determined to be 80%. Thus, if a plant is opened in this scenario, at least 80% of the capacity will be used to meet the demand for the products.

7.5.1 Results for the SCN Design Considering Minimum Capacity Allocation Enforcement for Every Opened Plant

The results of the plant location and resource allocation model with the minimum capacity enforcement for every opened plant are presented in this section. Total cost for this supply chain design is $241,725.2 per week. This means that enforcing the opened plants to have minimum percent capacity allocations increases the total cost for the supply chain from $230,965.7 to $241,725.2 per week, which corresponds to almost 4.7% increase in weekly costs.

Table 7.26 presents the opened plants at each stage for this scenario. Plants in Puerto Rico and Turkey are not selected for any manufacturing stage due to relatively higher labor, investment costs and transportation costs. Instead, plants are opened in the countries where lower labor and investment costs are available. Labor and investment costs of Mexico and Turkey close to each other, however since Mexico plant is closer to US market; it will require lower transportation costs. The China plant is the only plant opened at stage 1. At stage 2, plants in Mexico, Philippines and Dominican Republic are opened. At stage 3, Mexico, Philippines and India plants are opened.

Table 7.26 Opened plants at manufacturing stages considering minimum capacity enforcement for every opened plant

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	Open	0	N/A	N/A	0	0	0
Stage 2	N/A	Open	Open	N/A	0	0	Open
Stage 3	0	Open	Open	Open	N/A	0	0

The number of cells assigned to each plant at each stage is provided in Table 7.27. All of the cells are assigned to The China plant at stage 1. At stage 3, the number of cells assigned to the plants in Mexico, Philippines and India are 4, 10, and 5, respectively. Total number of cells are also provided in the table.

Table 7.27 Number of assigned manufacturing cells to opened plants at each stage

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.	Total
Stage 1	10	0	N/A	N/A	0	0	0	10
Stage 2	N/A	4	8	N/A	0	0	4	16
Stage 3	0	4	10	5	N/A	0	0	19
Total	10	8	18	5	0	0	4	45

Percent capacity allocation values are provided in Table 7.28. For all of the opened plants at all of the manufacturing stages, the percent capacity allocation is at least 80%. This minimum percent capacity allocation value is required for all the opened plants at individual stages.

Table 7.28 Percent capacity allocation of opened plants at each stage

Plants	China	Mexico	Philippines	India	Turkey	Puerto Rico	Dominican Rep.
Stage 1	100%	0%	N/A	N/A	0%	0%	0%
Stage 2	N/A	80%	80%	N/A	0%	0%	80%
Stage 3	0%	80%	100%	100%	N/A	0%	0%
Overall	50%	53%	90%	100%	0%	0%	20%

However, since the model is not forced to have a minimum percent capacity allocation value for the entire plant locations, the majority of the overall percent capacity allocations for the plants are lower than 80%. Plants in India and Philippines use at least

90% of their cell capacities when all of the manufacturing stages are considered together. The Dominican plant uses 20% of its capacity, and overall percent capacity allocations for China and Mexico plants are around 50%.

Table 7.29 presents the allocation of dedicated, shared and remainder cells to opened plants at each stage. Most of the opened plants have shared or remainder cells. SC stands for shared cells, and RC stands for remainder cells. The Dominican Republic plant has no shared or remainder cell assigned at stage 2. At stage 2, all of the shared/remainder cells are assigned to the Philippines plant. At stage 3, the Mexico and India plants have shared/remainder cells, but Philippines plant not.

Table 7.29 Assigned cells to opened plants at each stage

Plants	Cell type	CHN	MEX	PHL	IND	TUR	PRI	DOM
Stage 1	Dedicated	1, 2, 4, 5, 6, 8, 9, 10						
	SC/RC	3, 7						
Stage 2	Dedicated		14, 21, 23, 26	13, 17, 20, 22, 24, 25				11, 12, 16, 18
	SC/RC			15, 19				
Stage 3	Dedicated		33, 37, 40	29, 30, 31, 32, 35, 38, 39, 41, 42, 43	27, 28, 34			
	SC/RC		44		36, 45			

Table 7.30 shows assigned part families to each plant at manufacturing stages. All of the part families are produced in the same plant, China, at stage 1. Most of the part families are produced in more than one plant at manufacturing stages 2 and 3.

Table 7.30 Plants that produce each part family at each stage

Plants	stage 1	stage 2	stage 3
PF1	1	3, 7	3, 4
PF2	1	2, 7	2, 3
PF3	1	3, 7	3, 4
PF4	1	3	3, 4
PF5	1	2, 3	2, 3, 4
PF6	1	3	3, 4
PF7	1	2, 7	2, 4
PF8	1	N/A	2, 3, 4
PF9	1	3, 7	3, 4
PF10	1	3	2, 3

Figure 7.6 shows the opened plants and transportation relations among plants and stages for the SCN design considering minimum percent capacity allocations for opened plants.

7.5.2 Conclusions

In this section, every opened plant has to have a minimum percent capacity allocation value at each opened stage. The cheapest transportation routes are used as in the initial SCN design. The weekly cost for the entire supply chain decreased from \$230,965.7 per week to \$241,725.2 per week, which corresponds to 4.7% increase in total costs compared to the design without this enforcement.

The locations of the opened plants changed partially. Hence, the number of cells assigned changed for many of the plants. Plants have different manufacturing cells and product families assigned to them as well.

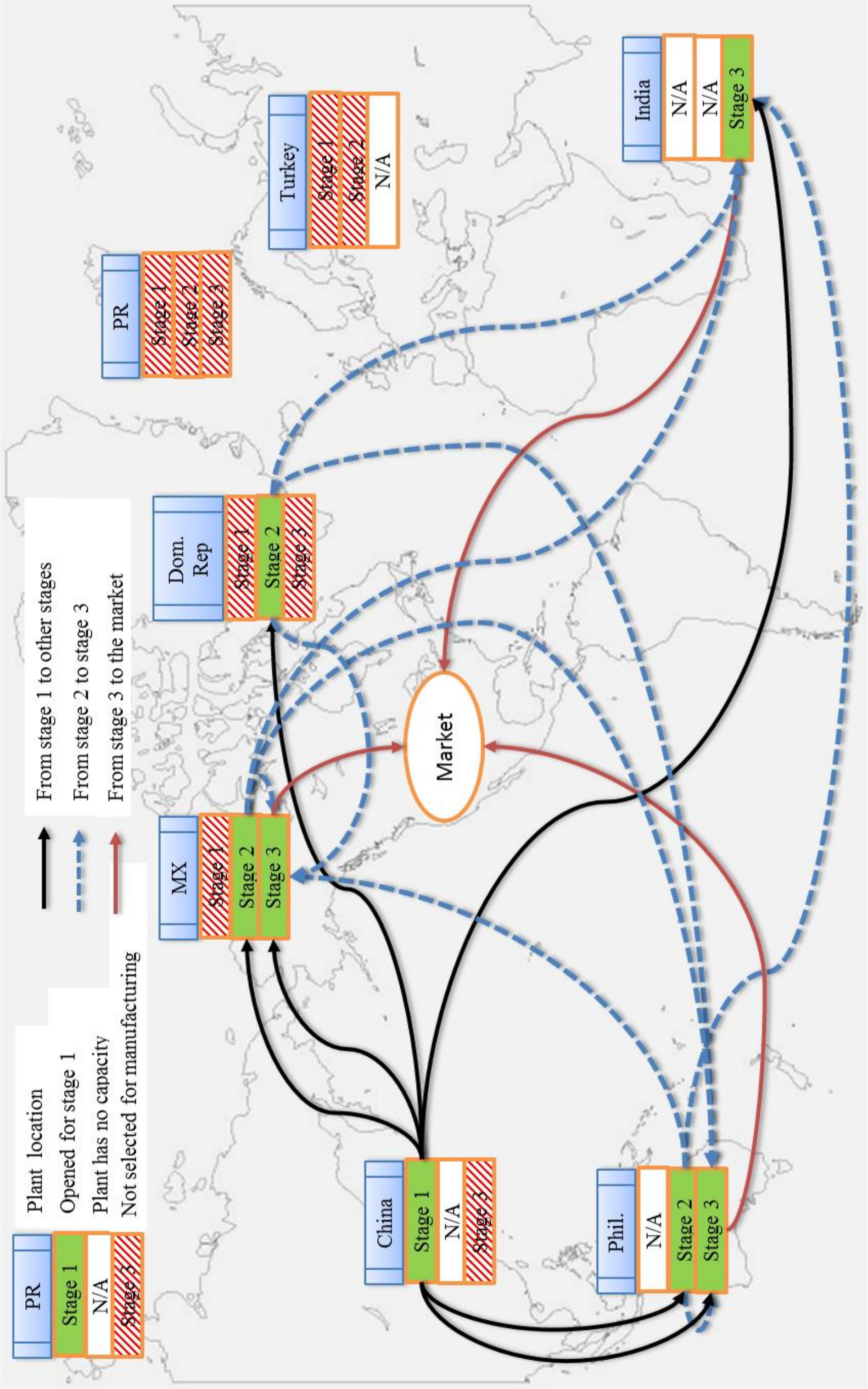


Figure 7.6 Opened plants at manufacturing stages considering minimum percent capacity allocations

7.6 Conclusions

In this chapter, five different supply chain designs are studied. The model presented in Chapter 6 is modified for each design. In three designs, new constraints are introduced to the model, for the other two designs, the different parameters are used as input to the model. The total supply chain costs of the design scenarios are compared with the initial design of Chapter 6. Table 7.31 shows the total weekly supply chain costs for each design and their differences from the initial design. In design 1 where a main plant is opened Puerto Rico, the total weekly cost increased by more than 80%. Using fastest transportation routes instead of cheapest ones resulted in slightly more than 1% reduction in total supply chain costs. Including machine setups and cell installments as new cost factors increased the total supply chain costs by more than 27%, as expected. Increasing the number of shifts from two to three led more than 23% cost reduction. Enforcing a minimum capacity allocation for every opened plant increased the costs by almost 5%.

Table 7.31 Summary table for supply chain networks designed in Chapter 7

Design #	Scenario	Total SC Cost ($/week)	Decrease/Increase from the initial design
Chapter 6	Initial design	$ 230,965.7	0.00%
Design 1	Main plant enforcement	$ 417,877.1	80.93%
Design 2	Fastest transportation routes	$ 228,220.6	-1.19%
Design 3	Machine setup and cell installment	$ 294,555.4	27.53%
Design 4	Three shift for Stage 2	$ 177,132.3	-23.31%
Design 5	Minimum capacity allocation	$ 241,725.2	4.66%

The factors considered in each design are summarized in Table 7.32. This table presents the opportunities to study the other possible combinations and their effects on the supply chain network and manufacturing systems design.

Table 7.32 The factors considered in each design

Factors considered	Initial design	Design 1	Design 2	Design 3	Design 4	Design 5
In-transit inventory carrying costs	√	√	√	√	√	√
Varying transportation costs	√	√	√	√	√	√
Cheapest transportation routes	√	√		√	√	√
Fastest transportation routes			√			
Machine setups				√		
Cell installments				√		
Two shifts for Stage 2	√	√	√	√		√
Three shifts for Stage 2					√	
Minimum capacity allocations for plant(s)		√				√
Main plant requirement		√				

In the first design, minimum percent capacity allocation is enforced for the selected main plant for all stages, which ensures that the selected plant is opened and used at a certain percent capacity allocation level. This scenario is similar to the multinational companies which have a main manufacturing facility at the home country, but seeks for presence in other countries as well.

In the second design, the transportation system of the supply chain is changed from the cheapest transportation routes to the fastest transportation routes. For most of the locations, the cheapest and the fastest transportation routes happened to be the same routes. The total supply chain costs of the shortest and the cheapest transportation cases are very close to each other, also the locations of the opened are same for both alternatives. Thus, it can be concluded that using faster transportation routes is a better option since the lead times for the two plant locations are lower than the cheapest transportation.

In the third design, machine setups and cell installments are taken into account while designing the supply chain network and manufacturing systems. The cheapest transportation routes are used. Since new costs are introduced into the design, the weekly cost for the entire supply chain increased almost 28% as expected. One other important result is that the manufacturing cells that process more than one part family, i.e., shared and remainder cells, are assigned to the countries with lower labor costs.

In the fourth design, the number of shifts at the second stage of supply chain is increased from two to three. This resulted in decrease in the manufacturing cells required to meet the demand from 16 to 10. The number of plants decreased as well. As a result, the total supply chain cost decreased by almost 23%.

In the fifth design, if a plant opened for any stage, it has to have a minimum capacity percent capacity allocation value. For 80% minimum capacity allocation value, the number of plants opened decreased from four to two plants, but total cost of the supply chain increased by almost 5%.

In this chapter, the effects of possible design scenarios on the total supply chain cost, and the location and usage of the plants are studied. More scenarios can be modeled and their effects can be studied.

8 CONCLUSIONS AND FUTURE STUDY

Global supply chain networks are complex systems that integrate mainly suppliers, manufacturers, warehouses and retailers to fulfill customer requirements. The decisions made for the global supply chains are considered strategic decisions and have long term effects on each tier of the supply chain and the profitability of the entire supply chain. Once the locations of the facilities are decided and realized, many other strategic decisions, such as manufacturing system design, and tactical decisions, such as number of workers in manufacturing cell, have to be made considering this factor. Many methods and approaches are available in the literature about supply chain network design, and manufacturing system design. Traditionally, manufacturing systems are designed after the locations of the plants are determined. There are very few studies in the literature that integrates supply chain and manufacturing system decisions. This dissertation provides a methodology to concurrently design multi-stage supply chain networks and manufacturing systems for labor-intensive manufacturing companies considering critical factors that affect the total cost of the entire supply chain.

The methodology implemented in this dissertation consists of seven stages; generating alternative manpower configurations for all stages, optimal cell size determination with heuristic procedure, finding expected cell utilizations and demand coverage probabilities with probability theory, cell type determination with a mathematical model, validating the cellular manufacturing systems with simulation models, locating plants and allocating cells concurrently, and experimenting various supply chain network and manufacturing system designs. Each stage is connected with one or more of the stages. Hence, the last two stages regarding supply chain network and manufacturing systems design decisions use the outcomes of the previous chapters.

In Chapter 3, the optimal number of operators required for all of the operations in a cell for each part is found in single-stage and multi-stage cellular manufacturing systems using a mathematical model. The objective is of the mathematical model is to find the optimal number of operators for each operation and to maximize the production rate of the part with the assigned number of operators. A new heuristic procedure is proposed to find the optimal cell size, i.e., total number of operators in a cell, for each part family in dedicated cells. The heuristic procedure is modified to find the optimal cell sizes for shared and remainder cells in Chapter 4. Then, based on this methodology, three different approaches, common cell size, optimal cell size, and a modified mathematical model, are developed to load product families to the manufacturing cells, as an extension of this work. The results showed that, in general, when the number of available operators in cells increases, the efficiency of that cell increases as well because of better fitting of the number of operators assigned to the operations to the processing times. Higher operator levels are more efficient than the lower operator levels.

In Chapter 4, layered cellular manufacturing system is designed with a mathematical for probabilistic demand. In layered cellular manufacturing systems, a cell can process many part families, and a part family can be processed in many cells. Shared cells process two part families, and remainder cells process more than two part families. A mathematical model is employed in order to determine the number of cells required to cover the demand. Demand coverage probabilities and expected cell utilizations are found using the probability theory developed by Süer and Ortega (1996). The expected cell utilization and demand coverage probability values are used in the mathematical model in order to determine cell configuration and cell types. The model minimizes the number of cells opened to meet the highly fluctuated uncertain demand. It also determines the number of dedicated, shared and remainder cells in the system. There are couple contributions to the cellular manufacturing literature in this chapter, namely shifting bottleneck machines in manufacturing cells, machine duplication, and multiple shifts. In order capture the performance of the system with respect to cell and machine utilization values, simulation models are developed for the manufacturing systems designed by using the mathematical model in Chapter 5. The system is fine tuned in order to approximate the cell utilization values of the simulation models to those of mathematical models.

In Chapter 6, major supply chain decisions are made using the results of Chapter 3 and Chapter 4. A plant location-manufacturing cell allocation model is developed to design the supply chain network and manufacturing systems considering the features of layered cellular systems, optimal manpower levels for operations, optimal cell sizes, individual machine costs, in-transit inventory carrying costs, varying transportation costs including insurance costs, machine duplication, and multiple shifts. Cost of capital, value of products, and lead times among supply chain stages are considered while calculating the in-transit inventory carrying costs. The plants selected to be opened among the candidate locations are the ones with lower labor costs, which was an expected result.

Also, few plants close to the US market are also opened due to lower transportation and in-transit inventory costs.

In Chapter 7, five different supply chain scenarios are studied. The supply chain network and manufacturing system design model is modified for each scenario. In the first design, it is assumed that the company keeps a plant open and uses a minimum percent of its maximum capacity to design and produce prototypes, or to cope with fluctuating demand. The model is enforced for a selected main plant for all stages. In the second design, the fastest transportation routes are used instead of the cheapest the transportation routes to carry among plants and to US warehouse. In the third design, machine setups and cell installments are considered as cost factors. In the fourth design, it is assumed that the plants at stage 2 will work three shifts instead of two shifts. This resulted in fewer manufacturing cells and fewer number of plants opened. The total supply chain cost decreased by more than 23%. In the fifth design, a minimum capacity allocation is enforced for each opened plant to better utilize the maximum capacity. The number of plants opened decreased by one, but total cost of the supply chain increased by almost 11% with this constraint.

All in all, this dissertation fills an important gap in concurrent global multi-stage supply chain network and manufacturing systems design literature by taking stochastic demand, cell sizes, operator assignments, varying transportation costs, multiple shifts, cell installments, machine setups and machine duplication into account. It provides various alternative manufacturing systems and supply chain designs considering different scenarios for transportation and capacity allocation. However, based on the work done, there are various future directions that can be drawn from this dissertation and many aspects that the current proposed approach to design manufacturing system and supply chain network can be improved. The following features can be studied.

- Machine based multiple-shift concept: In this dissertation, stage based multiple shifts are considered for manufacturing cells. However, in practice, manufacturing companies usually have only certain machines work overtime or in second shifts. Therefore, instead of having the entire plant to work for multiple shifts, machine based double shift concept may be considered.
- Machine setups: In this dissertation, the effect of the time required to setup a machine to the available hours of a manufacturing cell is ignored. Machine setup times can be deducted from cell capacities.
- Minimum demand coverage probability: The impacts of various minimum demand coverage probabilities on the cellular manufacturing system and its performance measures can be studied.
- Extending the model with multi-market: North America is assumed to be the only market for the products produced all over the world in the current model. The model can be extended by considering multiple markets with different demands.
- Procurement of raw materials to be added to SCN design: In the current model it is assumed that the location and costs of the raw materials do not affect the design of supply chain network. Procurement of raw materials and suppliers can be added to the system, and their effects might be investigated.

- Redesigning manufacturing systems and supply chain network periodically: Product mix of fashion jewelry changes on a continuous basis. Even though some seasonal items such as Christmas, New Year, mother's day etc., are reproduced every year, demand of some of the items on the market disappears and some new items are introduced into the market. In order to cope with the changes in the market, the design of manufacturing system and supply chain network will be revisited on a regular basis. After these changes are taken into account, if the cost of new design is within a specified percentage, like 5%, the previous design will be kept until the next redesign time.
- Similarly, some of the plants may be closed due to labor strikes, wars, fires and natural disasters, etc. The cost of labor may increase, or transportation of goods from certain geographic locations may become too risky. In this kind of situations, redesigning will allow the company to select a new location, or optimally distribute the demand of the closed plant to the rest of the plants in the system.
- Work in process inventory: In this dissertation, while calculating inventory costs, only pipeline inventory is considered. As an extension, WIP inventory in the plants may be added to the model.
- Varying scrap rates for countries: Investment cost is not the only factor while considering a country as a potential plant location. Skilled labor force is also another important factor. Some countries may offer very cheap land and

incentives to build a plant in them, but if they lack skilled labor force, the quality of the output of those plants should be considered as well.

- Inter-plant transportation between stages: In the current design, it is assumed that no cost incurs if a product family is processed in a plant for two consecutive stages. However, even though it is not comparable to ocean freight rates, inter-plant material/product movement yields cost.
- Part-family definition in stages: Part families in each stage can be defined independently in multi-stage cellular manufacturing. In the current study, part families are defined for single-stage cellular manufacturing, and these part families are kept throughout the multi-stage cellular manufacturing design.
- Transportation modes: In the current SCN model, the transportation mode is selected upfront and final transportation costs are used as parameters. Transportation modes can be another decision variable in the model. Thus, the models optimizes the decisions by considering freight insurance costs, freight shipment costs, pipeline inventory costs for various transportation mode options.
- In the SCN model, air transportation is not considered by any of the models. Air transportation can be used as one of the alternative transportation modes. This inclusion affect the results for the fastest transportation option.
- Probabilistic leadtimes: In this dissertation, leadtimes are assumed to be deterministic. Stochastic lead time component can be added to the SCN model.
- Customer preferences: Some customers may prefer cheaper transportation, the other may prefer faster transportation, even for the same product family. This

requires to divide the product families artificially while designing the manufacturing cells.

- FCL vs LCL : While calculating the international and domestic freight costs, it is assumed that the containers are fully loaded up to their maximum payloads. However, this may not be, and in many shipments is not, the case in reality. Using maximum payloads generally decreases the freight costs. Less than container loads can be studied.
- Various supply chain components: Port waiting times, loading/unloading to trucks, ships, trains and their effects to inventory and lead times are not considered.
- Setup times, hence setup costs are much higher between families, therefore remainder and shared cells are expected to have lower efficiencies. These relations can be factored into models.
- The effects of different values of minimum percent capacity allocation values for the opened plants on plant location and cell allocation can be investigated.
- Production planning: In order to study the operational aspects of the designed supply chain network and manufacturing system, production planning can be performed to verify the operational performance.

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APPENDIX A: OPTIMUM NUMBER OF OPERATORS FOR MANPOWER LEVELS

Number of assigned operators to operations and production rates at various manpower levels for single stage and multi-stage manufacturing

Table A.1 Number of assigned operators in single-stage manufacturing for 15 available operators

15	**Parts**																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	1	1	1	0	1	2	0	1	0	1	0	0	0	1	0	2	0	0	0	2	1	0	1	1	1	0	1	2	0	1	0	1	0	0	0	0	0	1	1
2	0	2	1	1	0	2	2	0	1	0	2	0	0	0	1	0	2	0	0	0	3	2	0	2	2	2	0	2	3	0	1	0	2	0	0	0	0	0	2	3
3	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	1	0	1	1	1	0	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	1	1	0	0
4	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	1	0	1	1	1	0	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	1	1	0	0
5	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	1	0	1	1	1	0	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	1	1	0	0
6	1	1	2	1	2	2	1	1	1	2	1	0	1	2	1	1	2	1	1	1	2	2	1	1	0	2	0	1	2	2	1	2	1	3	1	1	1	0	1	2
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	2	1	0	0	0	1	0	2	0	0	0	0	2	1	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0
11	3	0	0	1	2	2	0	1	2	0	0	3	3	2	1	3	0	0	0	0	0	2	1	2	3	2	0	3	3	0	0	2	2	4	2	0	1	2	2	3
12	0	3	3	3	3	0	2	0	3	0	3	0	0	0	2	0	0	3	3	0	0	0	2	0	4	4	0	0	0	0	2	3	3	0	0	3	2	3	2	2
13	0	3	3	3	0	2	2	3	3	3	3	3	0	2	3	0	0	3	0	3	0	2	2	0	0	0	4	0	0	0	3	0	2	0	3	3	2	3	2	0
14	2	2	0	0	1	1	2	1	1	0	0	0	2	0	1	2	3	2	2	0	0	2	1	2	0	2	3	0	0	2	2	2	0	0	0	0	1	0	2	0
15	1	1	1	1	0	1	2	1	0	2	2	2	0	0	1	1	2	1	1	1	2	1	1	2	0	0	2	2	0	2	1	0	0	0	2	1	1	1	1	2
16	2	0	1	1	0	2	0	2	2	2	0	0	3	2	1	2	0	0	2	2	2	2	1	0	0	0	0	3	3	2	1	0	2	0	2	1	0	0	0	0
17	2	2	2	2	1	1	2	0	1	2	1	2	3	1	0	2	2	1	0	2	3	1	2	2	3	2	2	2	2	2	0	2	2	3	2	2	1	2	2	0
18	0	0	1	1	1	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	1	0	2	0	1	0	0	0	0
19	1	0	0	0	0	0	0	2	0	0	2	0	0	2	2	0	0	0	2	3	1	0	0	3	0	0	0	1	0	2	2	0	0	0	0	0	2	0	0	2

Table A.2 Number of assigned operators in single-stage manufacturing for 20 available operators

20	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	1	1	1	0	1	2	0	1	0	1	0	0	0	1	0	2	0	0	0	3	2	0	2	2	2	0	1	2	0	2	0	1	0	0	0	0	0	2	1
2	0	3	2	1	0	3	3	0	2	0	2	0	0	0	2	0	3	0	0	0	4	2	0	3	3	2	0	3	4	0	2	0	2	0	0	0	0	0	3	4
3	1	0	0	0	1	0	0	1	0	1	0	2	1	1	0	1	0	1	1	1	0	0	1	0	0	0	1	0	0	1	0	1	0	2	1	1	1	1	0	0
4	1	0	0	0	1	0	0	1	0	2	0	1	1	2	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	2	1	1	1	1	0	0
5	1	0	0	0	1	0	0	1	0	1	0	1	2	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	2	0	1	0	2	1	1	1	1	0	0
6	2	2	2	2	2	2	2	1	1	2	2	0	2	2	1	2	3	2	2	2	2	2	1	2	0	2	0	2	3	2	1	2	2	3	2	1	1	0	2	3
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	2	1	0	0	0	2	0	2	0	0	0	0	3	1	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	2	2	0	0
11	4	0	0	2	3	3	0	2	4	0	0	4	4	3	2	3	0	0	0	0	0	2	2	3	3	3	0	3	4	0	0	3	3	5	3	0	2	3	3	4
12	0	4	4	4	4	0	3	0	3	0	4	0	0	0	3	0	0	4	4	0	0	0	3	0	6	5	0	0	0	0	3	4	4	0	0	5	2	4	3	4
13	0	4	4	4	0	3	3	5	3	4	4	4	0	3	4	0	0	4	0	4	0	2	4	0	0	0	4	0	0	0	4	0	4	0	5	4	3	4	2	0
14	3	2	0	0	2	2	3	2	2	0	0	0	2	0	2	2	3	2	2	0	0	3	1	2	0	3	4	0	0	4	2	3	0	0	0	0	2	0	2	0
15	2	2	1	1	0	1	2	1	0	2	2	3	0	0	1	2	3	2	2	2	2	2	1	2	0	0	2	2	0	2	1	0	0	0	2	1	1	2	1	2
16	2	0	2	2	0	2	0	2	2	3	0	0	4	3	1	3	0	0	3	3	3	3	2	0	0	0	0	4	4	3	2	0	2	0	2	2	0	0	0	0
17	2	2	3	2	2	2	2	0	1	3	2	3	4	2	0	3	3	2	0	2	4	2	2	3	4	3	3	3	3	3	0	3	2	4	3	3	2	2	2	0
18	0	0	1	1	2	0	0	1	0	0	0	0	0	0	1	2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	2	0	2	0	1	0	0	0	0
19	2	0	0	0	0	0	0	3	0	0	3	0	0	3	2	0	0	0	3	4	2	0	0	3	0	0	0	1	0	2	2	0	0	0	0	0	2	0	0	2

Table A.3 Number of assigned operators in single-stage manufacturing for 25 available operators

25	Parts																																						
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	2	1	1	0	1	3	0	2	0	2	0	0	0	1	0	3	0	0	0	4	3	0	2	2	2	0	2	3	0	2	0	1	0	0	0	0	0	2	2
2	0	3	2	2	0	3	4	0	2	0	2	0	0	0	2	0	4	0	0	0	5	3	0	3	3	3	0	4	5	0	2	0	3	0	0	0	0	0	3	5
3	2	0	0	0	1	0	0	1	0	2	0	2	2	2	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	2	1	1	1	2	0	0
4	2	0	0	0	2	0	0	1	0	2	0	2	1	2	0	1	0	2	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	2	2	1	1	1	0	0
5	1	0	0	0	1	0	0	1	0	1	0	2	2	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	2	0	2	0	2	1	1	1	1	0	0
6	2	2	3	2	3	3	2	2	2	3	2	0	2	3	2	2	4	2	2	3	3	3	1	2	0	3	0	2	4	3	1	3	2	5	2	2	2	0	2	4
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	3	2	0	0	0	2	0	3	0	0	0	0	3	2	0	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0	0	0	2	2	0	0
11	5	0	0	2	4	3	0	2	4	0	0	5	5	4	2	5	0	0	0	0	0	3	2	4	5	4	0	4	5	0	0	4	4	6	3	0	2	3	3	4
12	0	5	5	5	5	0	4	0	4	0	5	0	0	0	3	0	0	5	7	0	0	0	4	0	7	7	0	0	0	0	4	4	5	0	0	6	3	5	4	4
13	0	5	6	5	0	4	4	6	4	5	5	5	0	4	6	0	0	5	0	5	0	3	5	0	0	0	6	0	0	0	6	0	4	0	6	6	4	6	3	0
14	4	3	0	0	2	2	3	2	2	0	0	0	3	0	2	3	4	3	2	0	0	3	2	3	0	3	4	0	0	4	2	4	0	0	0	0	2	0	3	0
15	2	2	2	2	0	2	2	2	0	3	3	3	0	0	2	2	3	2	2	3	3	2	2	2	0	0	3	3	0	3	2	0	0	0	3	1	2	2	2	3
16	3	0	2	2	0	3	0	3	3	3	0	0	5	3	2	4	0	0	4	3	4	3	2	0	0	0	0	4	5	4	2	0	3	0	3	2	0	0	0	0
17	2	3	3	3	2	2	3	0	2	4	2	3	5	2	0	4	4	2	0	3	4	2	3	4	5	3	4	4	3	3	0	3	3	5	4	4	2	3	3	0
18	0	0	1	1	2	0	0	1	0	0	0	0	0	0	1	2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	2	0	3	0	1	0	0	0	0
19	2	0	0	0	0	0	0	3	0	0	4	0	0	4	2	0	0	0	4	5	2	0	0	5	0	0	0	2	0	2	3	0	0	0	0	0	3	0	0	3

Table A.4 Number of assigned operators in single-stage manufacturing for 30 available operators

30	Parts																																						
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	2	2	1	0	1	3	0	2	0	2	0	0	0	2	0	4	0	0	0	4	3	0	3	3	3	0	2	3	0	2	0	2	0	0	0	0	0	2	2
2	0	4	2	2	0	4	4	0	3	0	3	0	0	0	2	0	4	0	0	0	7	4	0	4	4	4	0	4	7	0	3	0	3	0	0	0	0	0	4	6
3	2	0	0	0	2	0	0	1	0	2	0	2	2	2	0	2	0	1	2	2	0	0	1	0	0	0	2	0	0	2	0	2	0	2	1	1	1	2	0	0
4	2	0	0	0	2	0	0	2	0	2	0	2	2	2	0	2	0	2	2	1	0	0	1	0	0	0	2	0	0	2	0	2	0	3	2	1	1	2	0	0
5	1	0	0	0	2	0	0	1	0	2	0	2	2	2	0	2	0	2	1	2	0	0	1	0	0	0	2	0	0	2	0	2	0	3	1	1	1	1	0	0
6	3	3	3	3	3	4	2	2	2	3	3	0	3	3	2	3	4	3	3	3	4	3	2	3	0	3	0	3	4	3	2	3	3	5	3	2	2	0	3	5
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	3	2	0	0	0	3	0	4	0	0	0	0	4	2	0	0	0	0	0	0	4	0	3	0	0	0	0	0	0	0	0	0	2	3	0	0
11	5	0	0	2	4	4	0	3	4	0	0	6	6	5	3	5	0	0	0	0	0	4	3	4	5	5	0	5	6	0	0	5	5	7	4	0	3	4	4	6
12	0	6	6	6	6	0	5	0	5	0	6	0	0	0	4	0	0	6	7	0	0	0	5	0	8	7	0	0	0	0	4	5	6	0	0	7	3	6	5	5
13	0	7	7	6	0	4	5	7	6	6	6	6	0	5	7	0	0	6	0	6	0	4	6	0	0	0	7	0	0	0	6	0	5	0	8	7	5	6	4	0
14	5	3	0	0	3	3	4	3	2	0	0	0	3	0	2	3	5	3	3	0	0	4	2	4	0	4	6	0	0	5	3	5	0	0	0	0	3	0	3	0
15	3	2	2	2	0	2	3	2	0	3	3	4	0	0	2	3	4	2	2	3	3	2	2	3	0	0	3	4	0	4	2	0	0	0	3	2	2	3	2	3
16	4	0	3	3	0	3	0	3	4	4	0	0	6	4	2	4	0	0	4	4	4	4	2	0	0	0	0	5	6	5	3	0	3	0	3	3	0	0	0	0
17	3	3	4	4	2	2	4	0	2	5	3	4	6	3	0	4	5	3	0	4	6	2	4	4	6	4	5	5	4	4	0	4	3	6	4	5	3	3	3	0
18	0	0	1	1	3	0	0	2	0	0	0	0	0	0	1	2	0	0	2	0	0	0	1	0	0	0	0	0	0	0	2	2	0	4	0	1	0	0	0	0
19	2	0	0	0	0	0	0	4	0	0	4	0	0	4	3	0	0	0	4	5	2	0	0	5	0	0	0	2	0	3	3	0	0	0	0	0	4	0	0	3

Table A.5 Number of assigned operators in stage 1 of multi-stage manufacturing for 5 available operators

5	Parts																																						
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	1	1	1	0	1	2	0	1	0	1	0	0	0	1	0	1	0	0	0	2	2	0	1	2	1	0	1	1	0	2	0	1	0	0	0	0	0	1	1
2	0	2	2	2	0	2	2	0	2	0	2	0	0	0	2	0	2	0	0	0	2	2	0	2	3	2	0	2	2	0	2	0	2	0	0	0	0	0	2	2
3	1	0	0	0	1	0	0	1	0	1	0	2	1	1	0	1	0	1	1	1	0	0	1	0	0	0	1	0	0	1	0	1	0	1	1	1	1	2	0	0
4	1	0	0	0	1	0	0	1	0	1	0	1	1	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	1	1	1	1	2	0	0
5	1	0	0	0	1	0	0	1	0	1	0	2	1	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	1	1	1	1	1	0	0
6	2	2	2	2	2	2	1	2	2	2	2	0	2	2	2	2	2	2	2	2	1	1	2	2	0	2	0	2	2	2	1	2	2	2	2	2	2	0	2	2

Table A.6 Number of assigned operators in stage 1 of multi-stage manufacturing for 6 available operators

6	Parts																																						
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	1	1	1	0	1	2	0	2	0	2	0	0	0	2	0	2	0	0	0	2	2	0	2	2	2	0	1	1	0	2	0	1	0	0	0	0	0	2	1
2	0	3	2	2	0	3	3	0	2	0	2	0	0	0	2	0	2	0	0	0	2	2	0	2	4	2	0	3	3	0	2	0	3	0	0	0	0	0	2	3
3	1	0	0	0	1	0	0	1	0	1	0	2	1	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	1	1	1	1	2	0	0
4	1	0	0	0	2	0	0	2	0	2	0	2	1	1	0	1	0	2	2	1	0	0	1	0	0	0	2	0	0	1	0	1	0	1	2	1	2	2	0	0
5	1	0	0	0	1	0	0	1	0	1	0	2	2	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	2	0	2	0	1	1	1	1	2	0	0
6	2	2	3	3	2	2	1	2	2	2	2	0	2	3	2	2	2	2	2	3	2	2	3	2	0	2	0	2	2	2	2	2	2	3	2	3	2	0	2	2

Table A.7 Number of assigned operators in stage 1 of multi-stage manufacturing for 7 available operators

7	Parts																																						
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	2	2	1	0	1	2	0	2	0	2	0	0	0	2	0	2	0	0	0	2	2	0	2	3	2	0	1	2	0	2	0	1	0	0	0	0	0	2	1
2	0	3	2	3	0	3	3	0	3	0	3	0	0	0	3	0	2	0	0	0	3	3	0	3	4	3	0	4	3	0	3	0	3	0	0	0	0	0	3	3
3	2	0	0	0	1	0	0	1	0	1	0	3	2	1	0	1	0	1	1	1	0	0	1	0	0	0	2	0	0	1	0	1	0	1	1	1	1	3	0	0
4	2	0	0	0	2	0	0	2	0	2	0	2	1	2	0	2	0	2	2	1	0	0	1	0	0	0	3	0	0	1	0	1	0	1	2	1	2	2	0	0
5	1	0	0	0	1	0	0	2	0	1	0	2	2	1	0	2	0	2	1	2	0	0	1	0	0	0	2	0	0	2	0	2	0	2	1	2	2	2	0	0
6	2	2	3	3	3	3	2	2	2	3	2	0	2	3	2	2	3	2	3	3	2	2	3	2	0	2	0	2	2	3	2	3	3	3	3	3	2	0	2	3

Table A.8 Number of assigned operators in stage 1 of multi-stage manufacturing for 8 available operators

8	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	2	2	1	0	1	2	0	2	0	2	0	0	0	2	0	2	0	0	0	3	2	0	2	3	2	0	2	2	0	3	0	2	0	0	0	0	0	2	1
2	0	4	3	3	0	4	4	0	3	0	3	0	0	0	3	0	3	0	0	0	3	3	0	4	5	3	0	4	4	0	3	0	3	0	0	0	0	0	3	4
3	2	0	0	0	1	0	0	2	0	2	0	3	2	2	0	1	0	1	1	2	0	0	2	0	0	0	2	0	0	1	0	2	0	1	1	2	1	3	0	0
4	2	0	0	0	2	0	0	2	0	2	0	2	1	2	0	2	0	2	2	1	0	0	2	0	0	0	3	0	0	2	0	1	0	2	2	1	2	3	0	0
5	1	0	0	0	2	0	0	2	0	1	0	3	2	1	0	2	0	2	2	2	0	0	1	0	0	0	3	0	0	2	0	2	0	2	2	2	2	2	0	0
6	3	2	3	4	3	3	2	2	3	3	3	0	3	3	3	3	3	3	3	3	2	3	3	2	0	3	0	2	2	3	2	3	3	3	3	3	3	0	3	3

Table A.9 Number of assigned operators in stage 1 of multi-stage manufacturing for 10 available operators

10	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	2	2	2	0	2	3	0	3	0	3	0	0	0	3	0	3	0	0	0	3	3	0	3	4	3	0	2	2	0	3	0	2	0	0	0	0	0	3	2
2	0	5	4	3	0	4	5	0	4	0	4	0	0	0	4	0	3	0	0	0	4	4	0	4	6	4	0	5	5	0	4	0	4	0	0	0	0	0	4	4
3	2	0	0	0	2	0	0	2	0	2	0	4	2	2	0	2	0	2	2	2	0	0	2	0	0	0	3	0	0	2	0	2	0	2	2	2	2	4	0	0
4	2	0	0	0	2	0	0	3	0	2	0	3	2	2	0	2	0	2	2	2	0	0	2	0	0	0	4	0	0	2	0	2	0	2	2	2	2	3	0	0
5	2	0	0	0	2	0	0	2	0	2	0	3	2	2	0	2	0	2	2	2	0	0	2	0	0	0	3	0	0	2	0	2	0	2	2	2	2	3	0	0
6	4	3	4	5	4	4	2	3	3	4	3	0	4	4	3	4	4	4	4	4	3	3	4	3	0	3	0	3	3	4	3	4	4	4	4	4	4	0	3	4

Table A.10 Number of assigned operators in stage 1 of multi-stage manufacturing for 12 available operators

12	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	3	3	2	0	2	4	0	3	0	3	0	0	0	3	0	4	0	0	0	4	4	0	3	5	3	0	2	3	0	4	0	2	0	0	0	0	0	3	2
2	0	5	4	4	0	5	5	0	5	0	5	0	0	0	5	0	4	0	0	0	5	4	0	5	7	5	0	6	5	0	5	0	5	0	0	0	0	0	5	5
3	3	0	0	0	2	0	0	2	0	2	0	4	3	3	0	2	0	2	2	2	0	0	2	0	0	0	4	0	0	2	0	2	0	2	2	2	2	5	0	0
4	3	0	0	0	3	0	0	3	0	3	0	4	2	2	0	3	0	3	3	2	0	0	2	0	0	0	4	0	0	2	0	2	0	3	3	2	3	4	0	0
5	2	0	0	0	2	0	0	3	0	2	0	4	3	2	0	3	0	3	2	3	0	0	2	0	0	0	4	0	0	3	0	3	0	2	2	3	3	3	0	0
6	4	4	5	6	5	5	3	4	4	5	4	0	4	5	4	4	4	4	5	5	3	4	6	4	0	4	0	4	4	5	3	5	5	5	5	5	4	0	4	5

Table A.11 Number of assigned operators in stage 3 of multi-stage manufacturing for 10 available operators

10	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	0	0	0	2	1	0	0	0	1	0	2	0	0	0	0	2	1	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0
2	3	0	0	1	2	2	0	1	2	0	0	2	3	2	1	3	0	0	0	0	0	2	1	2	2	2	0	2	4	0	0	2	2	4	2	0	1	2	2	3
3	0	3	2	2	3	0	2	0	2	0	3	0	0	0	2	0	0	3	3	0	0	0	2	0	3	4	0	0	0	0	2	3	2	0	0	3	1	2	2	3
4	0	3	3	2	0	2	2	3	2	3	3	2	0	2	2	0	0	3	0	3	0	2	2	0	0	0	3	0	0	0	3	0	2	0	3	2	2	2	2	0
5	2	2	0	0	1	1	2	1	1	0	0	0	2	0	1	1	3	1	1	0	0	2	1	2	0	2	2	0	0	2	1	2	0	0	0	0	1	0	2	0
6	1	1	1	1	0	1	2	1	0	2	1	2	0	0	1	1	2	1	1	1	2	1	1	1	0	0	2	2	0	2	1	0	0	0	1	1	1	1	1	2
7	2	0	1	1	0	2	0	1	2	2	0	0	2	2	1	2	0	0	2	2	3	2	1	0	0	0	0	3	4	2	1	0	2	0	2	1	0	0	0	0
8	1	1	2	2	1	1	2	0	1	2	1	2	3	1	0	2	3	1	0	2	3	1	1	2	3	2	2	2	2	2	0	2	2	4	2	2	1	2	1	0
9	0	0	1	1	1	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	1	0	2	0	1	0	0	0	0
10	1	0	0	0	0	0	0	2	0	0	2	0	0	3	1	0	0	0	2	2	2	0	0	3	0	0	0	1	0	2	1	0	0	0	0	0	2	0	0	2

Table A.12 Number of assigned operators in stage 3 of multi-stage manufacturing for 12 available operators

12	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	0	0	0	2	1	0	0	0	2	0	2	0	0	0	0	3	1	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0
2	3	0	0	1	2	2	0	1	2	0	0	3	4	3	1	3	0	0	0	0	0	2	1	2	3	3	0	3	4	0	0	3	2	5	2	0	2	2	2	4
3	0	3	3	3	3	0	3	0	3	0	3	0	0	0	2	0	0	3	4	0	0	0	2	0	4	5	0	0	0	0	2	3	3	0	0	3	2	3	3	4
4	0	4	3	3	0	3	3	3	3	3	3	3	0	3	3	0	0	3	0	3	0	2	3	0	0	0	4	0	0	0	3	0	3	0	4	3	2	3	2	0
5	2	2	0	0	1	2	2	2	1	0	0	0	2	0	1	2	3	2	2	0	0	2	1	2	0	2	3	0	0	3	2	3	0	0	0	0	1	0	2	0
6	2	1	1	1	0	1	2	1	0	2	2	2	0	0	1	2	3	1	1	2	2	2	1	2	0	0	2	2	0	2	1	0	0	0	2	1	1	1	1	2
7	2	0	2	1	0	2	0	2	2	2	0	0	3	2	1	2	0	0	2	2	3	2	1	0	0	0	0	3	5	3	1	0	2	0	2	1	0	0	0	0
8	2	2	2	2	1	1	2	0	1	3	2	2	3	2	0	2	3	2	0	2	5	2	2	3	3	2	2	3	3	2	0	2	2	4	2	3	1	2	2	0
9	0	0	1	1	1	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	1	0	3	0	1	0	0	0	0
10	1	0	0	0	0	0	0	2	0	0	2	0	0	2	2	0	0	0	2	3	2	0	0	3	0	0	0	1	0	2	2	0	0	0	0	0	2	0	0	2

Table A.13 Number of assigned operators in stage 3 of multi-stage manufacturing for 15 available operators

15	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	0	0	0	2	1	0	0	0	2	0	2	0	0	0	0	3	1	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	1	2	0	0
2	4	0	0	2	3	3	0	2	3	0	0	4	5	4	2	3	0	0	0	0	0	3	2	3	3	4	0	4	6	0	0	3	3	7	3	0	2	2	3	5
3	0	4	4	3	4	0	3	0	3	0	4	0	0	0	3	0	0	4	4	0	0	0	3	0	6	5	0	0	0	0	3	4	4	0	0	4	2	3	3	4
4	0	5	4	4	0	3	4	5	3	4	4	3	0	3	4	0	0	4	0	4	0	2	3	0	0	0	4	0	0	0	4	0	4	0	5	4	3	4	3	0
5	3	2	0	0	2	2	3	2	2	0	0	0	2	0	1	2	5	2	2	0	0	3	1	3	0	3	4	0	0	4	2	3	0	0	0	0	2	0	3	0
6	2	2	1	1	0	2	2	1	0	2	2	3	0	0	1	2	3	2	2	2	3	2	1	2	0	0	2	2	0	3	1	0	0	0	2	1	1	2	1	3
7	2	0	2	2	0	2	0	2	2	3	0	0	4	3	1	3	0	0	3	3	4	3	2	0	0	0	0	4	5	3	2	0	2	0	2	2	0	0	0	0
8	2	2	3	2	2	2	3	0	2	4	2	3	4	2	0	3	4	2	0	2	6	2	2	3	4	3	3	3	4	3	0	3	2	5	3	3	2	2	2	0
9	0	0	1	1	2	0	0	1	0	0	0	0	0	0	1	2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	2	0	3	0	1	0	0	0	0
10	2	0	0	0	0	0	0	2	0	0	3	0	0	3	2	0	0	0	3	4	2	0	0	4	0	0	0	2	0	2	2	0	0	0	0	0	2	0	0	3

Table A.14 Number of assigned operators in stage 3 of multi-stage manufacturing for 18 available operators

18	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	0	0	0	3	2	0	0	0	2	0	3	0	0	0	0	4	2	0	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0	0	0	2	2	0	0
2	5	0	0	2	4	3	0	2	3	0	0	5	5	4	2	5	0	0	0	0	0	3	2	4	4	4	0	4	7	0	0	4	4	8	3	0	2	3	3	6
3	0	5	5	4	5	0	4	0	4	0	5	0	0	0	3	0	0	5	6	0	0	0	4	0	6	7	0	0	0	0	4	5	4	0	0	5	2	4	4	5
4	0	5	5	5	0	4	4	6	4	5	5	4	0	4	5	0	0	5	0	5	0	3	4	0	0	0	5	0	0	0	5	0	4	0	6	5	3	4	3	0
5	4	3	0	0	2	2	4	2	2	0	0	0	3	0	2	2	5	2	2	0	0	4	1	3	0	3	4	0	0	5	2	4	0	0	0	0	2	0	3	0
6	2	2	2	1	0	2	3	2	0	3	2	3	0	0	1	2	4	2	2	3	4	2	1	2	0	0	3	3	0	3	1	0	0	0	3	1	2	2	2	4
7	3	0	2	2	0	3	0	2	3	4	0	0	5	4	2	3	0	0	3	3	5	4	2	0	0	0	0	5	7	4	2	0	3	0	3	2	0	0	0	0
8	2	3	3	3	2	2	3	0	2	4	2	3	5	2	0	3	5	2	0	3	6	2	3	4	5	4	4	4	4	3	0	3	3	6	3	4	2	3	3	0
9	0	0	1	1	2	0	0	1	0	0	0	0	0	0	1	2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	2	0	4	0	1	0	0	0	0
10	2	0	0	0	0	0	0	3	0	0	4	0	0	4	2	0	0	0	4	4	3	0	0	5	0	0	0	2	0	3	3	0	0	0	0	0	3	0	0	3

Table A.15 Number of assigned operators in stage 3 of multi-stage manufacturing for 20 available operators

20	Parts																																							
Operations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	0	0	0	0	3	2	0	0	0	2	0	3	0	0	0	0	5	2	0	0	0	0	0	0	3	0	2	0	0	0	0	0	0	0	0	0	2	2	0	0
2	5	0	0	2	4	4	0	3	4	0	0	5	6	4	2	5	0	0	0	0	0	4	2	4	5	5	0	5	8	0	0	4	4	9	4	0	2	3	4	6
3	0	6	6	5	6	0	4	0	4	0	6	0	0	0	3	0	0	5	7	0	0	0	4	0	7	7	0	0	0	0	4	5	5	0	0	6	3	5	5	6
4	0	6	6	5	0	4	5	6	5	6	5	5	0	5	6	0	0	5	0	5	0	4	4	0	0	0	6	0	0	0	6	0	5	0	6	6	4	5	3	0
5	4	3	0	0	2	3	4	2	2	0	0	0	3	0	2	3	6	3	2	0	0	4	2	4	0	4	5	0	0	5	2	5	0	0	0	0	2	0	3	0
6	3	2	2	2	0	2	3	2	0	3	3	3	0	0	2	2	4	2	2	3	4	2	2	3	0	0	3	3	0	3	2	0	0	0	3	1	2	2	2	4
7	3	0	2	2	0	3	0	3	3	4	0	0	5	4	2	4	0	0	4	4	6	4	2	0	0	0	0	5	7	5	2	0	3	0	3	2	0	0	0	0
8	3	3	3	3	2	2	4	0	2	5	2	4	6	3	0	4	5	3	0	3	7	2	3	4	5	4	4	5	5	4	0	4	3	7	4	4	2	3	3	0
9	0	0	1	1	2	0	0	1	0	0	0	0	0	0	1	2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	2	0	4	0	1	0	0	0	0
10	2	0	0	0	0	0	0	3	0	0	4	0	0	4	2	0	0	0	4	5	3	0	0	5	0	0	0	2	0	3	3	0	0	0	0	0	3	0	0	4

APPENDIX B: HEURISTIC PROCEDURE RESULTS FOR PART FAMILIES IN SINGLE AND MULTI-STAGE MANUFACTURING

Table B.1 Heuristic procedure results for part family 2 in single-stage manufacturing

Operator level	PF2 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
15	Part 2	3.33	15	3.66	81.3%	4.50	6450	29025	90495	32.1%	78.7%
	Part 9	3.85	15	3.28	84.1%	3.90	5700	22230	90495	24.6%	
	Part 11	3.85	15	3.12	80.0%	3.90	4350	16965	90495	18.7%	
	Part 33	3.03	15	3.41	68.9%	4.95	4500	22275	90495	24.6%	
20	Part 2	4.55	20	3.66	83.2%	4.40	6450	28380	87156	32.6%	81.7%
	Part 9	4.55	19	3.28	78.5%	4.18	5700	23826	87156	27.3%	
	Part 11	5.00	20	3.12	78.0%	4.00	4350	17400	87156	20.0%	
	Part 33	5.13	20	3.41	87.4%	3.90	4500	17550	87156	20.1%	
25	Part 2	5.81	25	3.66	85.1%	4.30	6450	27735	84679	32.8%	84.1%
	Part 9	6.15	25	3.28	80.7%	4.06	5700	23156	84679	27.3%	
	Part 11	7.14	25	3.12	89.1%	3.50	4350	15225	84679	18.0%	
	Part 33	6.06	25	3.41	82.7%	4.13	4500	18563	84679	21.9%	
30	Part 2	7.32	30	3.66	89.3%	4.10	6450	26445	82110	32.2%	86.7%
	Part 9	7.84	30	3.28	85.8%	3.83	5700	21803	82110	26.6%	
	Part 11	8.00	30	3.12	83.2%	3.75	4350	16313	82110	19.9%	
	Part 33	7.69	30	3.41	87.4%	3.90	4500	17550	82110	21.4%	

Table B.2 Heuristic procedure results for part family 3 in single-stage manufacturing

Operator level	PF3 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
15	Part 3	2.17	15	5.35	77.5%	6.90	5100	35190	102454	34.3%	77.2%
	Part 4	2.00	15	5.52	73.6%	7.50	5400	40500	102454	39.5%	
	Part 21	6.67	15	2.01	89.3%	2.25	4800	10800	102454	10.5%	
	Part 28	4.65	15	2.49	77.2%	3.22	4950	15964	102454	15.6%	
20	Part 3	2.96	20	5.35	79.3%	6.75	5100	34425	100552	34.2%	78.6%
	Part 4	2.67	20	5.52	73.6%	7.50	5400	40500	100552	40.3%	
	Part 21	8.33	20	2.01	83.7%	2.40	4800	11520	100552	11.5%	
	Part 28	6.67	19	2.49	87.4%	2.85	4950	14107	100552	14.0%	
25	Part 3	4.17	25	5.35	89.2%	6.00	5100	30600	90291	33.9%	87.6%
	Part 4	4.00	25	5.52	88.3%	6.25	5400	33750	90291	37.4%	
	Part 21	10.53	25	2.01	84.6%	2.37	4800	11400	90291	12.6%	
	Part 28	8.51	25	2.49	84.8%	2.94	4950	14541	90291	16.1%	
30	Part 3	4.65	30	5.35	82.9%	6.45	5100	32895	91404	36.0%	86.5%
	Part 4	4.80	30	5.52	88.3%	6.25	5400	33750	91404	36.9%	
	Part 21	13.33	30	2.01	89.3%	2.25	4800	10800	91404	11.8%	
	Part 28	10.64	30	2.49	88.3%	2.82	4950	13959	91404	15.3%	

Table B.3 Heuristic procedure results for part family 4 in single-stage manufacturing

PF4 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
Part 5	5.00	15	2.43	81.0%	3.00	7350	22050	77827	28.3%	75.7%
Part 13	4.76	15	2.18	69.2%	3.15	6000	18900	77827	24.3%	
Part 16	4.17	15	2.53	70.3%	3.60	3900	14040	77827	18.0%	
Part 32	4.55	15	2.53	76.7%	3.30	4350	14355	77827	18.4%	
Part 34	7.69	15	1.63	83.6%	1.95	4350	8482	77827	10.9%	
Part 5	6.67	20	2.43	81.0%	3.00	7350	22050	72070	30.6%	81.7%
Part 13	7.84	20	2.18	85.5%	2.55	6000	15300	72070	21.2%	
Part 16	5.88	20	2.53	74.4%	3.40	3900	13260	72070	18.4%	
Part 32	6.82	20	2.53	86.3%	2.93	4350	12760	72070	17.7%	
Part 34	10.00	20	1.63	81.5%	2.00	4350	8700	72070	12.1%	
Part 5	8.77	25	2.43	85.3%	2.85	7350	20947	68538	30.6%	85.9%
Part 13	9.52	25	2.18	83.0%	2.62	6000	15750	68538	23.0%	
Part 16	8.33	25	2.53	84.3%	3.00	3900	11700	68538	17.1%	
Part 32	8.33	24	2.53	87.8%	2.88	4350	12528	68538	18.3%	
Part 34	14.29	25	1.63	93.1%	1.75	4350	7613	68538	11.1%	
Part 5	10.00	30	2.43	81.0%	3.00	7350	22050	70164	31.4%	84.0%
Part 13	11.76	30	2.18	85.5%	2.55	6000	15300	70164	21.8%	
Part 16	9.80	30	2.53	82.7%	3.06	3900	11934	70164	17.0%	
Part 32	10.00	30	2.53	84.3%	3.00	4350	13050	70164	18.6%	
Part 34	16.67	30	1.63	90.6%	1.80	4350	7830	70164	11.2%	

Table B.4 Heuristic procedure results for part family 5 in single-stage manufacturing

PF5 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
P 6	3.70	15	3.20	79.0%	4.05	5550	22477	126818	17.7%	75.6%
P 7	4.08	15	3.00	81.6%	3.67	6300	23152	126818	18.3%	
P 22	3.45	15	2.83	65.1%	4.35	6450	28057	126818	22.1%	
P 26	5.41	15	2.14	77.1%	2.78	5700	15818	126818	12.5%	
P 29	6.12	15	2.20	89.8%	2.45	5550	13597	126818	10.7%	
P 39	2.94	15	3.56	69.8%	5.10	4650	23715	126818	18.7%	
P 6	5.00	20	3.20	80.0%	4.00	5550	22200	117832	18.8%	81.4%
P 7	5.13	20	3.00	76.9%	3.90	6300	24570	117832	20.9%	
P 22	5.56	20	2.83	78.6%	3.60	6450	23220	117832	19.7%	
P 26	8.00	20	2.14	85.6%	2.50	5700	14250	117832	12.1%	
P 29	8.16	20	2.20	89.8%	2.45	5550	13598	117832	11.5%	
P 39	4.65	20	3.56	82.8%	4.30	4650	19995	117832	17.0%	
P 6	6.25	25	3.20	80.0%	4.00	5550	22200	112597	19.7%	85.1%
P 7	6.90	25	3.00	82.8%	3.62	6300	22837	112597	20.3%	
P 22	7.89	25	2.83	89.4%	3.17	6450	20425	112597	18.1%	
P 26	10.34	25	2.14	88.6%	2.42	5700	13775	112597	12.2%	
P 29	10.20	25	2.20	89.8%	2.45	5550	13598	112597	12.1%	
P 39	5.88	25	3.56	83.8%	4.25	4650	19762	112597	17.6%	
P 6	8.00	29	3.20	88.3%	3.63	5550	20119	110292	18.2%	86.9%
P 7	8.70	30	3.00	87.0%	3.45	6300	21735	110292	19.7%	
P 22	8.70	30	2.83	82.0%	3.45	6450	22253	110292	20.2%	
P 26	12.07	30	2.14	86.1%	2.49	5700	14169	110292	12.8%	
P 29	13.33	30	2.20	97.8%	2.25	5550	12488	110292	11.3%	
P 39	7.14	30	3.56	84.8%	4.20	4650	19530	110292	17.7%	

Table B.5 Heuristic procedure results for part family 6 in single-stage manufacturing

PF6 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
P 18	3.57	15	2.82	67.1%	4.20	5550	23310	53670	43.4%	70.7%
P 19	3.41	15	3.23	73.4%	4.40	6900	30360	53670	56.6%	
P 18	6.25	20	2.82	88.1%	3.20	5550	17760	48120	36.9%	78.8%
P 19	4.55	20	3.23	73.4%	4.40	6900	30360	48120	63.1%	
P 18	7.14	25	2.82	80.6%	3.50	5550	19425	45300	42.9%	83.7%
P 19	6.67	25	3.23	86.1%	3.75	6900	25875	45300	57.1%	
P 18	9.09	30	2.82	85.5%	3.30	5550	18315	45225	40.5%	83.9%
P 19	7.69	30	3.23	82.8%	3.90	6900	26910	45225	59.5%	

Table B.6 Heuristic procedure results for part family 7 in single-stage manufacturing

PF7 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
Part 10	5.26	15	2.31	81.1%	2.85	6900	19665	95916	20.5%	73.7%
Part 14	3.85	14	2.95	81.0%	3.64	6150	22386	95916	23.3%	
Part 20	3.85	15	2.52	64.6%	3.90	6600	25740	95916	26.8%	
Part 35	4.00	15	2.66	70.9%	3.75	7500	28125	95916	29.3%	
Part 10	7.14	20	2.31	82.5%	2.80	6900	19320	83600	23.1%	84.5%
Part 14	5.77	20	2.95	85.1%	3.47	6150	21320	83600	25.5%	
Part 20	6.45	20	2.52	81.3%	3.10	6600	20460	83600	24.5%	
Part 35	6.67	20	2.66	88.7%	3.00	7500	22500	83600	26.9%	
Part 10	9.09	25	2.31	84.0%	2.75	6900	18975	84050	22.6%	84.1%
Part 14	7.14	25	2.95	84.3%	3.50	6150	21525	84050	25.6%	
Part 20	8.33	25	2.52	84.0%	3.00	6600	19800	84050	23.6%	
Part 35	7.89	25	2.66	84.0%	3.17	7500	23750	84050	28.3%	
Part 10	10.71	30	2.31	82.5%	2.80	6900	19320	83932	23.0%	84.2%
Part 14	8.00	30	2.95	78.7%	3.75	6150	23063	83932	27.5%	
Part 20	10.00	30	2.52	84.0%	3.00	6600	19800	83932	23.6%	
Part 35	10.00	29	2.66	91.7%	2.90	7500	21750	83932	25.9%	

Table B.7 Heuristic procedure results for part family 8 in single-stage manufacturing

PF8 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
Part 12	6.25	15	2.17	90.4%	2.40	7350	17640	113850	15.5%	74.6%
Part 18	3.57	15	2.82	67.1%	4.20	5550	23310	113850	20.5%	
Part 27	5.56	15	2.19	81.1%	2.70	7050	19035	113850	16.7%	
Part 37	2.63	15	3.85	67.5%	5.70	5250	29925	113850	26.3%	
Part 38	3.57	15	3.11	74.0%	4.20	5700	23940	113850	21.0%	
Part 12	7.14	20	2.17	77.5%	2.80	7350	20580	108090	19.0%	78.6%
Part 18	6.25	20	2.82	88.1%	3.20	5550	17760	108090	16.4%	
Part 27	7.14	20	2.19	78.2%	2.80	7050	19740	108090	18.3%	
Part 37	3.70	20	3.85	71.3%	5.40	5250	28350	108090	26.2%	
Part 38	5.26	20	3.11	81.8%	3.80	5700	21660	108090	20.0%	
Part 12	9.68	25	2.17	84.0%	2.58	7350	18988	102688	18.5%	82.8%
Part 18	7.14	25	2.82	80.6%	3.50	5550	19425	102688	18.9%	
Part 27	9.09	25	2.19	79.6%	2.75	7050	19388	102688	18.9%	
Part 37	5.26	25	3.85	81.1%	4.75	5250	24937	102688	24.3%	
Part 38	7.14	25	3.11	88.9%	3.50	5700	19950	102688	19.4%	
Part 12	12.50	30	2.17	90.4%	2.40	7350	17640	98865	17.8%	86.0%
Part 18	9.09	30	2.82	85.5%	3.30	5550	18315	98865	18.5%	
Part 27	12.00	30	2.19	87.6%	2.50	7050	17625	98865	17.8%	
Part 37	6.67	30	3.85	85.6%	4.50	5250	23625	98865	23.9%	
Part 38	7.89	30	3.11	81.8%	3.80	5700	21660	98865	21.9%	

Table B.8 Heuristic procedure results for part family 9 in single-stage manufacturing

PF9 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
Part 15	2.27	15	5.09	77.1%	6.60	4950	32670	82935	39.4%	77.6%
Part 31	2.63	15	4.47	78.4%	5.70	6300	35910	82935	43.3%	
Part 40	4.55	15	2.53	76.7%	3.30	4350	14355	82935	17.3%	
Part 15	3.03	20	5.09	77.1%	6.60	4950	32670	80710	40.5%	79.7%
Part 31	3.57	20	4.47	79.8%	5.60	6300	35280	80710	43.7%	
Part 40	6.82	20	2.53	86.3%	2.93	4350	12760	80710	15.8%	
Part 15	4.00	25	5.09	81.4%	6.25	4950	30938	76540	40.4%	84.1%
Part 31	4.76	25	4.47	85.1%	5.25	6300	33075	76540	43.2%	
Part 40	8.33	24	2.53	87.8%	2.88	4350	12528	76540	16.4%	
Part 15	5.00	30	5.09	84.8%	6.00	4950	29700	78188	38.0%	82.3%
Part 31	5.33	30	4.47	79.5%	5.63	6300	35438	78188	45.3%	
Part 40	10.00	30	2.53	84.3%	3.00	4350	13050	78188	16.7%	

Table B.9 Heuristic procedure results for part family 10 in single-stage manufacturing

PF10 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
Part 17	5.56	15	2.22	82.2%	2.70	5550	14985	50197	29.9%	81.2%
Part 24	4.35	15	2.64	76.5%	3.45	6450	22253	50197	44.3%	
Part 25	6.25	15	2.11	87.9%	2.40	5400	12960	50197	25.8%	
Part 17	7.50	20	2.22	83.3%	2.67	5550	14800	49620	29.8%	82.1%
Part 24	6.00	20	2.64	79.2%	3.33	6450	21500	49620	43.3%	
Part 25	8.11	20	2.11	85.5%	2.47	5400	13320	49620	26.8%	
Part 17	10.00	25	2.22	88.8%	2.50	5550	13875	45375	30.6%	89.8%
Part 24	8.33	25	2.64	88.0%	3.00	6450	19350	45375	42.6%	
Part 25	11.11	25	2.11	93.8%	2.25	5400	12150	45375	26.8%	
Part 17	12.12	30	2.22	89.7%	2.48	5550	13736	45844	30.0%	88.9%
Part 24	10.00	30	2.64	88.0%	3.00	6450	19350	45844	42.2%	
Part 25	12.70	30	2.11	89.3%	2.36	5400	12758	45844	27.8%	

Table B.10 Heuristic procedure results for part family 1 in stage 1 of multi-stage manufacturing

Operator level	PF1 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 1	6.67	5	0.62	82.7%	0.75	4950	3712	15412	24.1%	86.4%
	Part 23	8.00	5	0.53	84.8%	0.63	6150	3844	15412	24.9%	
	Part 30	7.69	5	0.55	84.6%	0.65	6750	4387	15412	28.5%	
	Part 36	8.00	5	0.59	94.4%	0.63	5550	3469	15412	22.5%	
6	Part 1	6.67	5	0.62	82.7%	0.75	4950	3712	15854	23.4%	84.0%
	Part 23	10.00	6	0.53	88.3%	0.60	6150	3690	15854	23.3%	
	Part 30	9.09	6	0.55	83.3%	0.66	6750	4455	15854	28.1%	
	Part 36	8.33	6	0.59	81.9%	0.72	5550	3996	15854	25.2%	
7	Part 1	9.09	7	0.62	80.5%	0.77	4950	3812	16889	22.6%	78.8%
	Part 23	10.00	6	0.53	88.3%	0.60	6150	3690	16889	21.8%	
	Part 30	10.00	7	0.55	78.6%	0.70	6750	4725	16889	28.0%	
	Part 36	8.33	7	0.59	70.2%	0.84	5550	4662	16889	27.6%	
8	Part 1	10.00	8	0.62	77.5%	0.80	4950	3960	17900	22.1%	74.4%
	Part 23	12.00	8	0.53	79.5%	0.67	6150	4100	17900	22.9%	
	Part 30	10.00	8	0.55	68.8%	0.80	6750	5400	17900	30.2%	
	Part 36	10.00	8	0.59	73.8%	0.80	5550	4440	17900	24.8%	
10	Part 1	13.33	10	0.62	82.7%	0.75	4950	3713	15412	24.1%	86.4%
	Part 23	16.00	10	0.53	84.8%	0.63	6150	3844	15412	24.9%	
	Part 30	15.38	10	0.55	84.6%	0.65	6750	4387	15412	28.5%	
	Part 36	16.00	10	0.59	94.4%	0.63	5550	3469	15412	22.5%	
12	Part 1	18.18	12	0.62	93.9%	0.66	4950	3267	15003	21.8%	88.8%
	Part 23	20.00	12	0.53	88.3%	0.60	6150	3690	15003	24.6%	
	Part 30	20.00	12	0.55	91.7%	0.60	6750	4050	15003	27.0%	
	Part 36	16.67	12	0.59	81.9%	0.72	5550	3996	15003	26.6%	

Table B.11 Heuristic procedure results for part family 2 in stage 1 of multi-stage manufacturing

Operator level	PF2 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 2	4.17	5	1.00	83.3%	1.20	6450	7740	21495	36.0%	80.5%
	Part 9	5.56	5	0.66	73.3%	0.90	5700	5130	21495	23.9%	
	Part 11	5.00	5	0.74	74.0%	1.00	4350	4350	21495	20.2%	
	Part 33	5.26	5	0.86	90.5%	0.95	4500	4275	21495	19.9%	
6	Part 2	4.55	6	1.00	75.8%	1.32	6450	8514	21069	40.4%	82.1%
	Part 9	7.69	6	0.66	84.6%	0.78	5700	4446	21069	21.1%	
	Part 11	7.14	6	0.74	88.1%	0.84	4350	3654	21069	17.3%	
	Part 33	6.06	6	0.86	86.9%	0.99	4500	4455	21069	21.1%	
7	Part 2	6.25	7	1.00	89.3%	1.12	6450	7224	20296	35.6%	85.2%
	Part 9	9.09	7	0.66	85.7%	0.77	5700	4389	20296	21.6%	
	Part 11	7.69	7	0.74	81.3%	0.91	4350	3958	20296	19.5%	
	Part 33	6.67	7	0.86	81.9%	1.05	4500	4725	20296	23.3%	
8	Part 2	6.67	8	1.00	83.3%	1.20	6450	7740	19884	38.9%	87.0%
	Part 9	11.11	8	0.66	91.7%	0.72	5700	4104	19884	20.6%	
	Part 11	10.00	8	0.74	92.5%	0.80	4350	3480	19884	17.5%	
	Part 33	7.89	8	0.86	84.9%	1.01	4500	4560	19884	22.9%	
10	Part 2	9.09	10	1.00	90.9%	1.10	6450	7095	19320	36.7%	89.5%
	Part 9	13.64	10	0.66	90.0%	0.73	5700	4180	19320	21.6%	
	Part 11	11.54	10	0.74	85.4%	0.87	4350	3770	19320	19.5%	
	Part 33	10.53	10	0.86	90.5%	0.95	4500	4275	19320	22.1%	
12	Part 2	10.42	12	1.00	86.8%	1.15	6450	7430	19118	38.9%	90.5%
	Part 9	16.67	12	0.66	91.7%	0.72	5700	4104	19118	21.5%	
	Part 11	15.00	12	0.74	92.5%	0.80	4350	3480	19118	18.2%	
	Part 33	13.16	12	0.86	94.3%	0.91	4500	4104	19118	21.5%	

Table B.12 Heuristic procedure results for part family 3 in stage 1 of multi-stage manufacturing

Operator level	PF3 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 3	4.00	5	1.17	93.6%	1.25	5100	6375	23464	27.2%	83.0%
	Part 4	4.00	5	0.99	79.2%	1.25	5400	6750	23464	28.8%	
	Part 21	4.17	5	0.98	81.7%	1.20	4800	5760	23464	24.5%	
	Part 28	5.41	5	0.70	75.7%	0.93	4950	4579	23464	19.5%	
6	Part 3	4.17	6	1.17	81.3%	1.44	5100	7344	23175	31.7%	84.1%
	Part 4	5.56	6	0.99	91.7%	1.08	5400	5832	23175	25.2%	
	Part 21	4.55	6	0.98	74.2%	1.32	4800	6336	23175	27.3%	
	Part 28	8.11	6	0.70	94.6%	0.74	4950	3663	23175	15.8%	
7	Part 3	4.65	7	1.17	77.7%	1.50	5100	7675	23173	33.1%	84.1%
	Part 4	6.00	7	0.99	84.9%	1.17	5400	6300	23173	27.2%	
	Part 21	6.67	7	0.98	93.3%	1.05	4800	5040	23173	21.7%	
	Part 28	8.33	7	0.70	83.3%	0.84	4950	4158	23173	17.9%	
8	Part 3	6.00	8	1.17	87.8%	1.33	5100	6800	22206	30.6%	87.7%
	Part 4	7.69	8	0.99	95.2%	1.04	5400	5616	22206	25.3%	
	Part 21	6.82	8	0.98	83.5%	1.17	4800	5632	22206	25.4%	
	Part 28	9.52	8	0.70	83.3%	0.84	4950	4158	22206	18.7%	
10	Part 3	8.00	10	1.17	93.6%	1.25	5100	6375	21798	29.2%	89.4%
	Part 4	8.33	10	0.99	82.5%	1.20	5400	6480	21798	29.7%	
	Part 21	9.09	10	0.98	89.1%	1.10	4800	5280	21798	24.2%	
	Part 28	13.51	10	0.70	94.6%	0.74	4950	3663	21798	16.8%	
12	Part 3	9.30	12	1.17	90.7%	1.29	5100	6579	21143	31.1%	92.1%
	Part 4	11.11	12	0.99	91.7%	1.08	5400	5832	21143	27.6%	
	Part 21	11.36	12	0.98	92.8%	1.06	4800	5069	21143	24.0%	
	Part 28	16.22	12	0.70	94.6%	0.74	4950	3663	21143	17.3%	

Table B.13 Heuristic procedure results for part family 4 in stage 1 of multi-stage manufacturing

Operator level	PF4 Parts	Prod. rate	Total operator time in cell/min	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 5	6.67	5	0.61	81.3%	0.75	7350	5512	18360	30.0%	85.4%
	Part 13	7.14	5	0.56	80.0%	0.70	6000	4200	18360	22.9%	
	Part 16	8.33	5	0.57	95.0%	0.60	3900	2340	18360	12.7%	
	Part 32	7.14	5	0.62	88.6%	0.70	4350	3045	18360	16.6%	
	Part 34	6.67	5	0.67	89.3%	0.75	4350	3262	18360	17.8%	
6	Part 5	8.33	6	0.61	84.7%	0.72	7350	5292	18248	29.0%	85.9%
	Part 13	9.09	6	0.56	84.8%	0.66	6000	3960	18248	21.7%	
	Part 16	8.33	5	0.57	95.0%	0.60	3900	2340	18248	12.8%	
	Part 32	8.00	6	0.62	82.7%	0.75	4350	3263	18248	17.9%	
	Part 34	7.69	6	0.67	85.9%	0.78	4350	3393	18248	18.6%	
7	Part 5	9.09	7	0.61	79.2%	0.77	7350	5660	20685	27.4%	75.8%
	Part 13	9.52	7	0.56	76.2%	0.73	6000	4410	20685	21.3%	
	Part 16	9.09	7	0.57	74.0%	0.77	3900	3003	20685	14.5%	
	Part 32	8.33	7	0.62	73.8%	0.84	4350	3654	20685	17.7%	
	Part 34	7.69	7	0.67	73.6%	0.91	4350	3958	20685	19.1%	
8	Part 5	9.09	8	0.61	69.3%	0.88	7350	6468	22356	28.9%	70.1%
	Part 13	10.00	8	0.56	70.0%	0.80	6000	4800	22356	21.5%	
	Part 16	9.09	8	0.57	64.8%	0.88	3900	3432	22356	15.4%	
	Part 32	9.09	8	0.62	70.5%	0.88	4350	3828	22356	17.1%	
	Part 34	9.09	8	0.67	76.1%	0.88	4350	3828	22356	17.1%	
10	Part 5	13.33	10	0.61	81.3%	0.75	7350	5513	18360	30.0%	85.4%
	Part 13	14.29	10	0.56	80.0%	0.70	6000	4200	18360	22.9%	
	Part 16	16.67	10	0.57	95.0%	0.60	3900	2340	18360	12.7%	
	Part 32	14.29	10	0.62	88.6%	0.70	4350	3045	18360	16.6%	
	Part 34	13.33	10	0.67	89.3%	0.75	4350	3263	18360	17.8%	
12	Part 5	18.18	12	0.61	92.4%	0.66	7350	4851	17730	27.4%	88.4%
	Part 13	19.05	12	0.56	88.9%	0.63	6000	3780	17730	21.3%	
	Part 16	18.18	12	0.57	86.4%	0.66	3900	2574	17730	14.5%	
	Part 32	16.67	12	0.62	86.1%	0.72	4350	3132	17730	17.7%	
	Part 34	15.38	12	0.67	85.9%	0.78	4350	3393	17730	19.1%	

Table B.14 Heuristic procedure results for part family 5 in stage 1 of multi-stage manufacturing

Operator level	PF5 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	P 6	4.35	5	0.97	84.3%	1.15	5550	6383	40436	15.8%	78.5%
	P 7	4.35	5	0.96	83.5%	1.15	6300	7245	40436	17.9%	
	P 22	3.45	5	0.93	64.1%	1.45	6450	9352	40436	23.1%	
	P 26	5.88	5	0.64	75.3%	0.85	5700	4845	40436	12.0%	
	P 29	4.08	5	1.01	82.4%	1.22	5550	6799	40436	16.8%	
	P 39	4.00	5	1.09	87.2%	1.25	4650	5813	40436	14.4%	
6	P 6	5.13	6	0.97	82.9%	1.17	5550	6494	39402	16.5%	80.6%
	P 7	5.00	6	0.96	80.0%	1.20	6300	7560	39402	19.2%	
	P 22	5.71	6	0.93	88.6%	1.05	6450	6772	39402	17.2%	
	P 26	8.00	6	0.64	85.3%	0.75	5700	4275	39402	10.8%	
	P 29	4.55	6	1.01	76.5%	1.32	5550	7326	39402	18.6%	
	P 39	4.00	6	1.09	72.7%	1.50	4650	6975	39402	17.7%	
7	P 6	6.52	7	0.97	90.4%	1.07	5550	5957	35534	16.8%	89.4%
	P 7	6.52	7	0.96	89.4%	1.07	6300	6762	35534	19.0%	
	P 22	6.90	7	0.93	91.6%	1.01	6450	6547	35534	18.4%	
	P 26	9.09	7	0.64	83.1%	0.77	5700	4389	35534	12.4%	
	P 29	6.12	7	1.01	88.3%	1.14	5550	6345	35534	17.9%	
	P 39	5.88	7	1.09	91.6%	1.19	4650	5533	35534	15.6%	
8	P 6	7.69	8	0.97	93.3%	1.04	5550	5772	37550	15.4%	84.6%
	P 7	6.67	8	0.96	80.0%	1.20	6300	7560	37550	20.1%	
	P 22	6.90	8	0.93	80.2%	1.16	6450	7482	37550	19.9%	
	P 26	11.76	8	0.64	94.1%	0.68	5700	3876	37550	10.3%	
	P 29	6.67	8	1.01	84.2%	1.20	5550	6660	37550	17.7%	
	P 39	6.00	8	1.09	81.8%	1.33	4650	6200	37550	16.5%	
10	P 6	8.70	10	0.97	84.3%	1.15	5550	6383	35015	18.2%	90.7%
	P 7	10.00	10	0.96	96.0%	1.00	6300	6300	35015	18.0%	
	P 22	10.34	10	0.93	96.2%	0.97	6450	6235	35015	17.8%	
	P 26	13.64	10	0.64	87.3%	0.73	5700	4180	35015	11.9%	
	P 29	9.09	10	1.01	91.8%	1.10	5550	6105	35015	17.4%	
	P 39	8.00	10	1.09	87.2%	1.25	4650	5813	35015	16.6%	

12	P 6	10.87	12	0.97	87.9%	1.10	5550	6127	35838	17.1%	88.6%
	P 7	10.87	12	0.96	87.0%	1.10	6300	6955	35838	19.4%	
	P 22	11.43	12	0.93	88.6%	1.05	6450	6773	35838	18.9%	
	P 26	17.65	12	0.64	94.1%	0.68	5700	3876	35838	10.8%	
	P 29	10.20	12	1.01	85.9%	1.18	5550	6527	35838	18.2%	
	P 39	10.00	12	1.09	90.8%	1.20	4650	5580	35838	15.6%	

Table B.15 Heuristic procedure results for part family 6 in stage 1 of multi-stage manufacturing

Operator level	PF6 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	P 18	6.67	5	0.61	81.3%	0.75	5550	4162	9337	44.6%	87.2%
	P 19	6.67	5	0.69	92.0%	0.75	6900	5175	9337	55.4%	
6	P 18	7.69	6	0.61	78.2%	0.78	5550	4329	10125	42.8%	80.5%
	P 19	7.14	6	0.69	82.1%	0.84	6900	5796	10125	57.2%	
7	P 18	8.70	7	0.61	75.8%	0.81	5550	4468	10747	41.6%	75.8%
	P 19	7.69	7	0.69	75.8%	0.91	6900	6279	10747	58.4%	
8	P 18	10.00	8	0.61	76.3%	0.80	5550	4440	11616	38.2%	70.1%
	P 19	7.69	8	0.69	66.3%	1.04	6900	7176	11616	61.8%	
10	P 18	13.33	10	0.61	81.3%	0.75	5550	4163	9338	44.6%	87.2%
	P 19	13.33	10	0.69	92.0%	0.75	6900	5175	9338	55.4%	
12	P 18	17.39	12	0.61	88.4%	0.69	5550	3830	9211	41.6%	88.4%
	P 19	15.38	12	0.69	88.5%	0.78	6900	5382	9211	58.4%	

Table B.16 Heuristic procedure results for part family 7 in stage 1 of multi-stage manufacturing

Operator level	PF7 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 10	6.67	5	0.67	89.3%	0.75	6900	5175	19327	26.8%	90.5%
	Part 14	6.67	5	0.74	98.7%	0.75	6150	4612	19327	23.9%	
	Part 20	7.69	5	0.59	90.8%	0.65	6600	4290	19327	22.2%	
	Part 35	7.14	5	0.59	84.3%	0.70	7500	5250	19327	27.2%	
6	Part 10	7.14	6	0.67	79.8%	0.84	6900	5796	21708	26.7%	80.6%
	Part 14	6.67	6	0.74	82.2%	0.90	6150	5535	21708	25.5%	
	Part 20	8.33	6	0.59	81.9%	0.72	6600	4752	21708	21.9%	
	Part 35	8.00	6	0.59	78.7%	0.75	7500	5625	21708	25.9%	
7	Part 10	7.69	7	0.67	73.6%	0.91	6900	6279	23068	27.2%	75.8%
	Part 14	6.67	7	0.74	70.5%	1.05	6150	6457	23068	28.0%	
	Part 20	9.09	7	0.59	76.6%	0.77	6600	5082	23068	22.0%	
	Part 35	10.00	7	0.59	84.3%	0.70	7500	5250	23068	22.8%	
8	Part 10	9.09	8	0.67	76.1%	0.88	6900	6072	24240	25.0%	72.2%
	Part 14	7.14	8	0.74	66.1%	1.12	6150	6888	24240	28.4%	
	Part 20	10.00	8	0.59	73.8%	0.80	6600	5280	24240	21.8%	
	Part 35	10.00	8	0.59	73.8%	0.80	7500	6000	24240	24.8%	
10	Part 10	13.33	10	0.67	89.3%	0.75	6900	5175	19328	26.8%	90.5%
	Part 14	13.33	10	0.74	98.7%	0.75	6150	4613	19328	23.9%	
	Part 20	15.38	10	0.59	90.8%	0.65	6600	4290	19328	22.2%	
	Part 35	14.29	10	0.59	84.3%	0.70	7500	5250	19328	27.2%	
12	Part 10	15.38	12	0.67	85.9%	0.78	6900	5382	19773	27.2%	88.5%
	Part 14	13.33	12	0.74	82.2%	0.90	6150	5535	19773	28.0%	
	Part 20	18.18	12	0.59	89.4%	0.66	6600	4356	19773	22.0%	
	Part 35	20.00	12	0.59	98.3%	0.60	7500	4500	19773	22.8%	

Table B.17 Heuristic procedure results for part family 8 in stage 1 of multi-stage manufacturing

Operator level	PF8 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 12	8.33	5	0.41	68.3%	0.60	7350	4410	19875	22.2%	75.4%
	Part 18	6.67	5	0.61	81.3%	0.75	5550	4162	19875	20.9%	
	Part 27	8.33	5	0.41	68.3%	0.60	7050	4230	19875	21.3%	
	Part 37	6.67	5	0.66	88.0%	0.75	5250	3937	19875	19.8%	
	Part 38	9.09	5	0.39	70.9%	0.55	5700	3135	19875	15.8%	
6	Part 12	13.33	6	0.41	91.1%	0.45	7350	3308	17784	18.6%	84.2%
	Part 18	7.69	6	0.61	78.2%	0.78	5550	4329	17784	24.3%	
	Part 27	13.33	6	0.41	91.1%	0.45	7050	3173	17784	17.8%	
	Part 37	7.14	6	0.66	78.6%	0.84	5250	4410	17784	24.8%	
	Part 38	13.33	6	0.39	86.7%	0.45	5700	2565	17784	14.4%	
7	Part 12	14.29	7	0.41	83.7%	0.49	7350	3602	19079	18.9%	78.5%
	Part 18	8.70	7	0.61	75.8%	0.81	5550	4468	19079	23.4%	
	Part 27	14.29	7	0.41	83.7%	0.49	7050	3455	19079	18.1%	
	Part 37	7.41	7	0.66	69.8%	0.95	5250	4961	19079	26.0%	
	Part 38	15.38	7	0.39	85.7%	0.45	5700	2593	19079	13.6%	
8	Part 12	16.67	8	0.41	85.4%	0.48	7350	3528	18060	19.5%	82.9%
	Part 18	10.00	8	0.61	76.3%	0.80	5550	4440	18060	24.6%	
	Part 27	16.67	8	0.41	85.4%	0.48	7050	3384	18060	18.7%	
	Part 37	10.00	8	0.66	82.5%	0.80	5250	4200	18060	23.3%	
	Part 38	18.18	8	0.39	88.6%	0.44	5700	2508	18060	13.9%	
10	Part 12	21.43	10	0.41	87.9%	0.47	7350	3430	17290	19.8%	86.6%
	Part 18	13.33	10	0.61	81.3%	0.75	5550	4163	17290	24.1%	
	Part 27	21.43	10	0.41	87.9%	0.47	7050	3290	17290	19.0%	
	Part 37	13.33	10	0.66	88.0%	0.75	5250	3938	17290	22.8%	
	Part 38	23.08	10	0.39	90.0%	0.43	5700	2470	17290	14.3%	
12	Part 12	26.67	12	0.41	91.1%	0.45	7350	3307	17070	19.4%	87.7%
	Part 18	17.39	12	0.61	88.4%	0.69	5550	3830	17070	22.4%	
	Part 27	26.67	12	0.41	91.1%	0.45	7050	3172	17070	18.6%	
	Part 37	14.81	12	0.66	81.5%	0.81	5250	4253	17070	24.9%	
	Part 38	27.27	12	0.39	88.6%	0.44	5700	2508	17070	14.7%	

Table B.18 Heuristic procedure results for part family 9 in stage 1 of multi-stage manufacturing

Operator level	PF9 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 15	4.17	5	0.93	77.5%	1.20	4950	5940	15600	38.1%	82.7%
	Part 31	4.76	5	0.89	84.8%	1.05	6300	6615	15600	42.4%	
	Part 40	7.14	5	0.62	88.6%	0.70	4350	3045	15600	19.5%	
6	Part 15	5.00	6	0.93	77.5%	1.20	4950	5940	16384	36.3%	78.8%
	Part 31	5.26	6	0.89	78.1%	1.14	6300	7182	16384	43.8%	
	Part 40	8.00	6	0.62	82.7%	0.75	4350	3263	16384	19.9%	
7	Part 15	6.90	7	0.93	91.6%	1.01	4950	5024	15293	32.9%	84.4%
	Part 31	6.67	7	0.89	84.8%	1.05	6300	6615	15293	43.3%	
	Part 40	8.33	7	0.62	73.8%	0.84	4350	3654	15293	23.9%	
8	Part 15	7.50	8	0.93	87.2%	1.07	4950	5280	15492	34.1%	83.3%
	Part 31	7.89	8	0.89	87.8%	1.01	6300	6384	15492	41.2%	
	Part 40	9.09	8	0.62	70.5%	0.88	4350	3828	15492	24.7%	
10	Part 15	10.00	10	0.93	93.0%	1.00	4950	4950	14295	34.6%	90.3%
	Part 31	10.00	10	0.89	89.0%	1.00	6300	6300	14295	44.1%	
	Part 40	14.29	10	0.62	88.6%	0.70	4350	3045	14295	21.3%	
12	Part 15	12.50	12	0.93	96.9%	0.96	4950	4752	13630	34.9%	94.7%
	Part 31	13.16	12	0.89	97.6%	0.91	6300	5746	13630	42.2%	
	Part 40	16.67	12	0.62	86.1%	0.72	4350	3132	13630	23.0%	

Table B.19 Heuristic procedure results for part family 10 in stage 1 of multi-stage manufacturing

Operator level	PF10 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
5	Part 17	4.00	5	0.89	71.2%	1.25	5550	6938	16462	42.1%	75.8%
	Part 24	4.55	5	0.81	73.6%	1.10	6450	7095	16462	43.1%	
	Part 25	11.11	5	0.43	95.6%	0.45	5400	2430	16462	14.8%	
6	Part 17	6.06	6	0.89	89.9%	0.99	5550	5495	15052	36.5%	82.9%
	Part 24	5.56	6	0.81	75.0%	1.08	6450	6966	15052	46.3%	
	Part 25	12.50	6	0.43	89.6%	0.48	5400	2592	15052	17.2%	
7	Part 17	6.45	7	0.89	82.0%	1.08	5550	6022	13991	43.0%	89.2%
	Part 24	8.33	7	0.81	96.4%	0.84	6450	5418	13991	38.7%	
	Part 25	14.81	7	0.43	91.0%	0.47	5400	2552	13991	18.2%	
8	Part 17	8.00	8	0.89	89.0%	1.00	5550	5550	13817	40.2%	90.4%
	Part 24	8.70	8	0.81	88.0%	0.92	6450	5934	13817	42.9%	
	Part 25	18.52	8	0.43	99.5%	0.43	5400	2333	13817	16.9%	
10	Part 17	9.68	10	0.89	86.1%	1.03	5550	5735	13970	41.1%	89.4%
	Part 24	11.11	10	0.81	90.0%	0.90	6450	5805	13970	41.6%	
	Part 25	22.22	10	0.43	95.6%	0.45	5400	2430	13970	17.4%	
12	Part 17	12.12	12	0.89	89.9%	0.99	5550	5495	13670	40.2%	91.3%
	Part 24	13.64	12	0.81	92.0%	0.88	6450	5676	13670	41.5%	
	Part 25	25.93	12	0.43	92.9%	0.46	5400	2499	13670	18.3%	

Table B.20 Heuristic procedure results for part family 2 in stage 3 of multi-stage manufacturing

Operator level	PF2 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 2	2.70	10	2.66	71.9%	3.70	6450	23865	70305	33.9%	76.7%
	Part 9	3.08	10	2.62	80.6%	3.25	5700	18525	70305	26.3%	
	Part 11	3.45	10	2.38	82.1%	2.90	4350	12615	70305	17.9%	
	Part 33	2.94	10	2.55	75.0%	3.40	4500	15300	70305	21.8%	
12	Part 2	3.70	12	2.66	82.1%	3.24	6450	20898	65700	31.8%	82.1%
	Part 9	3.92	12	2.62	85.6%	3.06	5700	17442	65700	26.5%	
	Part 11	4.00	12	2.38	79.3%	3.00	4350	13050	65700	19.9%	
	Part 33	3.77	12	2.55	80.2%	3.18	4500	14310	65700	21.8%	
15	Part 2	4.88	15	2.66	86.5%	3.07	6450	19834	62899	31.5%	85.7%
	Part 9	4.55	15	2.62	79.4%	3.30	5700	18810	62899	29.9%	
	Part 11	5.88	15	2.38	93.3%	2.55	4350	11092	62899	17.6%	
	Part 33	5.13	15	2.55	87.2%	2.93	4500	13163	62899	20.9%	
18	Part 2	5.81	18	2.66	85.9%	3.10	6450	19969	62535	31.9%	86.2%
	Part 9	5.88	18	2.62	85.6%	3.06	5700	17442	62535	27.9%	
	Part 11	6.90	18	2.38	91.2%	2.61	4350	11353	62535	18.2%	
	Part 33	5.88	18	2.55	83.3%	3.06	4500	13770	62535	22.0%	
20	Part 2	6.98	20	2.66	92.8%	2.87	6450	18490	58760	31.5%	91.8%
	Part 9	6.82	20	2.62	89.3%	2.93	5700	16720	58760	28.5%	
	Part 11	7.69	20	2.38	91.5%	2.60	4350	11310	58760	19.2%	
	Part 33	7.35	20	2.55	93.7%	2.72	4500	12240	58760	20.8%	

Table B.21 Heuristic procedure results for part family 3 in stage 3 of multi-stage manufacturing

Operator level	PF3 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 3	1.69	10	4.18	70.8%	5.90	5100	30090	81058	37.1%	73.5%
	Part 4	1.60	10	4.53	72.5%	6.25	5400	33750	81058	41.6%	
	Part 21	7.89	10	1.03	81.3%	1.27	4800	6080	81058	7.5%	
	Part 28	4.44	10	1.79	79.6%	2.25	4950	11138	81058	13.7%	
12	Part 3	2.22	12	4.18	77.4%	5.40	5100	27540	73062	37.7%	81.6%
	Part 4	2.13	12	4.53	80.3%	5.64	5400	30456	73062	41.7%	
	Part 21	10.00	12	1.03	85.8%	1.20	4800	5760	73062	7.9%	
	Part 28	6.38	12	1.79	95.2%	1.88	4950	9306	73062	12.7%	
15	Part 3	2.96	15	4.18	82.6%	5.06	5100	25819	73845	35.0%	80.7%
	Part 4	2.54	15	4.53	76.8%	5.90	5400	31860	73845	43.1%	
	Part 21	13.33	15	1.03	91.6%	1.13	4800	5400	73845	7.3%	
	Part 28	6.90	15	1.79	82.3%	2.17	4950	10766	73845	14.6%	
18	Part 3	3.70	18	4.18	86.0%	4.86	5100	24786	68956	35.9%	86.4%
	Part 4	3.39	18	4.53	85.3%	5.31	5400	28674	68956	41.6%	
	Part 21	15.79	18	1.03	90.4%	1.14	4800	5472	68956	7.9%	
	Part 28	8.89	18	1.79	88.4%	2.02	4950	10024	68956	14.5%	
20	Part 3	4.29	20	4.18	89.6%	4.67	5100	23800	65581	36.3%	90.9%
	Part 4	4.00	20	4.53	90.6%	5.00	5400	27000	65581	41.2%	
	Part 21	18.42	20	1.03	94.9%	1.09	4800	5211	65581	7.9%	
	Part 28	10.34	20	1.79	92.6%	1.93	4950	9570	65581	14.6%	

Table B.22 Heuristic procedure results for part family 4 in stage 3 of multi-stage manufacturing

Operator level	PF4 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 5	5.00	10	1.82	91.0%	2.00	7350	14700	51487	28.6%	84.0%
	Part 13	4.65	10	1.62	75.3%	2.15	6000	12900	51487	25.1%	
	Part 16	4.00	10	1.96	78.4%	2.50	3900	9750	51487	18.9%	
	Part 32	4.55	10	1.91	86.8%	2.20	4350	9570	51487	18.6%	
	Part 34	9.52	10	0.96	91.4%	1.05	4350	4567	51487	8.9%	
12	Part 5	5.00	10	1.82	91.0%	2.00	7350	14700	49257	29.8%	87.8%
	Part 13	6.98	12	1.62	94.2%	1.72	6000	10320	49257	21.0%	
	Part 16	5.00	12	1.96	81.7%	2.40	3900	9360	49257	19.0%	
	Part 32	5.00	12	1.91	79.6%	2.40	4350	10440	49257	21.2%	
	Part 34	11.76	12	0.96	94.1%	1.02	4350	4437	49257	9.0%	
115	Part 5	6.67	15	1.82	80.9%	2.25	7350	16537	51739	32.0%	83.5%
	Part 13	8.00	15	1.62	86.4%	1.88	6000	11250	51739	21.7%	
	Part 16	5.88	15	1.96	76.9%	2.55	3900	9945	51739	19.2%	
	Part 32	6.82	15	1.91	86.8%	2.20	4350	9570	51739	18.5%	
	Part 34	14.71	15	0.96	94.1%	1.02	4350	4437	51739	8.6%	
18	Part 5	8.77	18	1.82	88.7%	2.05	7350	15082	48329	31.2%	89.4%
	Part 13	9.80	18	1.62	88.2%	1.84	6000	11016	48329	22.8%	
	Part 16	7.89	17	1.96	91.0%	2.15	3900	8398	48329	17.4%	
	Part 32	8.33	18	1.91	88.4%	2.16	4350	9396	48329	19.4%	
	Part 34	17.65	18	0.96	94.1%	1.02	4350	4437	48329	9.2%	
20	Part 5	10.00	19	1.82	95.8%	1.90	7350	13965	47347	29.5%	91.3%
	Part 13	11.63	20	1.62	94.2%	1.72	6000	10320	47347	21.8%	
	Part 16	8.33	20	1.96	81.7%	2.40	3900	9360	47347	19.8%	
	Part 32	9.30	20	1.91	88.8%	2.15	4350	9352	47347	19.8%	
	Part 34	20.00	20	0.96	96.0%	1.00	4350	4350	47347	9.2%	

Table B.23 Heuristic procedure results for part family 5 in stage 3 of multi-stage manufacturing

Operator level	PF5 Parts	Prod. rate	Total operator time in cell (min)	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 6	3.70	10	2.23	82.6%	2.70	5550	14985	81517	18.4%	78.7%
	Part 7	4.08	10	2.04	83.3%	2.45	6300	15435	81517	18.9%	
	Part 22	4.35	10	1.90	82.6%	2.30	6450	14835	81517	18.2%	
	Part 26	5.41	10	1.50	81.1%	1.85	5700	10545	81517	12.9%	
	Part 29	6.90	10	1.19	82.1%	1.45	5550	8047	81517	9.9%	
	Part 39	2.63	10	2.47	65.0%	3.80	4650	17670	81517	21.7%	
12	Part 6	4.00	12	2.23	74.3%	3.00	5550	16650	76819	21.7%	83.5%
	Part 7	4.88	12	2.04	82.9%	2.46	6300	15498	76819	20.2%	
	Part 22	5.26	12	1.90	83.3%	2.28	6450	14706	76819	19.1%	
	Part 26	6.90	12	1.50	86.2%	1.74	5700	9918	76819	12.9%	
	Part 29	8.89	12	1.19	88.1%	1.35	5550	7492	76819	9.8%	
	Part 39	4.44	12	2.47	91.5%	2.70	4650	12555	76819	16.3%	
15	Part 6	5.56	15	2.23	82.6%	2.70	5550	14985	77767	19.3%	82.5%
	Part 7	6.52	15	2.04	88.7%	2.30	6300	14490	77767	18.6%	
	Part 22	5.71	15	1.90	72.4%	2.62	6450	16931	77767	21.8%	
	Part 26	8.62	15	1.50	86.2%	1.74	5700	9918	77767	12.8%	
	Part 29	11.11	15	1.19	88.1%	1.35	5550	7493	77767	9.6%	
	Part 39	5.00	15	2.47	82.3%	3.00	4650	13950	77767	17.9%	
18	Part 6	6.25	18	2.23	77.4%	2.88	5550	15984	73946	21.6%	86.7%
	Part 7	7.69	18	2.04	87.2%	2.34	6300	14742	73946	19.9%	
	Part 22	8.33	18	1.90	88.0%	2.16	6450	13932	73946	18.8%	
	Part 26	10.81	18	1.50	90.1%	1.67	5700	9491	73946	12.8%	
	Part 29	13.79	18	1.19	91.2%	1.31	5550	7243	73946	9.8%	
	Part 39	6.67	18	2.47	91.5%	2.70	4650	12555	73946	17.0%	
20	Part 6	8.00	20	2.23	89.2%	2.50	5550	13875	73111	19.0%	87.7%
	Part 7	8.70	20	2.04	88.7%	2.30	6300	14490	73111	19.8%	
	Part 22	8.70	20	1.90	82.6%	2.30	6450	14835	73111	20.3%	
	Part 26	12.07	20	1.50	90.5%	1.66	5700	9446	73111	12.9%	
	Part 29	15.56	20	1.19	92.6%	1.29	5550	7136	73111	9.8%	
	Part 39	6.98	20	2.47	86.2%	2.87	4650	13330	73111	18.2%	

Table B.24 Heuristic procedure results for part family 6 in stage 3 of multi-stage manufacturing

Operator level	PF6 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 18	3.33	10	2.21	73.7%	3.00	5550	16650	37350	44.6%	79.8%
	Part 19	3.33	10	2.54	84.7%	3.00	6900	20700	37350	55.4%	
12	Part 18	4.55	12	2.21	83.7%	2.64	5550	14652	35352	41.4%	84.3%
	Part 19	4.00	12	2.54	84.7%	3.00	6900	20700	35352	58.6%	
15	Part 18	6.25	15	2.21	92.1%	2.40	5550	13320	36090	36.9%	82.5%
	Part 19	4.55	15	2.54	77.0%	3.30	6900	22770	36090	63.1%	
18	Part 18	6.67	18	2.21	81.9%	2.70	5550	14985	34443	43.5%	86.5%
	Part 19	6.38	18	2.54	90.1%	2.82	6900	19458	34443	56.5%	
20	Part 18	7.94	20	2.21	87.7%	2.52	5550	13986	34686	40.3%	85.9%
	Part 19	6.67	20	2.54	84.7%	3.00	6900	20700	34686	59.7%	

Table B.25 Heuristic procedure results for part family 7 in stage 3 of multi-stage manufacturing

Operator level	PF7 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 10	5.26	10	1.64	86.3%	1.90	6900	13110	66510	19.7%	79.9%
	Part 14	3.85	10	2.21	85.0%	2.60	6150	15990	66510	24.0%	
	Part 20	3.85	10	1.93	74.2%	2.60	6600	17160	66510	25.8%	
	Part 35	3.70	10	2.07	76.7%	2.70	7500	20250	66510	30.4%	
12	Part 10	6.00	12	1.64	82.0%	2.00	6900	13800	63792	21.6%	83.3%
	Part 14	4.00	12	2.21	73.7%	3.00	6150	18450	63792	28.9%	
	Part 20	5.66	12	1.93	91.0%	2.12	6600	13992	63792	21.9%	
	Part 35	5.13	12	2.07	88.5%	2.34	7500	17550	63792	27.5%	
15	Part 10	8.00	15	1.64	87.5%	1.88	6900	12938	61147	21.2%	87.0%
	Part 14	5.77	15	2.21	85.0%	2.60	6150	15990	61147	26.1%	
	Part 20	6.45	15	1.93	83.0%	2.32	6600	15345	61147	25.1%	
	Part 35	6.67	15	2.07	92.0%	2.25	7500	16875	61147	27.6%	
18	Part 10	10.00	18	1.64	91.1%	1.80	6900	12420	59211	21.0%	89.8%
	Part 14	7.69	18	2.21	94.4%	2.34	6150	14391	59211	24.3%	
	Part 20	8.00	18	1.93	85.8%	2.25	6600	14850	59211	25.1%	
	Part 35	7.69	18	2.07	88.5%	2.34	7500	17550	59211	29.6%	
20	Part 10	10.53	20	1.64	86.3%	1.90	6900	13110	61842	21.2%	86.0%
	Part 14	7.69	20	2.21	85.0%	2.60	6150	15990	61842	25.9%	
	Part 20	9.43	20	1.93	91.0%	2.12	6600	13992	61842	22.6%	
	Part 35	8.00	20	2.07	82.8%	2.50	7500	18750	61842	30.3%	

Table B.26 Heuristic procedure results for part family 8 in stage 3 of multi-stage manufacturing

Operator level	PF8 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 12	4.17	10	1.76	73.3%	2.40	7350	17640	94275	18.7%	74.3%
	Part 18	3.33	10	2.21	73.7%	3.00	5550	16650	94275	17.7%	
	Part 27	4.55	10	1.78	80.9%	2.20	7050	15510	94275	16.5%	
	Part 37	2.27	10	3.19	72.5%	4.40	5250	23100	94275	24.5%	
	Part 38	2.67	10	2.72	72.5%	3.75	5700	21375	94275	22.7%	
12	Part 12	6.25	12	1.76	91.7%	1.92	7350	14112	84564	16.7%	82.8%
	Part 18	4.55	12	2.21	83.7%	2.64	5550	14652	84564	17.3%	
	Part 27	5.56	12	1.78	82.4%	2.16	7050	15228	84564	18.0%	
	Part 37	2.94	12	3.19	78.2%	4.08	5250	21420	84564	25.3%	
	Part 38	3.57	12	2.72	81.0%	3.36	5700	19152	84564	22.6%	
15	Part 12	7.14	15	1.76	83.8%	2.10	7350	15435	85710	18.0%	81.7%
	Part 18	6.25	15	2.21	92.1%	2.40	5550	13320	85710	15.5%	
	Part 27	7.14	15	1.78	84.8%	2.10	7050	14805	85710	17.3%	
	Part 37	3.33	15	3.19	70.9%	4.50	5250	23625	85710	27.6%	
	Part 38	4.62	15	2.72	83.7%	3.25	5700	18525	85710	21.6%	
18	Part 12	9.52	18	1.76	93.1%	1.89	7350	13891	83117	16.7%	84.2%
	Part 18	6.67	18	2.21	81.9%	2.70	5550	14985	83117	18.0%	
	Part 27	8.93	18	1.78	88.3%	2.02	7050	14213	83117	17.1%	
	Part 37	4.55	18	3.19	80.6%	3.96	5250	20790	83117	25.0%	
	Part 38	5.33	18	2.72	80.6%	3.38	5700	19238	83117	23.1%	
20	Part 12	10.00	20	1.76	88.0%	2.00	7350	14700	78896	18.6%	88.7%
	Part 18	7.94	20	2.21	87.7%	2.52	5550	13986	78896	17.7%	
	Part 27	10.71	20	1.78	95.4%	1.87	7050	13160	78896	16.7%	
	Part 37	5.26	20	3.19	83.9%	3.80	5250	19950	78896	25.3%	
	Part 38	6.67	20	2.72	90.7%	3.00	5700	17100	78896	21.7%	

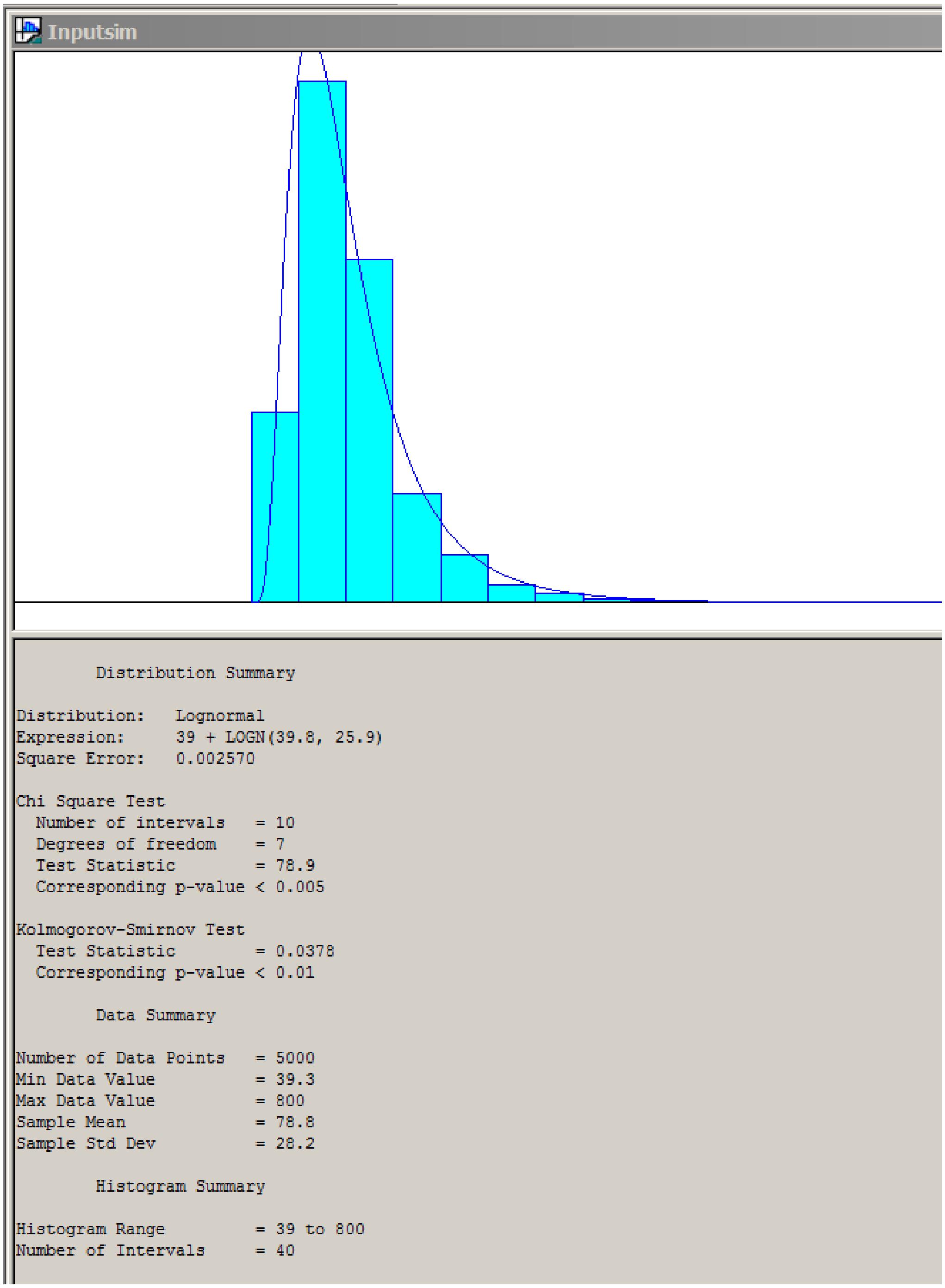
Table B.27 Heuristic procedure results for part family 9 in stage 3 of multi-stage manufacturing

Operator level	PF9 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 15	1.52	10	4.16	63.0%	6.60	4950	32670	73740	44.3%	69.8%
	Part 31	2.00	10	3.58	71.6%	5.00	6300	31500	73740	42.7%	
	Part 40	4.55	10	1.91	86.8%	2.20	4350	9570	73740	13.0%	
12	Part 15	2.27	12	4.16	78.8%	5.28	4950	26136	65304	40.0%	78.8%
	Part 31	2.63	12	3.58	78.5%	4.56	6300	28728	65304	44.0%	
	Part 40	5.00	12	1.91	79.6%	2.40	4350	10440	65304	16.0%	
15	Part 15	2.70	15	4.16	75.0%	5.55	4950	27472	63502	43.3%	81.0%
	Part 31	3.57	15	3.58	85.2%	4.20	6300	26460	63502	41.7%	
	Part 40	6.82	15	1.91	86.8%	2.20	4350	9570	63502	15.1%	
18	Part 15	3.79	18	4.16	87.5%	4.75	4950	23522	59000	39.9%	87.2%
	Part 31	4.35	18	3.58	86.5%	4.14	6300	26082	59000	44.2%	
	Part 40	8.33	18	1.91	88.4%	2.16	4350	9396	59000	15.9%	
20	Part 15	4.00	20	4.16	83.2%	5.00	4950	24750	59302	41.7%	86.8%
	Part 31	5.00	20	3.58	89.5%	4.00	6300	25200	59302	42.5%	
	Part 40	9.30	20	1.91	88.8%	2.15	4350	9352	59302	15.8%	

Table B.28 Heuristic procedure results for part family 10 in stage 3 of multi-stage manufacturing

Operator level	PF10 Parts	Prod. rate	Total operator time in cell per minute	Theoretical time spent per unit (min)	Efficiency	Actual time spent per unit (min)	Demand (/week)	Total prod. time of parts (min)	Total prod. time of PF (min)	Weight	Cell size efficiency
10	Part 17	6.67	10	1.33	88.7%	1.50	5550	8325	35145	23.7%	80.4%
	Part 24	4.17	10	1.83	76.3%	2.40	6450	15480	35145	44.0%	
	Part 25	4.76	10	1.68	80.0%	2.10	5400	11340	35145	32.3%	
12	Part 17	7.50	12	1.33	83.1%	1.60	5550	8880	33792	26.3%	83.6%
	Part 24	5.26	12	1.83	80.3%	2.28	6450	14706	33792	43.5%	
	Part 25	6.35	12	1.68	88.9%	1.89	5400	10206	33792	30.2%	
15	Part 17	10.00	15	1.33	88.7%	1.50	5550	8325	31215	26.7%	90.5%
	Part 24	7.50	15	1.83	91.5%	2.00	6450	12900	31215	41.3%	
	Part 25	8.11	15	1.68	90.8%	1.85	5400	9990	31215	32.0%	
18	Part 17	12.50	18	1.33	92.4%	1.44	5550	7992	32130	24.9%	87.9%
	Part 24	8.33	18	1.83	84.7%	2.16	6450	13932	32130	43.4%	
	Part 25	9.52	18	1.68	88.9%	1.89	5400	10206	32130	31.8%	
20	Part 17	13.89	20	1.33	92.4%	1.44	5550	7992	30612	26.1%	92.3%
	Part 24	10.00	20	1.83	91.5%	2.00	6450	12900	30612	42.1%	
	Part 25	11.11	20	1.68	93.3%	1.80	5400	9720	30612	31.8%	

APPENDIX C: ARRIVAL DISTRIBUTION ANALYSIS FOR PRODUCT 1



```
        Distribution Summary

Distribution:   Lognormal
Expression:     39 + LOGN(39.8, 25.9)
Square Error:   0.002570

Chi Square Test
  Number of intervals   = 10
  Degrees of freedom    = 7
  Test Statistic        = 78.9
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0378
  Corresponding p-value < 0.01

        Data Summary

Number of Data Points   = 5000
Min Data Value          = 39.3
Max Data Value          = 800
Sample Mean             = 78.8
Sample Std Dev          = 28.2

        Histogram Summary

Histogram Range         = 39 to 800
Number of Intervals     = 40
```

Figure C.1 Arrival distribution analysis for Product 1 with Arena Input Analyzer

APPENDIX D: FREIGHT RATE RANGES AMONG CANDIDATE PLANT LOCATIONS AND FROM CANDIDATE PLANT LOCATIONS TO US PORTS

Table D.1 Minimum and maximum quoted ocean freight rates among ports of candidate locations

Range of ocean freight rates ($)	Shanghai, China	Veracruz, Mexico	Manila, Philippines	Mumbai, India	Mersin, Turkey	San Juan, Puerto Rico	Santo Domingo, Dominican Rep.
Shanghai	0	3044--3364	1291--1427	1628--1799	1989--2199	2843--3141	2875--3178
Veracruz	1897--2096	0	3932--4346	2322-2578	4287--4738	1115--1232	1131--1250
Manila	1291--1425	2612--2887	0	1763--1949	2218--2451	3663--4049	3699--4089
Mumbai	2054--2270	2332--2578	2201--2434	0	1506--1664	4440--4908	4457--4926
Mersin	1307--1445	4743--5242	1612--1782	1103--1219	0	5330--5892	5437--5910
San Juan	3334--3686	1632--1803	4105--4538	2548--2816	3931--4345	0	848--937
Santo Domingo	3353--3708	1644--1817	4123--4558	2560--2829	3944--4359	848--937	0

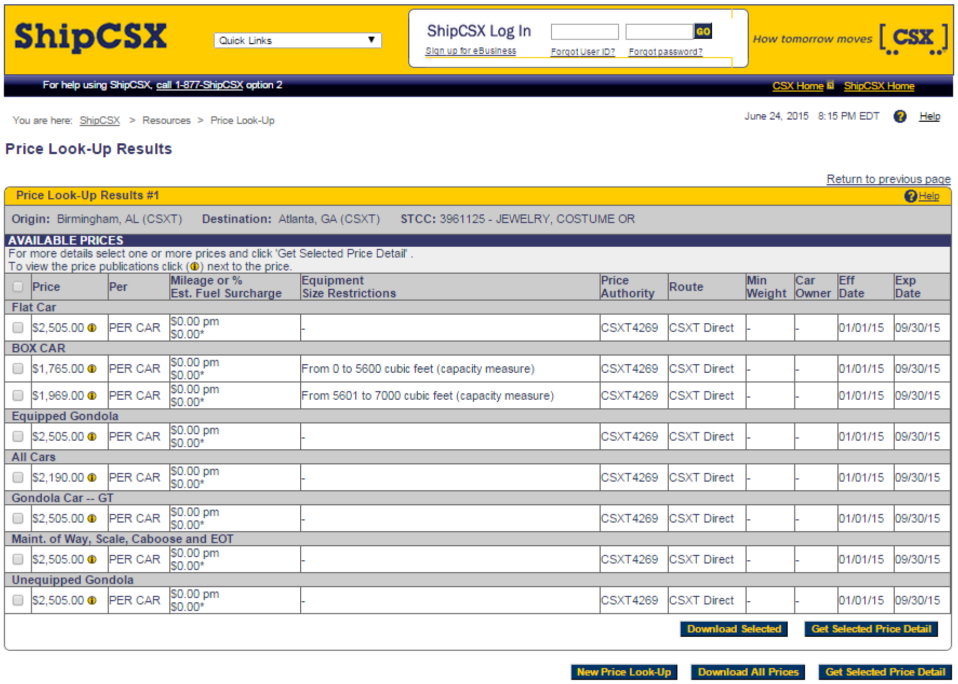
Table D.2 Minimum and maximum quoted ocean freight rates from ports of candidate locations to US ports ($)

Range of ocean freight rates ($)	Savannah, GA	Los Angeles, CA
Shanghai	2971--3284	2786--3079
Veracruz	1399--1546	1691--1869
Manila	3854--4260	3909--4321
Mumbai	3596--3753	3954--4370
Mersin	4286--4737	4951--5472
San Juan	610--674	2941--3251
Santo Domingo	622--688	2559--3271

APPENDIX E: AVERAGE DOMESTIC TRANSPORTATION TIMES AND COSTS FOR RAIL AND ROAD TRANSPORTATION

Table E.1 Average transportation time from Los Angeles, CA to Birmingham, AL

Day of Week	Days : Hrs	Hours
Monday	12 : 03	291
Tuesday	11 : 03	267
Wednesday	11 : 03	267
Thursday	15 : 03	363
Friday	14 : 03	339
Saturday	13 : 03	315
Sunday	12 : 03	291
Average	12 : 17	304.7



Price Look-Up Results

Price Look-Up Results #1

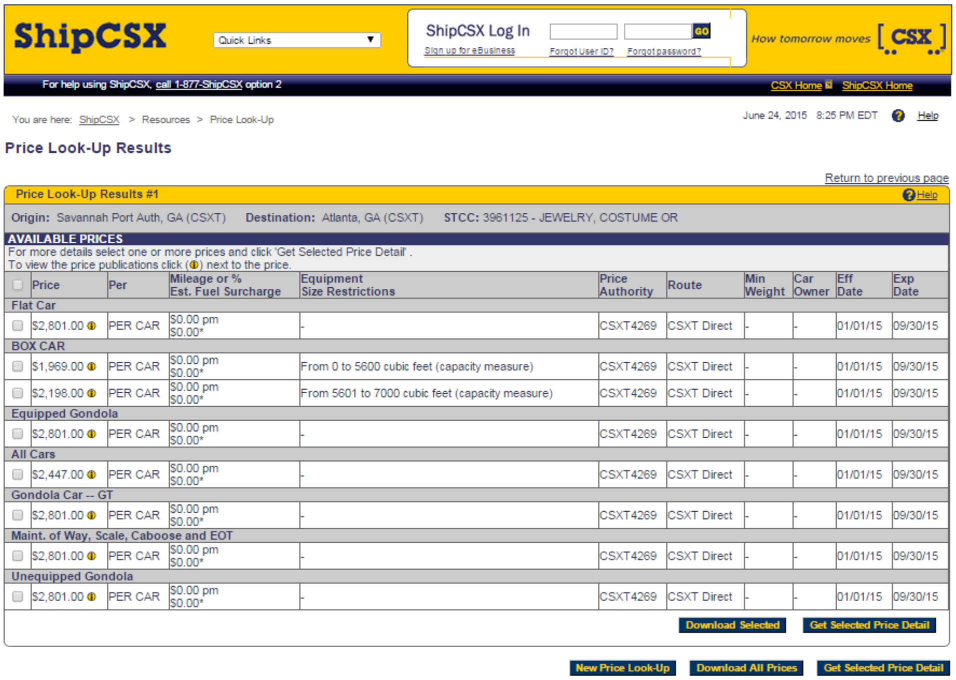
Origin: Birmingham, AL (CSXT) **Destination:** Atlanta, GA (CSXT) **STCC:** 3961125 - JEWELRY, COSTUME OR

AVAILABLE PRICES

For more details select one or more prices and click 'Get Selected Price Detail' .
To view the price publications click (ⓘ) next to the price.

☐	Price	Per	Mileage or % Est. Fuel Surcharge	Equipment Size Restrictions	Price Authority	Route	Min Weight	Car Owner	Eff Date	Exp Date
Flat Car										
☐	$2,505.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
BOX CAR										
☐	$1,765.00 ⓘ	PER CAR	$0.00 pm $0.00*	From 0 to 5600 cubic feet (capacity measure)	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
☐	$1,969.00 ⓘ	PER CAR	$0.00 pm $0.00*	From 5601 to 7000 cubic feet (capacity measure)	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Equipped Gondola										
☐	$2,505.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
All Cars										
☐	$2,190.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Gondola Car -- GT										
☐	$2,505.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Maint. of Way, Scale, Caboose and EOT										
☐	$2,505.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Unequipped Gondola										
☐	$2,505.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15

Figure E.1 CSX shipping rates from Birmingham, AL to Atlanta, GA (CSX Price Look-up, 2015)



Price Look-Up Results

Price Look-Up Results #1

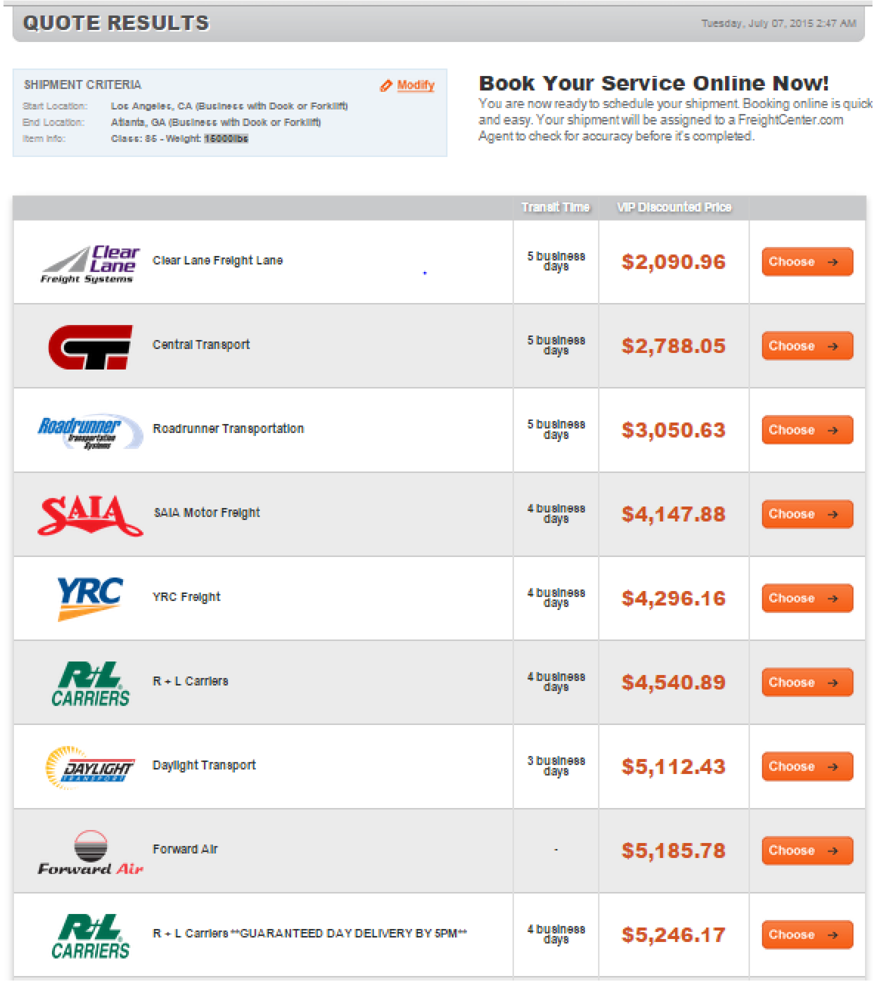
Origin: Savannah Port Auth, GA (CSXT) **Destination:** Atlanta, GA (CSXT) **STCC:** 3961125 - JEWELRY, COSTUME OR

AVAILABLE PRICES

For more details select one or more prices and click 'Get Selected Price Detail' .
To view the price publications click (ⓘ) next to the price.

☐	Price	Per	Mileage or % Est. Fuel Surcharge	Equipment Size Restrictions	Price Authority	Route	Min Weight	Car Owner	Eff Date	Exp Date
Flat Car										
☐	$2,801.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
BOX CAR										
☐	$1,969.00 ⓘ	PER CAR	$0.00 pm $0.00*	From 0 to 5600 cubic feet (capacity measure)	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
☐	$2,198.00 ⓘ	PER CAR	$0.00 pm $0.00*	From 5601 to 7000 cubic feet (capacity measure)	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Equipped Gondola										
☐	$2,801.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
All Cars										
☐	$2,447.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Gondola Car -- GT										
☐	$2,801.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Maint. of Way, Scale, Caboose and EOT										
☐	$2,801.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15
Unequipped Gondola										
☐	$2,801.00 ⓘ	PER CAR	$0.00 pm $0.00*	-	CSXT4269	CSXT Direct	-	-	01/01/15	09/30/15

Figure E.2 CSX shipping rates from Savannah, GA to Atlanta, GA (CSX Price Look-up, 2015)



QUOTE RESULTS

Tuesday, July 07, 2015 2:47 AM

SHIPMENT CRITERIA

Start Location: Los Angeles, CA (Business with Dock or Forklift)
End Location: Atlanta, GA (Business with Dock or Forklift)
Item Info: Class: 85 - Weight: 15000lbs

Book Your Service Online Now!

You are now ready to schedule your shipment. Booking online is quick and easy. Your shipment will be assigned to a FreightCenter.com Agent to check for accuracy before it's completed.

	Transit Time	VIP Discounted Price	
Clear Lane Freight Lane	5 business days	$2,090.96	Choose →
Central Transport	5 business days	$2,788.05	Choose →
Roadrunner Transportation	5 business days	$3,050.63	Choose →
SAIA Motor Freight	4 business days	$4,147.88	Choose →
YRC Freight	4 business days	$4,296.16	Choose →
R + L Carriers	4 business days	$4,540.89	Choose →
Daylight Transport	3 business days	$5,112.43	Choose →
Forward Air	-	$5,185.78	Choose →
R + L Carriers **GUARANTEED DAY DELIVERY BY 5PM**	4 business days	$5,246.17	Choose →

Figure E.3 Freight quotes from ground transportation companies from Los Angeles, CA, to Atlanta, GA