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EVALUATION OF TRUCK WEIGHT ENFORCEMENT TECHNOLOGIES: A MULTICRITERIA APPROACH

DISSERTATION

Presented in Partial Fulfillment of the Requirements for
the Degree Doctor of Philosophy in the Graduate
School of The Ohio State University

By

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*****

The Ohio State University

1996

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To my parents
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CHAPTER I

Introduction

1.1 Background

Heavy trucks are one of the major causes of pavement deterioration and bridge damage. The General Accounting Office (GAO) concluded that truck overloads were responsible for some $562 million of premature pavement deterioration each year on the interstate highway system alone (Wilbur Smith and Associates, 1987). A more recent study concluded the damage to state highways to be approximately $20 million annually in the State of Oregon (Wilbur Smith and Associates, 1987).

To prevent trucks from damaging highways and bridges, government agencies set weight regulations and established truck weighing programs to enforce legal weight limits. The States of Maine, Massachusetts, Pennsylvania, and Washington became the first states to place limits on truck weight in 1913 (Terrell and Bell, 1987). The federal government entered this regulatory arena in 1956 by setting national truck weight limits for the Interstate Highway System (Terrell and Bell, 1987). In 1956 and 1975, Congress passed the Federal-Aid Highway Acts that set up weight regulations to reduce the damage caused to pavement and bridges (Johnson, 1980). However, grandfather provisions in the federal statutes allow states to retain higher regulation standards than these limits if such regulations had been in effect when the applicable federal statutes were enacted. Many
states have stricter regulations to protect their own highway systems. For example, Colorado, Arkansas, and Montana's weight regulations on single axles are 18,000 lb. instead of 20,000 lb. Besides the grandfather exemptions, all states have permit systems that allow trucks to exceed federal and state size and weight regulations under special circumstances (Terrell and Bell, 1987) Recently, the federal government forced states to adopt the federal weight regulations on Interstate highways. The federal weight regulations on Interstate highways include: (1) a total gross weight limit on the vehicle of 80,000 lb., (2) limits on axle loads, specifically 20,000 lb. for single axles and 34,000 lb. for tandem axles; and (3) a bridge formula that specifies the maximum allowable weight on any group of consecutive axles (Ohio Department of Transportation, 1992). This bridge formula is meant to ensure integrity of bridges.

The current truck weight enforcement practice is not totally effective, however. Weigh stations' operation hours and service capacities are two major constraints to truck weight enforcement. As for weigh station operation hours, most weigh stations only operate eight hours a day, and are only open on weekdays. Trucks are left unchecked on weekday evenings and weekends. Weigh station service capacity is another important factor. When a weigh station is operating, only a limited fraction of the total number of trucks arriving at the station can be checked. As a result, the percentage of trucks being checked is not very high. According to one study (Downs, 1981), the estimated percentage of trucks weighed at Alma station, Arkansas on I-40 and Marion station, Arkansas on I-55, were 64% and 38%, respectively. Note that these numbers represent percentage of trucks weighed only on these specific interstate highways. When considering that many highways have no stations, the percentage would drop dramatically. From an interview with an
official in the Ohio Department of Transportation, the estimated percentage of trucks being weighed in Ohio is only about 2%.

The current weight enforcement practice also causes truck time delays and safety problems (Terrell and Bell, 1987). States set up weigh stations at state borders and along major routes to enforce weight regulations. Currently, static scales are widely used. They are called static because trucks have to stop on the scale platforms so that their weights can be measured directly. This system requires trucks to be separated from the main traffic stream and to wait in line to be weighed. After being checked, legally laden trucks have to merge back to the main traffic stream. The separating, waiting, and merging process imposes time delays on the trucks and cause losses in productivity for the trucking industry. Furthermore, during peak periods, trucks can queue up back to the highway (Cambridge Systematics, Inc., 1993) and disturb the main traffic flow. This increases the potential for accidents.

Since Norman and Hopkins invented their first dynamic weighing equipment in 1952 (Cunagin, 1986), weigh-in-motion (WIM) technologies have offered new alternatives for weight enforcement. Different types of WIM systems have been developed and tested in the United States and other countries in recent years (Cunagin, 1986). The main idea of WIM systems is to weigh trucks without stopping them. This would reduce time delays and traffic hazards. WIM scales can be installed in or on the pavement surface. The scales weigh trucks electronically as the trucks' wheels pass over them (Downs, 1981).

WIM systems can be placed in pre-constructed pits in the through traffic lanes. In this case, the trucks are weighed at prevailing highway speeds. Since WIM systems detect trucks' dynamic loadings instead of their static weights, trucks can pass through the scales without stopping or decreasing their speeds (Downs, 1981). WIM systems can also be
installed in ramps (by-pass lanes) at permanent weigh station sites (Downs, 1981). In this setup, trucks are required to decelerate to lower than highway speeds when they go through the by-pass lanes. Normally, the speeds of the trucks are between 30 to 45 mph (Izadmehr and Lee, 1987; Spiegel, 1995; Downs, 1981).

Although WIM offers potential advantages for increasing productivity and safety and decreasing delays, static scale equipment is the only kind that has been certified to be used in weight enforcement at present (Izadmehr and Lee, 1987). Some pioneering projects (Castle Rock Consultant, 1994; JHK & Associates, 1992) proposed to use WIM technologies as screening devices. A WIM device can be placed on traffic traveling lanes or on a separated by-pass lane to screen out suspicious trucks. In the HELP/Crescent project (Heavy Vehicle Electronic License Plate Program/ Crescent Demonstration Project), six stations were equipped with mainline WIM screening, and seven other stations screened trucks on a separated by-pass lane (Castle Rock Consultant, 1994).

The advantages of using WIM are mainly in weigh station operations, truck data collection, and safety improvement. In weigh station operations, the deployment of WIM can increase the weigh station vehicle processing rate so that the percentage of trucks checked will be increased. Although the total costs for WIM systems might be higher, the costs per truck weighed will be reduced (Cunagin, 1986). In truck data collection, WIM can automate the processing of truck-weight data and operate 24 hours a day. This will offer states a better capability in truck traffic data collection that can be used for planning purposes. Finally, as a result of the improvement of weigh station operations, truck queues will be less likely to reach the traveling lanes. Therefore, the safety of both the truckers and the driving public are improved (Cunagin, 1986).
Deploying WIM also has some disadvantages. The first disadvantage of deploying WIM is its high initial costs. WIM equipments are more expensive and they also have high initial costs (Cunagin, 1986). Second, the accuracies of the WIM equipments are big issues. Several studies (Izadmehr and Lee, 1987; Cottrell, 1992) showed that WIM systems have a lower accuracy, especially when used in weighing trucks at high speeds. Third, additional information often obtained from inspection for safety reasons would be unavailable. Alcohol and drug influence checks for truck drivers and safety inspections for vehicles at station sites would be eliminated. Finally, WIM systems are more complex and also require more sophisticated technical skills of the staff (Cunagin, 1986).

Previously, only static scales were available for weight enforcement. Now, WIM systems offer additional potential alternatives for state government agencies. States can switch to WIM technologies and weigh trucks in main traffic lanes or on a separated lane. States can also deploy WIM technologies as screening devices, screening traffic in mainline or on separated ramps. The different systems have advantages and disadvantages. Therefore, it is difficult to determine an appropriate weight enforcement technology.

It is difficult to determine the appropriate weight enforcement technology because the accuracy of the technologies might be an important factor. WIM systems have lower accuracy than the static scales (Izadmehr and Lee, 1987). Since WIM technologies can process trucks at a higher speed, the question is whether the advantage of checking more trucks outweighs the disadvantage of inferior accuracy. The answer to the accuracy versus throughput rates may depend on "environmental" factors. Specifically, state government budgets and highway traffic characteristics could influence the evaluation.

Another complicating factor in the determination of an appropriate weight enforcement technology is that the technology will have different impacts on different groups, each
with different concerns. For example, state governments are concerned with pavement
deterioration, while the trucking industry is interested in reducing truck time delays at
weigh stations.

In recent years, there have been several studies conducted by the government to
evaluate the new technologies. These studies can be divided into two categories: technical
performance evaluations and cost-benefit evaluations. The purpose of a technical
performance evaluation is to evaluate the technical performance of the systems. A cost-
benefit analysis type of evaluation attempts to evaluate the benefit versus the cost of
deploying new technologies.

Cottrell's (1992) and Izadmehr and Lee's (1987) technical performance research
investigated scale performance. Cottrell (1992) evaluated three types of weigh-in-motion
systems: weight mat system, bridge weighing systems, and piezoelectric cable sensor
system. The studies evaluated data quality, ease of use, and system durability. The report
concluded that all three weigh-in-motion systems met the specifications. Izadmehr and Lee
(1987) also studied the accuracy of WIM systems at different truck operating speeds.
They concluded that WIM systems are adequate for gathering weight data at high speeds
and as a means of sorting overweight trucks in enforcement programs.

HELP evaluation proposed to analyze WIM system field data to confirm the scale
performance question. The former study proposed a technical performance evaluation plan
for WIM systems on I-75. The latter project also conducted the same type of evaluation
for the installed WIM systems in the HELP Program. This type of evaluation evaluated the
systems exclusively from the technical point of view and checked accuracy of data,
systems durability and ease of use.
Castle Rock Consultant's HELP evaluation (1994) also performed a cost-benefit analysis for the HELP/Crescent Program. Present value discounting was used in estimating the benefits and costs. The costs were estimated in three categories: regional cost, states' costs, and carriers' costs. Benefits were estimated in terms of states' benefits and carriers' benefits. The costs and benefits considered in the analysis were estimated with monetary values. The evaluation concluded that deploying WIM technologies can generate net benefits.

The technical performance evaluations of WIM technologies offered excellent information in the WIM accuracy. The cost-benefit studies offered good insight on the possible benefits of deploying WIM technologies. These studies did not, however, address the general issue of which type of system should be deployed under what circumstances.

Despite the difficulties mentioned above, a decision on weight enforcement technology that considers the impacts on and concerns of affected interest groups under different circumstances must be made. Even if a government decides to stay with static systems, it is making a decision that the impact on the different interest groups remain at the current levels. It would, therefore, be valuable to specify the important factors of weight technology selection. From this, the important factors could be considered when selecting a technology and less significant factors could be ignored. For example, if the accuracy of a weight enforcement system is an important factor, state government agencies should not consider new systems until the system accuracy meets their requirement. If costs are important factors, they should not deploy new systems when there are budget difficulties. If interest groups' preferences are important, they should study the preferences more carefully before making any decisions.
1.2 Research Objective and Scope

This study investigates which truck weight enforcement technology is optimal under various conditions. Here the optimal solution we refer to is the weigh system determined to be the best based on the preferences of the involved interest groups. The two involved interest groups in this evaluation are the government agencies and the private motor carriers. In this study, we also use a parameter to represent the relative importance of these two interest groups. We call this parameter the group tradeoff parameter. In this research, the conditions are specified by truck traffic volume and the group tradeoff parameter. That is, we investigate the optimal solution as a function of truck traffic volume and the group tradeoff parameter.

We investigate five truck weight enforcement technologies at a single weigh station in this study. The first weight enforcement technology we investigate is a static scale for weight enforcement. Then we investigate the option of upgrading the static weigh station by replacing the static scale with a high-speed weigh-in-motion scale. We also investigate the option of replacing the static scale with a medium-speed weigh-in-motion scale. In addition to the single enforcement scale type of weigh station, we investigate the option of adding a high-speed weigh-in-motion scale as a screening device to screen out those most likely to be weight regulation violating trucks; such trucks would later be checked by a static scale. Finally, we investigate the addition of a medium-speed weigh-in-motion scale as a screening device to screen truck traffic in by-pass lanes.

We also investigate which parameters and variables can affect these optimal solutions under different conditions. The parameters we investigate can be divided into two
categories: the prediction parameter and the preference parameters. The prediction parameters are those parameters which we use to model the weigh station performance. The preference parameters are those parameters which we use to describe preferences for various performance levels. Specifically, the prediction parameters which we investigate are the accuracy of the weight scale, the truck gross weight changes, and the percentage of the highest percentage weight regulation violating truck type. The preference parameters include the preference parameters of the government agencies and the preference parameters of the private motor carriers.

1.3 Overview of Thesis

This thesis contains eight chapters. Chapter 1 serves as an introduction to the problem of evaluation of truck weight enforcement technologies. We describe the background and motivation of this study in Section 1.1. Section 1.2 details the research scope and the specific research questions addressed. Section 1.3 is an overview of this thesis.

Because of the nature of the truck weight enforcement technology evaluation problem, we propose to use Multi-Attribute Expected Utility (MAEU) evaluation to address the problem. The MAEU evaluation includes five steps: identifying alternatives, identifying the involved interest groups and attributes, predicting the attribute levels for a given alternative, assessing the utility function which models the preferences toward the attributes, and calculating the expected utility of the alternatives. We introduce the MAEU evaluation and its framework in Section 2.1. Then we present the first two steps of the MAEU procedure. Specifically, in Section 2.2, we define the five alternatives described above. In Section 2.3, we define the interest groups as the government agencies and
private motor carriers. We also define the concerns of the interest groups as attributes (criteria). The attributes we consider for the government agencies are revenue from fines in a typical year, yearly weight enforcement system costs, number of ESAL's in a typical year, and number of bridge violation truck trips in a typical year. The attributes we consider for of the private motor carriers are fine for a random truck, offloading for a random truck, and time delay for a random truck at the weigh station.

In Chapter 3, we predict the attribute levels for each of the five alternatives. Some attribute levels can be estimated from existing data, while some cannot. First, in Section 3.1, we estimate those attribute levels which can be assessed from existing data. In Section 3.2, we propose to use a computer simulation to predict the rest of the attribute levels. Specifically, in Section 3.2.1, we define the weigh station operation as the studied system. Its characteristics are also presented. In Section 3.2.2, we define trucks as the entities of the system. Their characteristics are also presented. In Section 3.2.3, we describe the simulation program structure. Finally, we present a model validation in Section 3.2.4.

The last two steps of the MAEU analysis are presented in Chapter 4. First, in Section 4.1, we formulate the Multi-Attribute utility function. We also define the single-attribute disutility functions and the scaling parameters of the attributes. In Section 4.2, we show how to calculate the disutility function and how to approximate the disutility function.

In order to use the MAEU evaluation to address the truck weight technology evaluation problem, we still need values for the scaling parameters of the attributes. In Chapter 5, we discuss how we obtain a set of benchmark scaling parameters. In this research, we calculate a set of benchmark data by using the Marginal Rates of Substitution (MRS) approach and data from literature and other sources. The mathematical expressions are presented in Section 5.1. With the equations we obtained from Section 5.1, we
calculate the scaling parameters of the government agency attributes, private motor carrier attributes, and the tradeoff parameter which represents the relative importance between the two interest groups in Section 5.2, 5.3, and 5.4, respectively.

In Chapter 6, we analyze the truck weight technology evaluation problem with the formulated MAEU function and the set of benchmark data. First in Section 6.1, we analyze the weight enforcement system performance in terms of their single-attributes as a function of truck volume. We also analyze the optimal weight enforcement systems as a function of truck volume and the tradeoff parameter that represents the relative importance of the government agencies and the motor carriers. However, in the truck weight enforcement technology evaluation, there are two categories of parameters that would affect the optimal solution as formulated in this research, namely, the prediction parameters and scaling parameters. The prediction parameters are those which we use to predict the performance of the weight enforcement technologies. The scaling parameters are those which we use to describe the preference for the attributes. We use sensitivity analysis to analyze the influence of those parameters. In Section 6.2.1, we present the general design of the sensitivity analysis. In Section 6.2.2, we present the results of the sensitivity analysis.

In Chapter 7, we determine what the optimal weight enforcement systems for our evaluation are. We find that the traditional static station begins to face capacity problems at truck volume of approximately 3,500 trucks/day. When volumes exceed 6,700 trucks/day, adding a medium-speed screening weigh-in-motion device can catch more overweight trucks than adding a high-speed screening device. In addition, we also determine the influential prediction parameters and the preference parameters to the optimal weight enforcement system solutions. None of the fairly large changes in
preference parameters investigated will change the optimal weight enforcement systems under low, medium, and high truck volume conditions. Under low and high truck volume conditions, the fairly large changes in prediction parameters investigated will not change the optimal weight enforcement system solutions. Under medium truck volume condition, a decrease in the percentage of overweight trucks will increase the probability of switching to weight enforcement systems other than the base case optimal. Finally at the end of Chapter 7, suggestions for future studies are put forth.
CHAPTER II

Multi-Attribute Evaluation Framework

2.1 Introduction

Evaluation problems are usually complicated because they involve different interest groups. The impact of implementing different decisions will affect each group differently. These groups often have interests directly in conflict with each other, thereby making the problem even more complicated (Keeney, 1980). In the truck weight technology evaluation problem, the state governments are concerned about pavement damage. All other things being equal, they would prefer trucks that are as light as possible so that the pavement can last longer. On the other hand, the private motor carriers are concerned about productivity and, eventually, profits. They want to ship the most cargo at the least cost. In general, this would occur if every truck carried as much as it could. The concerns of these two groups are, therefore, in conflict.

In addition to the conflicts between different interest groups, some of these groups themselves might have multiple competing objectives. It is often the case that an interest group has more than one concern. Different alternatives will have different impacts on these concerns. An interest group has to decide how to balance one concern against another competing concern. In the truck weight technology evaluation problem, the state government agencies have to decide the relative importance between weight enforcement system costs and pavement damage. For example, system C might be more expensive but
would catch more violators and, therefore, leads to less pavement damage. On the other hand, system D might be less expensive but would catch fewer violators and, therefore, lead to more pavement damage. The government agencies have to decide whether they are willing to pay more cost for a weight enforcement system to decrease the pavement damage. In the truck weight technology evaluation problem, the private motor carriers also have to decide the relative importance between overweight fines and time delays caused by weight regulation enforcement at the weigh station. For example, system A might weigh trucks faster but be more accurate. Therefore, fewer trucks can escape from being caught, leading to more fines. On the other hand, system B might weigh trucks more slowly but be less accurate. Therefore, more overweight trucks can escape from being caught, leading to less fines. To determine whether they would prefer system A or B, the private motor carriers would have to decide how much more in fines they would be willing to pay to decrease time delays.

Finally, the consequences that would result from each system would be uncertain. This will add to the difficulties in the evaluation. For example, the future truck volume and the truck weight characteristics are unknown. As a result, prediction of the concerns mentioned above—pavement damage, time delays, and fines—will all be uncertain for any technology.

In an evaluation problem, it is often true that no existing alternative is better than all other choices in terms of all the objectives. Faced with such a complex decision problem which involves multiple conflicting objectives, multi-attribute evaluation techniques are warranted. A multi-attribute evaluation considers all the involved interest groups and their concerns. It explicitly recognizes trade-offs in the concerns and leads to a compromised alternative that is most preferred to the interest groups according to their preferences.
Basically, the technique seeks a way to combine several criteria together to measure and rank a system's performance associated with different options or alternatives. The way in which this is done often leads to an alternative (or an option) being represented by a single numerical value (Keeney, 1980).

Multi-Attribute Expected Utility (MAEU) is one of the most commonly used multi-attribute analysis techniques. MAEU combines mathematical, logical, and economic analysis with applied probability concepts to analyze complex evaluation problems. In MAEU analysis, the best alternative is the one which is most preferred by the decision maker as represented by a preference function. The power of Multi-Attribute Expected Utility (MAEU) decision analysis is that it transforms this idea of most preferred into an operational and behaviorally appealing process (McCord, et al. 1993; McCord and Leu, 1995). By operational, we mean that the required inputs to the process can be obtained and necessary calculations can be performed. By appealing, we mean that the methodology is based on a few axioms which represent preference properties that a decision maker would like to exhibit. The theory simply allows a way to represent that one set of outcomes is preferred to another, given that future is unknown for all of the options. The theory is well-established and arguably one of the most appealing for handling future uncertainties and outcomes that are not easily transformed into monetary values (Keeney, 1980; McCord et al., 1993).

In this study, we therefore propose to use Multi-Attribute Expected Utility (MAEU) to analyze the weight enforcement technology problem. The basic steps involved in the application of MAEU Evaluation model are: 1) identifying the alternative; 2) identifying the criteria or attributes; 3) predicting the attribute level for the given alternatives; 4) assessing the utility function which models the preference towards the criteria; and 5)
calculating the expected utility of the alternative (Keeney, 1980). We identify the alternatives of truck weight technology evaluation problems in Section 2.2. In Section 2.3, we define the involved interest groups. We define the attributes or criteria of the interest groups in Section 2.4. We predict the attribute levels, assess the utility functions, and calculate the expected utility of the alternatives latter in Chapter 3 and Chapter 4.

2.2 Alternatives Investigated

As described in Section 2.1, the first step in the MAEU analysis is to identify the alternatives. We now discuss the existing technologies and define the truck weight technology alternatives that we will examine in our evaluation.

Basically weight scales can be classified into two categories: static scales and weigh-in-motion technologies. Static scales are platform type of scales (Cunagin, 1986), and they measure a truck's static weight directly. There are mainly two types of static scales: beam (mechanical) scales and electronic scales. Beam scales have a platform, commonly of concrete, on a steel weighbridge, suspended on a system of levers and pivots connected to a weight readout system. Electronic scales involve a platform supported at the periphery on load-cell rocker bearing assemblies. Their readout is an electronic digital display (Cunagin, 1986). In order to measure truck static loads, static scales require trucks to stop on the platforms while the weight is taken.

Instead of weighing trucks by static weight, weigh-in-motion scales detect the dynamic wheel force of the trucks. They then approximate the static wheel loads from these dynamic measurements (Cunagin, 1986). There are three categories of factors that affect wheel loads of a moving vehicle: roadway factors, vehicular factors, and environmental
factors. The roadway factors include longitudinal profile, transverse profile, grade, cross slope, and curvature. The vehicular factors include speed, acceleration, axle configuration, body type, suspension system, tires, load, load shift, aerodynamic characteristics, and center of gravity. Environmental factors include wind, temperature and ice (Cunagin, 1986). In order to approximate static wheel loads with WIM equipment, it is necessary to minimize the roadway, vehicular and environmental factors. The roadway factors can be controlled by improving the layout of the weigh stations. The vehicular and environmental factors, however, can not so easily be controlled. Fortunately, studies show that reducing trucks' speeds, even under the influences of those uncontrollable factors, can improve the accuracy of the WIM scales greatly (Izadmehr and Lee, 1987; Arizona DOT, 1989; Downs, 1981; Cunagin, 1986). WIM scales can achieve about 10 percent measuring error at prevailing highway speeds (high-speed) (Downs, 1981), 5 percent measuring error at speeds of 25-40 mph (medium speed) (Arizona DOT, 1989), and 1 percent measuring error at speeds of 3 to 5 mph (low speed) (Cunagin, 1986).

In this study, the first category of our alternatives are weigh stations equipped only with enforcement weigh scales. The first alternative is the traditional type of weigh station--using a single static scale in weight enforcement. We define this alternative as STATIC-ONLY. A typical layout of a STATIC-ONLY weigh station is shown in Figure 1.

The second alternative assumed is to replace the static scale with a weigh-in-motion scale to weigh trucks on mainline travel lanes at the prevailing highway speed. We define this alternative as HSWIM-ONLY. A typical HSWIM-ONLY layout is shown in Figure 2.

The third alternative is to replace the static scale with a weigh-in-motion scale to weigh trucks on a bypass lane at a speed of 20-40 mph. We define this alternative as MSWIM-
ONLY. A typical MSWIM-ONLY layout is show in Figure 3. Using WIM at low speed is very similar to a static scale. Therefore we will not consider this alternative in our study.

The second category of our alternatives are weigh stations equipped with a weigh enforcement scale and a screening device. In addition to being used as weight enforcement scales, weigh-in-motion technologies can also serve as screening devices. By adding a screening device to the static weigh stations, the weigh station personnel are able to determine which trucks are most likely to be violating the weight regulations. These trucks can then be directed to the weigh enforcement scale and weighed statically. In this study, we consider two possible alternatives-- the fourth and the fifth alternatives-- related to screening devices.

The fourth alternative, then, is to keep the static scale as the weight enforcement scale and add a weigh-in-motion system to screen trucks at prevailing highway speeds on main traveling lanes. We define this alternative as STATIC-with-HSWIM. The layout for a STATIC-with-HSWIM is shown in Figure 4.

The fifth alternative is adding a weigh-in-motion to a static weight station to screen trucks at a lower speed on a separate lane to provide more accurate screening results. We define this alternative as STATIC-with-MSWIM. The layout for a STATIC-with-MSWIM is shown in Figure 5.

We use $X_i$, $i = 1, ..., 5$, to represent the possible alternatives. Therefore, in this study, the alternatives are:

$X_1$: Static weigh scale used alone for enforcement (STATIC-ONLY)
$X_2$: High-speed WIM scale used alone for enforcement (HSWIM-ONLY)
$X_3$: Medium-speed WIM scale used alone for enforcement (MSWIM-ONLY)
$X_4$: Static scale used for enforcement with high-speed WIM used as a screening device

(STATIC-with-HSWIM)

$X_5$: Static scale used for enforcement with medium-speed WIM as a screening device

(STATIC-with-MSWIM).

We summarize the alternatives and notation in Table 1.

2.3 Major Interest Groups and Concerns

Government agencies and private motor carriers were the two major interest groups included in recent weigh-in-motion evaluation studies (Castle Rock Consultant, 1994; JHK & Associates, 1992). In our evaluation, we shall include government agencies and private motor carriers as the first and second interest groups, respectively. In addition to these two interest groups, non-truck road users and non-road users might be considered. The non-truck road users we refer to are those road users other than trucks; most of these are drivers and passengers in cars and buses. The non-road users we refer to are the general public who are affected by what happens on the highway when they are not using the highway. In this section, we first discuss the two major interest groups and their concerns. Then we discuss the non-truck road users and the non-road users to support why we chose not to analyze their concerns in this study.

2.3.1 Interest Group 1--The Government Agencies

Governments are the providers and operators of the highway infrastructure. They are responsible for providing safe and efficient highway systems for the road users. Pavement and bridges are the important highway system elements affected by truck weight.
Protecting pavement and bridges from premature damage is the main reason states set up weight regulations and enforcement (Cunagin, 1986; Castle Rock Consultant, 1994; JHK & Associates, 1992). Therefore, we believe that the government agencies' primary concerns are pavement damage and bridge damage.

Cost is always a concern in evaluation. We, therefore, consider weigh system costs as a government agency's concern. Here the system costs we refer to are the costs to upgrade a traditional weigh station equipped with a single static scale to another weight enforcement system. We will discuss which cost items are included and which are not included in this study in detail later.

We also consider the revenues collected from overweight trucks as a concern of the government agencies. These collected revenues have been important resources for different government agencies and purposes—e.g., education, health, welfare, the court system, and highway maintenance funds (Downs, 1981). In addition, those government agencies which receive the revenues might be different from the agencies who pay for the weight enforcement system. Therefore, in this study, we believe that the revenue and costs for the government should be considered separately.

2.3.2 Interest Group 2-- The Private Motor Carriers

The private motor carriers are private enterprises. They generate profits by providing fast and safe delivery of goods. To offer the same quality and quantity of service, lower costs often mean higher profits. We believe that the concerns of the private carriers are principally cost and productivity related.
Penalties for overweight trucks are costs to the carriers. Among the penalties, fines are the most common. They are used by all states (Johnson, 1980). In this study, we include fines as the first concern of the private motor carriers.

In addition to fines, offloading is a common practice in weight regulation enforcement. Most states require an overweight truck that has been caught to rectify the problem--become legal--before it is allowed to continue its trip (Downs, 1981). This not only causes time delays but also imposes extra costs in shipping unloaded cargo to the carriers. We include offloading penalties as one the motor carriers' concerns.

Finally, time delays at the weigh stations due to weight enforcement will cause excess costs in equipment, personnel, and fuel consumption to the motor carriers. Many studies (JHK & Associates, 1992; Castle Rock Consultant, 1994) consider the reduction of unnecessary time delay as the major benefit of the deployment of new weight technologies. We include time delay as a concern to the motor carriers in our evaluation.

2.3.3 Interest Group 3--Non-Truck Road Users

The non-truck road users include all other highway users except for trucks. They share the highway systems with the truck traffic. Due to physical characteristics, truck traffic always creates a certain level of disturbance for other vehicles, especially for passenger cars. Therefore, we believe that the major concern of the non-truck road users related to truck weight technology evaluation is primarily safety. Here the safety we refer to is the traffic safety near weight station sites.

The traffic safety issues related to truck weight enforcement near a weigh station site include two major problems. The first problem is the queue created near weigh station
sites by the trucks waiting for weighing. Some states require that all trucks be weighed. In high truck traffic volume conditions, due to the operational characteristics of the static scales, trucks often queue up to the main travel lanes (Cambridge Systematics, 1993). Some states let trucks pass by the weigh station without weighing the trucks when a queue is forming. In our research, we use this latter weight enforcement policy. Therefore, the safety problem created by a truck queue will not be an issue in our evaluation.

The second traffic safety problem related to truck weight enforcement is the trucks' maneuvers when entering and exiting weigh stations. In traditional weigh station operations, trucks are required to separate from and merge back into the mainline traffic. Because of the speed difference and traffic conflicts, the weight enforcement procedure might create potential traffic hazards. Truck accident studies have shown that the merging and exiting of trucks should not deserve more concern than other regular traffic maneuvers, however. On 45 miles of sampled freeway segments in Michigan and Washington, the number of truck accidents caused by exiting and merging maneuvers are less than 13% of the total number of truck accidents that occurred from 1985 to 1989. On the other hand, 75% of the total number of truck related accidents happened in the freeway proper (Bowman and Lum, 1990). That is, truck merging and separating maneuvers are secondary safety concerns. We, therefore, will not explicitly consider the safety impacts of reducing the separating and merging maneuvers near the weigh station sites in this analysis. This would allow us to eliminate the non-truck road users group in this study.
2.3.4 Interest Group 4 -- Non-Road Users

The non-road users we refer to are the general public who do not use a certain section of road directly. There might be impacts from deploying truck weight technologies to them, however. The concerns for the non-road users group would seem to be those related to energy conservation and air pollution.

When trucks are waiting at weigh stations, additional gas is wasted. If the wait can be avoided, energy could be conserved. In this research, however, we argue that the benefit from deploying new weight technologies in energy conservation is very limited. For example, in 1993, 22.8% of the energy consumed in the US was used in transportation (U. S. Department of Energy, 1994). Heavier types of trucks consumed only 15.4% of this energy (Oak Ridge National Laboratory, 1995); i.e., heavy trucks consumed only 3.5% of the total energy consumed in the US. (In that study, heavier trucks are defined as all the truck types except for two-axle and four-tire trucks.) Now, let us assume an extremely large percentage of energy savings that could be obtained from the implementation of the new weight enforcement technologies. Specifically, we assume that if new weight enforcement technologies are implemented at all weigh station sites around the country, 10% of the energy consumed by the trucks could be saved. Note that, as mentioned in Section 1.1, the percentage of trucks weighed in Ohio is only approximately 2%. The assumed 10% fuel saving would only conserve less than 0.35% of the total energy consumed in the U. S. Furthermore, in this research, we are evaluating a single weigh station operation. The energy saved from the implementation of new technologies will, therefore, be far less than the estimated 0.35%. If there were only 100 weigh station sites in the country (an extremely conservative assumption)--i.e., only two weight stations in
each state—the implementation of new technologies in one weigh station site would only help conserve 0.0035% of the total annual energy consumption. Even this conservative number is insignificant, and we shall not consider energy savings for the implementation of new weight enforcement technologies.

For air pollution issues, if unnecessary gasoline consumption can be prevented, then some emissions can also be reduced. Emissions would be directly related to the burning of fuel, however. The conservative arguments above showed that total fuel burning reduction is insignificant. Therefore, reduction in emissions would also be insignificant.

We conclude that implementing new weight technology would have little impact on the general public. Therefore, we consider the weigh technology evaluation problem without explicitly considering the non-road users interest group.

From the discussion above, we approximate the weight technology evaluation problem by including only the government agencies and the private motor carriers as the interest groups in this study.

2.4 Attributes of the Interest Groups

Attributes (or criteria) are used to describe the objectives of the interest groups. In this evaluation, we use the concerns of the two interest groups—government agencies and motor carriers—to form attributes. We discuss the attributes of the government agencies in Section 2.4.1. The attribute of the private motor carriers are discussed in Section 2.4.2.
2.4.1 Attributes of the Government Agencies

In our evaluation, we choose to analyze the impacts of different weight enforcement systems for a typical year after the implementation of the technologies. This formulation avoids assumptions about growth rates in truck volume. However, we shall investigate the effect of truck volume in the typical year in our sensitivity analysis.

We define the first attribute of the government agencies as the revenue from fines in a typical year. We let notation $Y_1$ represent the attribute of revenue from fines in a typical year. Then revenue from fines in a typical year ($Y_1$) can be expressed as:

$$Y_1 = \sum_{i=1}^{N} f(i)$$

(2-1a)

where $f(i)$ is the fine collected from truck $i$ and $N$ is the total number of trucks passing the weigh station in the year.

We define the second attribute of the government agencies as the weight enforcement system cost in a typical year. We let $Y_2$ represent the attribute of weight enforcement system cost in a typical year.

In this study, the system costs we considered are those costs associated with updating a traditional static weigh station to other kinds of systems. The weight enforcement systems costs we considered in this evaluation are those related to the upgrading. Since we are considering one year, these costs should be distributed into annual costs by using proper interest discount rates.

In the truck weight enforcement technologies evaluation, the weigh system costs can be classified into three categories: the initial capital costs, the annual maintenance costs, and the weigh station operation costs. The initial capital costs include equipment purchasing.
and installation costs and weigh station remodeling costs. The remodeling costs are the costs needed to modify the existing facility of a weigh station to meet the required standards of a new weigh system operation (Michigan DOT, 1992). The annual maintenance costs are mainly the labor required for weigh scale calibration. The weigh station operation costs are mainly the salaries of the weigh station personnel and miscellaneous costs (Castle Rock Consultant, 1994).

For this study, we make the following assumptions in estimating the initial capital costs. First, we assume that the weigh station has enough space for additional by-pass lanes and ramps (Castle Rock Consultant, 1994). Therefore, costs to purchase extra land are not included in the remodeling costs. Second, we assume that the weigh station facility has a life span of twenty years and that the salvage value is zero at the end of the twentieth year. Therefore, the initial remodeling costs have to be distributed over twenty years using proper interest discount rates. Third, we assume that the life span of the WIM scales is five years (Castle Rock Consultant, 1994). Therefore, the system purchase and installation costs have to be distributed over five years with proper interest discount rates. Finally, we assume that the existing static systems do not have to be replaced at the time of upgrading and that they still can serve for the life time of our project. In our case, it is 20 years. In recent weigh station upgrading projects, the cost of replacing the existing static scales were not considered explicitly (Castle Rock Consultant, 1994). Like these studies, then, we ignore the costs of the static weight scale purchase and installation costs.

Weigh station operation costs include weigh station personnel costs and the miscellaneous costs. For personnel costs, most state governments prefer to keep their weigh station personnel the same in their recent efforts to upgrade weight enforcement capability (JHK & Associates, 1992). We also assume that the level of personnel remains
constant when upgrading the weigh systems. That is, the personnel costs will be the same for all alternatives.

The miscellaneous costs of the weigh station operation includes electricity costs, communication costs, and other spending. In this study, we assume that the miscellaneous costs are roughly the same for all types of weigh systems.

The weigh station operation costs are the sum of personnel costs and miscellaneous costs. Since these costs are the same for all alternatives, in this study, we do not include the weigh station operation costs in the weigh system costs.

Therefore, in this research, the system cost is the sum of station remodeling cost, equipment purchase and installation cost, and annual maintenance cost. We have:

\[ Y_2 = RMC + EPIC + AMC \]  

where RMC is the discounted yearly weigh station remodeling costs, EPIC is the discounted yearly equipment purchasing and installation costs, and AMC is the annual maintenance costs.

We define the third attribute of the government agencies as the number of ESAL's produced by trucks downstream of the weigh station in the year. We use the concept of equivalent single-axle load (ESAL) to measure the pavement damage. This concept measures pavement deterioration in units equivalent to pavement damage caused by a standard axle load. An ESAL is defined as an 18,000-pound single axle load (AASHTO, 1986). We let notation \( Y_3 \) represent the attribute of pavement damage in ESAL in a typical year.

We use ESAL's to measure pavement damage for two reasons. First, ESAL is a widely accepted concept in measuring pavement damage. Since the 1950s, ESAL's have been used by pavement engineers in pavement design and in estimating pavement wear.
The second reason for using ESAL's is the accessibility of data needed to the model. The ESAL method is based on axle loadings. We had access to truck weight data collected by the Ohio Department of Transportation. These truck weight data are truck axle loadings recorded in the Federal Highway Administration standard format (FHWA, 1990).

Rigid type and flexible type of pavements have different characteristics. The same truck will cause different pavement wear to these two kind of pavement. To simplify the evaluation problem in this research, we assume that the highway pavements considered are flexible pavements with a standard design.

Therefore, the attribute relating to pavement damage—specifically, the number of ESAL's in the year—can be expressed as:

\[
Y_3 = \sum_{i=1}^{N} \sum_{j=1}^{k} (AGPD(i,j)) (2-1c)
\]

where AGPD(i, j) is the number of ESAL's imposed by the jth axle group of truck i, k is the number of axles groups for truck i, and N is the total number of trucks passing the weigh station in the year.

We define the fourth attribute of the government agencies as the number of bridge formula violation truck trips in a typical year. The major impact of heavy trucks to bridges are bridge fatigue (Moses, 1992). Fatigue concerns the cumulative damage caused by repetitive load passages, which can cause cracks or rupture of key elements in the structure. To measure bridge fatigue, in this study, we use the number of bridge formula violation truck trips to measure bridge damage \(Y_4\). Therefore, we have:

\[
Y_4 = \sum_{i=1}^{N} BVTT(i) (2-1d)
\]
where BVTT(i) is a 0/1 variable— if truck i is a bridge formula violator that has not been caught by the weigh station enforcement system, BVTT(i)=1; otherwise, BVTT(i)=0—and N is the number of trucks passing the weigh station in the year.

2.4.2 Attributes of the Private Motor Carriers

We also consider the attribute levels for the motor carriers in a typical year. With this approach, we face difficulties in comparing the attribute levels under different truck volume conditions, however. For example, under the truck volume condition of 100 trucks per year, if we deploy weight enforcement System A, the total collected overweight fines may be $100. Under the truck volume condition of 10 trucks per year, if we deploy weight enforcement System B, the total collected overweight fines might only be $20. Based only on fines, the private motor carriers should prefer System B to System A. But in reality, System B collects a higher average fine from a single truck than System A does, and the higher total fines associates with System A is due to increased volume, which would be considered beneficial to the trucking industry.

To account for different number of trucks, we consider the attributes for a single truck. In this study, we use a random truck concept to predict the costs and benefits to the private motor carriers. That is, we predict the impact of deploying different weight enforcement systems to a random truck that arrives at a weigh station. By random truck, we mean a truck chosen at random from the population of trucks passing the weigh station.
We define the first attribute of the private motor carriers as the fines for a random truck. We let \( Y_5 \) represent the attribute of the fines in dollars for a random truck. Therefore, we have:

\[
Y_5 = f(i)
\]  
(2-1e)

where \( f(i) \) is the fine collected from random truck \( i \).

We define the second attribute of the private motor carriers as the number of offloadings for a random truck. When an overweight truck been caught, it is required to offload some of its goods to become legally laden. In the case that an overweight truck escapes from the weigh enforcement system, it can continue its trip without being offloaded. Therefore, a random truck is either offloaded or not offloaded. We let \( Y_6 \) represent the attribute that indicates whether a random truck is offloaded. Therefore, we have:

\[
Y_6 = \text{OFFL}(i)
\]  
(2-1f)

where \( \text{OFFL}(i) \) is a 0/1 variable— if random truck \( i \) is offloaded, \( \text{OFFL}(i)=1 \); otherwise, \( \text{OFFL}(i)=0 \).

We define the third attribute of the private motor carriers as the time delay for a random truck. We let notation \( Y_7 \) represent the attribute of the time delay for a random truck.

We define truck time delays as the time that a truck spends at the weigh station. The time delays include the screening time of the weigh system (if any), the waiting time in the queue, and the weighing time at the weight enforcement scale. That is, the time delay of a truck is equal to the time when the truck leaves the weigh station minus the time when the truck arrives at the weigh station. The time delays we defined here, however, do not include the time needed for overweight trucks to rectify their weight problems. This time
is included in the offloading attribute as captured by its scaling parameter (see Chapter 5). We have:

\[ Y_\gamma = t(i) \]  \hspace{1cm} (2.1g)

where \( t(i) \) is the time delays for random truck \( i \). We summarize the attributes of the government agencies and the private motor carriers in Table 2.

Finally, we let the criteria or attribute vector be \( \mathbf{Y} \). Then, the criteria or attribute vector is:

\[ \mathbf{Y} = \begin{bmatrix} (Y_1, Y_2, Y_3, Y_4), (Y_5, Y_6, Y_7) \end{bmatrix} \]  \hspace{1cm} (2-2)

where the attributes of the government agencies are:

- \( Y_1 \): annual revenue from fines,
- \( Y_2 \): annualized weigh enforcement system cost,
- \( Y_3 \): annual number of ESAL’s downstream of the weigh station, and
- \( Y_4 \): annual number of bridge formula violation truck trips downstream of the weigh station;

The attributes of the private motor carriers are:

- \( Y_5 \): fine assessed to a random truck,
- \( Y_6 \): binary variable indicating whether a random truck is offloaded, and
- \( Y_7 \): truck time delay for a random truck.
Table 1: List of Alternatives in Truck Weight Enforcement Technologies Evaluation

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>X₁: STATIC-ONLY</td>
<td>Static weigh scale used alone for enforcement</td>
</tr>
<tr>
<td>X₂: HSWIM-ONLY</td>
<td>High-speed WIM scale used alone for enforcement</td>
</tr>
<tr>
<td>X₃: MSWIM-ONLY</td>
<td>Medium-Speed WIM scale used alone for enforcement</td>
</tr>
<tr>
<td>X₄: STATIC-with-HSWIM</td>
<td>Static scale used for enforcement with High-speed WIM used as a screening device</td>
</tr>
<tr>
<td>X₅: STATIC-with-MSWIM</td>
<td>Static scale used for enforcement with Medium-speed WIM used as a screening device</td>
</tr>
</tbody>
</table>

Table 2: List of Attributes in Truck Weight Enforcement Technologies Evaluation

<table>
<thead>
<tr>
<th>ATTRIBUTES</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Government Agencies</strong></td>
<td></td>
</tr>
<tr>
<td>Y₁: Annual revenue from fines</td>
<td>Dollars</td>
</tr>
<tr>
<td>Y₂: Annualized weight enforcement system cost</td>
<td>Dollars</td>
</tr>
<tr>
<td>Y₃: Annual number of ESAL's downstream the weight station</td>
<td>ESAL's</td>
</tr>
<tr>
<td>Y₄: Annual number of bridge formula violation truck trips downstream of the weigh station</td>
<td>Number of Trips</td>
</tr>
<tr>
<td><strong>Private Motor Carriers</strong></td>
<td></td>
</tr>
<tr>
<td>Y₅: Fine assessed to a random truck</td>
<td>Dollars</td>
</tr>
<tr>
<td>Y₆: Binary variable indicating whether a random truck is offloaded</td>
<td>Binary values (0/1)</td>
</tr>
<tr>
<td>Y₇: Time delay for a random truck</td>
<td>Minutes</td>
</tr>
</tbody>
</table>
Figure 1: Typical Layout of a STATIC-ONLY Weigh Station
(Source: Downs, 1981)
Figure 2: Typical Layout of a HSWIM-ONLY Weigh Station
(Source: Downs, 1981)
Figure 3: Typical Layout of a MSWIM-ONLY Weigh Station
(Author's adaptation of source: Downs, 1981)
Figure 4: Typical Layout of a STATIC-with-HSWIM Weigh Station
(Author's adaptation of source: Downs, 1981)
Figure 5: Typical Layout of a STATIC-with-MSWIM Weigh Station
(Source: Downs, 1981)
CHAPTER III

Predicting the Attribute Levels

In Chapter 2 we defined the interest groups and their attributes. The next step in the truck weight enforcement technology evaluation problem is to predict the attribute levels. In this chapter we discuss how to predict these attribute levels. For some attribute levels, the predictions can be made based on existing data. For others, however, such data are not available. We used a computer simulation model to predict the levels of those attributes which we cannot predict based on existing data.

We have arranged this chapter into two parts. The attributes whose levels can be obtained from existing data will be described in Section 3.1. Weigh system cost ($Y_1$) is the only attribute that can be predicted with the existing data. Therefore, in Section 3.1 we only discuss the weigh system cost attribute.

The attributes whose levels cannot be predicted based on the existing data will be described in Section 3.2. We used a simulation model to predict the levels of these attributes. Section 3.2.1 addresses the operational characteristics of the weigh station. Section 3.2.2 addresses the characteristics of the trucks. In Section 3.2.3, the weigh station computer simulation program is presented. Finally, in Section 3.2.4, we discuss the validation of the simulation model.
3.1 Predicting Attributes Levels from Existing Data

The weigh system cost attribute \( (Y_1) \) is the only one that can be estimated from the existing data. In this section we discuss how to predict weigh system costs from the existing data. As defined in Chapter 2, we model weigh system cost as the sum of weigh station remodeling costs (RMC), equipment purchase and installation costs (EPIC), and maintenance costs (AMC). We first discuss the weigh station remodeling costs. Next, we discuss the equipment purchase and installation costs. Then, we discuss the maintenance costs. Finally, we calculate the weigh system costs for different weigh systems by summing these three costs.

3.1.1 Weigh Station Remodeling Costs (RMC)

The weigh station remodeling costs, as defined previously, are the costs spent to modify a weigh station to meet the requirements for different weigh station operations. Since we are evaluating the upgrade of a station from a static system in our study, a STATIC-ONLY system needs no modification or remodeling. Therefore, the weigh station remodeling cost is zero.

The HSWIM-ONLY system and MSWIM-ONLY system are still single-scale enforcement type weigh stations. We assume that the existing facility does not need major modifications for upgrading (Downs, 1981). In this evaluation, we assume the remodeling cost for the HSWIM-ONLY and MSWIM-ONLY to be zero.

The STATIC-with-HSWIM system and STATIC-with-MSWIM system are dual-scale types of weigh systems. Facility modifications are always needed when adding a screening scale to the existing systems (Michigan DOT, 1992). The Michigan Department of
Transportation estimated that the remodeling cost for most of the port-of-entry sites were $458,000. In this research, we use $458,000 as the remodeling costs for the STATIC-with-HSWIM system and STATIC-with-MSWIM system.

In this research, we assumed that the life span of the facility is twenty years. In addition, the final salvage value is also assumed to be zero. We must distribute the remodeling cost over twenty years with a proper discount rate. In this study, we use an interest rate of five percent. Discounting $458,000 at 5% over twenty years leads to $36,732/year. Therefore, the remodeling costs for a typical year are $0, $0, $0, $36,732 and $36,732 for STATIC-ONLY, HSWIM-ONLY, MSWIM-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems, respectively.

### 3.1.2 Equipment Purchase and Installation Costs (EPIC)

The equipment purchase and installation costs refer to all the cost items associated with the purchase and installation of a new weigh scale. In our study, a STATIC-ONLY system needs no new weigh-in-motion scale. Therefore, the equipment purchase and installation cost for a STATIC-ONLY system is zero.

For the rest of the four systems, we need to install a weigh-in-motion scale to the existing system. Since weigh-in-motion systems can be used at different truck speeds to obtain different accuracies (Izadmehr and Lee, 1987), we assume that the same weigh-in-motion device is used as the weight enforcement scale for a HSWIM-ONLY system and a MSWIM-ONLY system and as the screening device for a STATIC-with-HSWIM system and a STATIC-with-MSWIM system. As a result, the system purchase and installation
costs are the same for HSWIM, MSWIM, STATIC-with-HSWIM, and STATIC-with-MSWIM systems.

In this evaluation, we estimate the equipment purchase and installation cost as $75,000 (Michigan DOT, 1992). We assumed that the life span of the equipment is five years (Castle Rock Consultant, 1994). We also assumed the final salvage value to be zero. We distribute the equipment purchase and installation costs over five years with the 5% discount rate used above. Note that the static scales are already existing before our upgrade for STATIC-with-HSWIM and STATIC-with-MSWIM systems. We assume that they can still serve for another 20 years (see Chapter 2). In this research the equipment purchase and installation costs of static scales for these two weight enforcement systems should be 0. Therefore, the equipment purchase and installation cost for a typical year are $0, $13,575, $13,575, $13,575, and $13,575 for STATIC-ONLY, HSWIM-ONLY, MSWIM-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems, respectively.

3.1.3 Annual Maintenance Costs (AMC)

Weigh system maintenance costs are mainly attributable to scale calibration costs (Castle Rock Consultant, 1994). For our study, we assume that the maintenance costs are roughly the same for weigh-in-motion scales and static scales. Under this assumption, the maintenance costs for those weigh systems which have an enforcement scale and a screening scale are twice as much as those which only have one scale.

The maintenance costs for a scale is estimated at approximately $20,000 per year (Castle Rock Consultant, 1994). Therefore, the maintenance costs in a typical year are
$20,000, $20,000, $20,000, $40,000, and $40,000 for STATIC-ONLY, HSWIM-ONLY, MSWIM-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems, respectively.

Finally, we predict the weigh system cost by summing the remodeling cost, equipment purchase and installation costs, and maintenance costs. The weigh system costs in a typical year are, therefore, $20,000, $33,375, $33,375, $90,307, and $90,307 for STATIC-ONLY, HSWIM-ONLY, MSWIM-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems, respectively. We summarize the costs of the various weight enforcement systems in Table 3.

3.2 Predicting Attributes Levels with Simulation Model

Those attributes which cannot be estimated with data from the literature are discussed in this section. These attributes are the revenues from fines in a typical year ($Y_1$), number of ESAL's in a typical year ($Y_3$), number of bridge formula violation truck trips in a typical year ($Y_4$), fine for a random truck ($Y_5$), offloading indicator for a random truck ($Y_6$), and time delay to a random truck ($Y_7$). We used a computer simulation to predict the attribute levels for these six attributes.

Operations at a weigh station can be modeled as a typical stochastic process where trucks arrive at random and are serviced at the station with random service times. We believe simulation models are able to capture the characteristics of weight station operations better than queuing models for several reasons. First, the truck arrival process is non-stationary; i.e., the number of trucks which arrive at the station varies over time. In addition, the weigh station does not operate 24 hours a day. Finally, trucks are not
identical—they have different weight characteristics and length. Therefore, we used a computer simulation to predict the attribute levels which cannot be predicted from the existing data in this study.

To develop our computer simulation model, we define a weigh station as the system and trucks as entities in the system. The weigh station characteristics are addressed in Section 3.2.1. The trucks' (entities of the system) data are presented in Section 3.2.2. In Section 3.2.3, we describe the computer simulation program. Finally, in Section 3.2.4, we present a validation of the simulation.

3.2.1 Weigh Station Characteristics

In this research, we define our weigh station as a single independent weigh-station used to enforce weight regulations, even though other useful procedures are conducted at the station. For example, the states can check the required credentials, such as fuel tax decals, operating authority, commercial driver's license, special weight and size permits. The states can also use the weigh station to enforce safety related regulations, such as those pertained to driver's driving hours, alcohol and drug consumption, and vehicle safety inspections (Cambridge Systematics, 1993). In our study, we ignore tasks other than weight enforcement. These tasks might eventually be taken care of by other advanced means (JHK & Associates, 1992; Castle Rock Consultant, 1994).

In our study, the weigh station is assumed to be open from 8:30 a.m. to 4:30 p.m. on weekdays only. When a weigh station is closed, a truck can bypass the station without being weighed. In the case that a weigh station is open, theoretically every truck would be weighed. However, in high truck volume conditions, this is not the case. In our study, the
waiting lane is assumed to be 500 ft. If it is full, the arriving trucks are assumed to by-pass the station without being weighed. When considering alternatives that use a screening device ($X_4$ and $X_5$), we assumed that only those trucks that "fail the screening" are required to go into the weigh station and be weighed.

In this study we use the federal weight regulations (Ohio DOT, 1992). These include a total gross weight limit on a vehicle of 80,000 lb., a single axle load limit of 20,000 lb., a tandem axle load limit of 34,000 lb., and a bridge formula that specifies the maximum allowable weight on any group of consecutive axles. The bridge formula can be found in Appendix-A. In this study, the penalties for violating the weight regulations include fines and offloading penalties. Fines are calculated from the Ohio Motor Vehicle Law (Ohio Department of Highway Safety, 1988). Offloading is assumed to be required for every truck which violates the weight regulations.

Weigh scale accuracies and weigh system service time are two important weigh system characteristics. We discuss them in the following.

3.2.1.1 Weigh Scale Accuracies

There are two measurement accuracies which have to be addressed: truck axle spacings and truck weights. In this research, we assume that the same type of trucks have the same axle spacings. Once the truck type is known, we, there, know its axle spacings. That is, we assume perfect spacing data can be obtained, and do not model this component in our model.
We explicitly model errors involved in weight measurements. We assume these measurement errors to be random. If we let WT be the true axle weight, then we model the measured weight MWT as:

\[ MWT = WT + \varepsilon \]  

(3-1)

where \( \varepsilon \) is a random measurement error.

In this evaluation, we use uniform distributions and percentages to model the weight measurement errors. Specifically, we use:

\[ \varepsilon = \text{Uniform}(-P*WT, P*WT). \]  

(3-2)

where WT is the true truck axle weight and P is the maximum factor of the scale measurement error. That is, the upper and lower bounds of the measurement errors are \( P*WT \) and \( -P*WT \), respectively, and the density function of \( \varepsilon \) is assumed to be uniform between these bounds.

Technical evaluations of WIM scale accuracies have shown that the maximum percentage of measurement errors for MSWIM scales and HSWIM scales are within 5% and 10% of the true weight, respectively (Arizona DOT, 1989; Izadmehr and Lee, 1987). In our study, we set the percentage errors P of the HSWIM scale and MSWIM scale as 10% and 5%, respectively. We assume that the measurement errors for static scales can obtain the true static weight. That is, the P value for static scales is 0%.

In addition, we must recognize the fact that errorless performance of measurement is unattainable for WIM scales. For example, the single axle load limit is 20,000 lb. for our study. Now assume that a truck has a true axle weight of 20,000 lb. If we use the HSWIM scale defined previously to weigh the axle, the measurement will be the true axle weight plus measurement error. Since a HSWIM scale is assumed to have a maximum percentage measurement error of ±10%, the measured axle weight could be as low as 18,000 lb. and
as high as 22,000 lb. In the case that the maximum measurement error occurs, the scale reading is 22,000 lb. However, the truck axle loading is legal. In order to be able to use the WIM scales in weight law enforcement, tolerances have to be established to define the range of errors for the WIM scales (Izadmehr and Lee, 1987).

In our study, we set the weight enforcement tolerance as the maximum error of the weight scales. A weigh station can penalize a truck only when the scale measured weight is over the legal limit plus the tolerance. That is, when we use HSWIM scales, the tolerance is set as 2,000 lb., 3,400 lb., and 8,000 lb. for single axle load, tandem axle load, and gross weight, respectively. When we use MSWIM scales, the tolerance is set at 1,000 lb., 1,700 lb., and 4,000 lb. for single axle load, tandem axle load, and gross weight, respectively. When we use static scales, since we assumed 0% of measurement error, the tolerance for single axle load, tandem axle load, and gross weight are all 0 lb.

In the case of using WIM scales as screening devices, they also can not perform perfectly. For example, assume that there is a single axle load just slightly over 20,000 lb. Since a HSWIM scale is assumed to have a maximum percentage measurement error of ±10%, the measured axle weight could be as low as 18,000 lb. and as high as 22,000 lb. That is, even if the reading of a single axle load is 18,000 lb., there is still a possibility that it might be overloaded.

In our study, we require all the trucks which have a possibility of violating the weight laws to be weighed statically. Therefore, in this study, we assume that every truck whose weight measurement is more than the legal limit minus the maximum scale measurement error to be weighed statically unless the waiting lane is full. That is, when we use HSWIM scales, any truck whose weight measurement is more than 18,000 lb., 30,600 lb., and 72,000 lb. for single axle load, tandem axle load, and gross weight, respectively, has to be
weighed statically. When we use MSWIM scales, any truck whose weight measurement is more than 19,000 lb., 32,300 lb., and 76,000 lb. for single axle load, tandem axle load, and gross weight, respectively, has to be weighed statically.

3.2.1.2 Weigh Station Service Time

Weigh station service time refers to the time of weighing a truck in our study. The service time for HSWIM scales are zero since they weigh the trucks at prevailing traffic speeds.

In the case of using a MSWIM scale, trucks are required to separate from mainline traffic and go through a by-pass lane with a speed of approximately 35 mph. For a typical weigh station, the total distance of deceleration lane plus weighing area plus acceleration lane is about 2,000 ft (Johnson, 1980). In this study we use 2,000 ft as the by-pass length. We model the time delay for the MSWIM scale as a deterministic value with the time difference of traveling at 55 mph and 35 mph. That will give us about 0.24 minutes.

For static scale service time, we use an Erlang (0.24, 2) distribution to describe the station service time (Spiegel, 1995).

3.2.2 Truck Characteristics

Trucks are entities that go through the weigh station (system) in our study. We address their characteristics in this section. The truck characteristic include truck arrival, truck traffic composition, truck weight and truck axle spacing data. To understand these truck characteristics, we analyzed a set of data obtained from the Ohio Department of Transportation (ODOT). We call this the ODOT data set in the rest of this study.
The ODOT data set we acquired was based on weigh-in-motion data collected on I-70 east-bound, just east of Columbus, Ohio. We studied 24-hour truck data on two days: July 25, 1993 (Wednesday) and July 22, 1993 (Sunday). After our analysis, we made several conclusions. First, the Wednesday data showed much more truck traffic than the Sunday data. Second, the hourly arrival rates in the Wednesday data had a greater variation than those in the Sunday data. Third, the percentages of each truck type in the traffic were not very different on these two days. Finally, the truck weight characteristics were different on these two days. Specifically, trucks are slightly heavier on average in the Sunday data than in the Wednesday data. We attach the hourly truck arrival data and truck weight data of the ODOT data set in Appendix-A and Appendix-B.

Based on the ODOT data set, we modeled the characteristics of the truck traffic. These include truck arrival characteristics, truck traffic composition characteristics, truck weight characteristics, and truck length and spacing data. They are detailed in the following.

3.2.2.1 Truck Arrival Characteristics

We model the truck inter-arrival time as an exponential probability distribution. That is, we assume that the times between successive truck arrivals are exponential and independent. The exponential distribution has only one parameter-- the mean arrival rate. In our study, the mean arrival rates depend on the time of the day and the day of the week. In this way, the truck arrival is a non-homogeneous (non-stationary) Poisson process.

As a first cut, we assume that every weekday has the same truck arrival pattern. We, therefore, model the truck arrival rates in three categories to represent the variation in days of the week: weekdays, Saturdays, and Sundays.
After observing the truck hourly arrival rates in the ODOT data set, we use simplified patterns to model the mean truck arrival rates. For weekdays, the hourly arrival rates had extreme rates during the time periods of 2:00-3:00, 10:00-12:00, 18:00-19:00, and 19:00-20:00 in the ODOT data set. Here the extreme rates we refer to are those hourly truck arrival rates which differ strongly from those of their neighboring time periods. We use these rates as our mean arrival rates for the corresponding time periods in our study. Between these time periods, the hourly arrival rates decreased or increased gradually in the ODOT data set. To model this, we linearly interpolate the mean arrival rates between those extreme periods.

For Sundays, the hourly arrival rates had extreme rates during the time periods of 0:00-8:00 and 12:00-24:00 in the ODOT data set. Within each of these two time periods, the hourly arrival rates were roughly the same. Therefore, we model the mean arrival rates in each period as the average hourly arrival rate of that time period from the ODOT data set. The truck hourly arrival rates during the period of 8:00-12:00 increased gradually in the ODOT data set. In this research, the mean arrival rates during this period are interpolated linearly with the two extreme rates.

We model Saturdays as a transition period between weekdays and Sundays. For the mean truck arrival rates on Saturdays, we interpolated linearly between the mean arrival rate at the end of weekdays and the mean arrival rate at the beginning of Sundays. The modeled truck mean arrival rates of weekdays, Saturdays, and Sundays are shown in Figure 6.
3.2.2.2 Truck Traffic Composition

The truck traffic composition refers to the percentage of each type of trucks in the total truck traffic. In truck weight data collection, trucks can be classified into thirteen categories (FHWA, 1990). According to the ODOT data set, there are seven most common truck categories. These are listed and described in Table 4.

In the ODOT data set, the seven most common categories of trucks contribute more than 98% of the traffic. In this study, we only included these seven most common categories. To determine the percentages of each truck category, we also used the ODOT data. In addition, since the percentages of each categories of trucks are not very different on Wednesdays and Sundays in the ODOT data set (see above), we used the same traffic composition for weekdays and weekends. The percentage of each type of truck is shown in Table 5.

3.2.2.3 Truck Weight and Axle Spacing Characteristics

In this study, we model a truck’s gross weight first and then distribute the gross weight to its axle groups. As a first cut, we model the truck gross weights as triangular distributions. The gross weight triangular distributions have three parameters—minimum weight, mode weight, and maximum weight—which determine the triangular distributions. For our study, we estimate the parameters of the triangular distribution from the ODOT data set. In addition, we obtained estimated empty truck vehicle weight data from an interview with an official from the Ohio Department of Transportation. A gross weight triangular distribution is illustrated in Figure 7. The parameters of the truck gross weights are listed in Table 6. Percentage of overweight trucks could depend on the effectiveness of the
weight enforcement system. We ignore this issue in this study, but it could be an interesting topic for future studies.

As shown in Table 6, the empty truck vehicle weights are greater than the weights corresponding to the minimum of the triangular distributions for all truck categories. That is, when trucks are generated by our simulations with the truck gross weight triangular distributions, it is possible that their gross weights may be lower than their empty vehicle weights. To avoid this problem, we assume that a truck's gross weight equals its empty vehicle weight when the simulation generated truck gross weight is lower than its empty vehicle weight.

The next step in modeling truck weight characteristics is to distribute the gross weights to the axle groups of the trucks. To achieve this, we use a set of uniform distributions to describe the percentages of gross weight on the axle groups. In our formulation, each uniform distribution has two parameters: the maximum percentage of gross weight and the minimum percentage of gross weight. In addition, the total percentages of the weights across axle groups must sum to 100%. Therefore, the percentage of the last axle group is the difference of 100% and the sum of the percentages of the previous axle groups. If we let $PW(i)$ be the percentage of gross weight on the $i$th axle group for a truck category which has $k$ axle groups, then the percentage of gross weight on each axle group can be expressed as:

$$PW(i) = \text{Uniform}(\text{MINP}(i), \text{MAXP}(i)), i=1,2, ..., k-1.$$  
$$PW(k) = 1 - \sum_{i=1}^{k-1} PW(i)$$  \hspace{1cm} (3-3)

where $\text{MINP}(i)$'s and $\text{MAXP}(i)$'s are the lower bounds and the upper bounds of the uniform distributions, respectively.
We estimate the parameters of the uniform distributions from the ODOT data set. As a first cut, the maximum percentage is set as the mean calculated from the data set plus one standard deviation of the data set. The minimum percentage is set as the mean calculated from the data set minus one standard deviation of the data set. The parameters of these uniform distributions are summarized in Table 7.

Since we assumed trucks in the same category are all the same, the percentages of gross weight distributed on each axle groups of empty trucks should be the same for trucks of the same category. In this study, the percentage of gross weight on each axle group of an empty truck are modeled as deterministic and estimated with the means calculated from the empty trucks from the ODOT data set. The percentages of empty truck gross weight distributed on each axle groups are summarized in Table 8.

Finally, we assume that all trucks of the same type have the same axle spacings. In this study, we define the first axle spacing as the distance between the first axle and the second; the second axle spacing as the distance between the second axle and the third, and so forth. For our study, we use the average axle spacing data calculated from the ODOT data set. These spacings are summarized in Table 9.

3.2.3 Computer Simulation Program

We used discrete-event simulation to model our weigh station operation. That is, the weigh station simulation evolves over time, and its variables change only at a countable number of points in time. These points in time are the ones at which an event occurs (Law and Kelton, 1982; Pritsker, 1986). Here an event is defined to be an instantaneous
occurrence which may change the state of a system; a change would occur when a truck arrives at the station, for example, or when the station finishes weighing a truck.

We developed our computer simulation codes in SLAM II (Pritsker, 1986). To use SLAM II, the logic of the weigh station simulation was first modeled in a network representation (Pritsker, 1986). Here, the network representation is a pictorial representation of the weigh station operation process. The network representation of the weigh station operation is presented in Figure 8. We discuss the network representation in detail later in this section. Then we translated the network representation into SLAM II codes. In addition, some special calculations were coded in FORTRAN functions and subroutines to support the simulation. We list the functions and subroutines in Appendix-D.

We define the weigh station operation in our study as follows. When the weigh station is closed, trucks by-pass the weigh station without being checked. On the other hand, if the weigh station is open, a truck must go through the screening device. In the case that a truck "fails the screening", it has to wait in the line to be weighed by a static scale; otherwise, it by-passes the weigh station. In the case that a weigh station is not equipped with a screening device, trucks are directed to the end of the waiting line to be weighed by the weigh scale. If the waiting lane is full, trucks can by-pass the weigh station without being weighed. When a truck is weighed, if it is legally laden, it can also leave the station and continue its trip. On the other hand, if an overweight truck is caught, it will be fined and asked to rectify its weight problem—i.e., to offload the cargo. Only after being fined and offloaded, can these truck continue their trips.

We model the weigh station operation in a network representation. In the network representation, we declare a screening scale as RESOURCE-1 and a weigh scale as
RESOURCE-2. A RESOURCE is a mechanism in the computer simulation to serve the entities.

In the beginning of the simulation, trucks are generated to arrive at the station according to the time of the day and the day of the week. EVENT-1 assigns a truck its eight characteristics: arrival time, truck classification category, weight on the 1st axle-group, weight on the 2nd axle-group, weight on the 3rd axle-group, weight on the 4th axle-group, weight on the 5th axle-group, and an overweight indicator. Here the overweight indicator is a 0/1 parameter which indicates whether a truck is overweight—namely, 1 is overweight and 0 is legally laden. We summarize these truck attributes in Table 10.

EVENT-2 controls the open/closed status of the weigh station. If the station is closed, trucks skip the station screening and weighing processes. If the station is open, the truck has to wait for screening. When RESOURCE-1 (the screening scale) is available, the first truck in the waiting queue is removed from the queue and screened. The screening process is defined as ACTIVITY-1. The screen time depends on the type of screening device. After finishing the screening, the truck is removed from RESOURCE-1 and the screening scale is freed so that it can screen the next truck in the queue. In the case that the screening device is a HSWIM on the mainline, there would be no queue. That is, a truck is screened at the time of its arrival. Our formulation still works for this situation.

In the cases that the weigh system is not equipped with a screening device, trucks skip the screening process—i.e., ACTIVITY 1— and are directed to join the second queue and wait for the weight enforcement scale—i.e., they are directed to EVENT 3.

When a truck is screened as legally laden, it skips the weighing process. On the other hand, if a truck is screened as overweight, it is usually put in the end of the second queue.
and weighed. Whether the truck will be put in the queue depends on if the waiting lane is full. EVENT-3 is used to check if the waiting lane is at its capacity. In the case that the waiting lane is full, the truck skips the weigh process. Otherwise, the truck is put at the end of the second waiting queue and will be weighed by the weight enforcement scale. At the same time, EVENT-4 adds the truck length to the queue.

When RESOURCE-2 (the weight enforcement scale) is available, the first truck in the second queue will be removed from the queue and weighed. The weighing process is defined as ACTIVITY-2. The weighing time depends on the type of scale. After finishing the weighing, the truck is removed from the scale and the weight enforcement scale is freed so that the next truck can be weighed. At the same time, EVENT-5 subtracts the truck length from the queue.

In the case that a truck is weighed as overweight, it will be fined and offloaded. EVENT-6 assesses the fines with the Ohio State Motor Vehicle Laws (Ohio Department of Highway Safety, 1988). EVENT-6 also changes the offloading indicator of the truck to "1" and changes the overweight indicator of the truck to "0". To estimate the number of ESAL's after offloading, we assume one third of the truck weight is transferred to another two-axle truck. In this way, we are sure that an offloaded truck is legally laden. On the other hand, if a truck is weighed as legally laden, no fines or offloading will be imposed to it.

At the end of the simulation, EVENT-7 records the results of the simulation. The results of all trucks (both by-pass or weighed) are recorded. Fines, number of ESAL's, number of bridge formula violation truck trips, and number of offloadings are cumulated in total sums. Also, the total number of trucks is also counted. As to truck time delay, it is calculated by using the time when the truck leaves the weigh station minus the time when
the truck arrives at the station. In addition, the truck time delays are collected in 2-minute
time intervals in the model. When a truck is leaving the system, the program increases the
cumulated number of trucks in the corresponding time delay interval by one. After their
data have been recorded, trucks leave the modeled system.

3.2.4 Model Validation

We perform two tasks to validate the computer simulation model in this study. First, we
compare the simulation generated data with the ODOT data set. The objective is to assure
that the truck volume and weight characteristics generated from the simulation model--
with the assumptions we made-- are not very different from the ODOT data set. Next, we
compare the simulation output with that of a queuing analysis to validate the simulation
process.

For the first task, we compare the ODOT data set with the average data from a
hundred simulation runs on daily truck traffic volumes, number of ESAL's, number of
weight violations, and fines collected. We conclude that the simulation data are close to
the ODOT data set. We attach the detailed comparison data in Appendix-E.

To validate the computer simulation process further, we compare the simulation results
with that of a queuing model. For the computer simulation, we assume that trucks arrive
according to a homogeneous Poisson process with a mean arrival rate of 1.5
trucks/minute. We also assume that the weigh station has a single scale and its service is
also a homogeneous Poisson process with a mean service rate of 5 trucks/minute. Finally,
we run a hundred simulations. The average queue length of the simulation output is 4.183
trucks.
In the queuing model, we let $\lambda$ be the truck arrival rate and $\mu$ be the weigh station service rate. Then we have

$$\lambda = 1.5 \text{ trucks/minute} \quad (3-4a)$$
$$\mu = 5 \text{ trucks/minute.} \quad (3-4b)$$

We calculate the expected queue length $E(Q)$ in a stationary state (Bhat, 1984):

$$E(Q) = \frac{\lambda}{\mu - \lambda} = \frac{1.5}{5 - 1.5} = 4.2 \text{ trucks.} \quad (3-5)$$

The result of our simulation is very close to that of the queuing model.
Table 3: Costs of Different Weight Enforcement Systems

<table>
<thead>
<tr>
<th>Weight Enforcement Systems</th>
<th>Equivalent Annual Equipment Purchasing and Installation Costs</th>
<th>Equivalent Annual Station Remodeling Costs</th>
<th>Annual Maintenance Costs</th>
<th>Total System Costs in a Typical Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>STATIC-ONLY</td>
<td>$0</td>
<td>$0</td>
<td>$20,000</td>
<td>$20,000</td>
</tr>
<tr>
<td>HSWIM-ONLY</td>
<td>$13,375</td>
<td>$0</td>
<td>$20,000</td>
<td>$33,375</td>
</tr>
<tr>
<td>MSWIM-ONLY</td>
<td>$13,375</td>
<td>$0</td>
<td>$20,000</td>
<td>$33,375</td>
</tr>
<tr>
<td>STATIC-with-HSWIM</td>
<td>$13,375</td>
<td>$36,732</td>
<td>$40,000</td>
<td>$90,107</td>
</tr>
<tr>
<td>STATIC-with-MSWIM</td>
<td>$13,375</td>
<td>$36,732</td>
<td>$40,000</td>
<td>$90,107</td>
</tr>
</tbody>
</table>

Table 4: Most Common FHWA Truck Types, Weight Data Collection Truck Categories, and Their Characteristics

<table>
<thead>
<tr>
<th>FHWA Truck Types</th>
<th>FHWA Truck Categories for Weight Data Collection</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TYPE-5</td>
<td>220000</td>
<td>2-axle single unit truck</td>
</tr>
<tr>
<td>TYPE-6</td>
<td>230000</td>
<td>3-axle single unit truck</td>
</tr>
<tr>
<td>TYPE-8</td>
<td>322000</td>
<td>2-axle tractor + 2-axle semitrailer</td>
</tr>
<tr>
<td>TYPE-9(A)</td>
<td>332000</td>
<td>3-axle tractor + 2-axle semitrailer</td>
</tr>
<tr>
<td>TYPE-10</td>
<td>333000</td>
<td>3-axle tractor + 3-axle semitrailer</td>
</tr>
<tr>
<td>TYPE-9</td>
<td>337000</td>
<td>3-axle tractor + 2-axle semitrailer with axles in a spread tandem configuration</td>
</tr>
<tr>
<td>TYPE-11</td>
<td>521200</td>
<td>2-axle tractor + 1-axle semitrailer + 2-axle full trailer</td>
</tr>
</tbody>
</table>
Table 5: Truck Percentage by Type in Traffic Stream of ODOT Data Set

<table>
<thead>
<tr>
<th>Categories Number</th>
<th>Truck Categories</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>220000</td>
<td>9.05%</td>
</tr>
<tr>
<td>2</td>
<td>230000</td>
<td>3.82%</td>
</tr>
<tr>
<td>3</td>
<td>322000</td>
<td>2.90%</td>
</tr>
<tr>
<td>4</td>
<td>332000</td>
<td>73.25%</td>
</tr>
<tr>
<td>5</td>
<td>333000</td>
<td>1.08%</td>
</tr>
<tr>
<td>6</td>
<td>337000</td>
<td>7.75%</td>
</tr>
<tr>
<td>7</td>
<td>521200</td>
<td>2.15%</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Table 6: Modeled Truck Gross Weights in Hundreds of Pounds by Truck Categories

<table>
<thead>
<tr>
<th>Truck Categories</th>
<th>Empty Weight</th>
<th>Weekends Gross Weight</th>
<th>Weekdays Gross Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>220000</td>
<td>100</td>
<td>TRIANG(80,160,360)</td>
<td>TRIANG(50,200,550)</td>
</tr>
<tr>
<td>230000</td>
<td>150</td>
<td>TRIANG(100,200,550)</td>
<td>TRIANG(100,300,600)</td>
</tr>
<tr>
<td>322000</td>
<td>250</td>
<td>TRIANG(150,350,650)</td>
<td>TRIANG(150,350,550)</td>
</tr>
<tr>
<td>332000</td>
<td>300</td>
<td>TRIANG(250,700,950)</td>
<td>TRIANG(200,750,925)</td>
</tr>
<tr>
<td>333000</td>
<td>350</td>
<td>TRIANG(400,750,850)</td>
<td>TRIANG(300,700,1000)</td>
</tr>
<tr>
<td>337000</td>
<td>350</td>
<td>TRIANG(300,750,950)</td>
<td>TRIANG(250,750,900)</td>
</tr>
<tr>
<td>521200</td>
<td>350</td>
<td>TRIANG(350,700,850)</td>
<td>TRIANG(300,600,850)</td>
</tr>
</tbody>
</table>

* The numbers listed are the three parameters of a triangular distribution: minimum, mode, and maximum.
Table 7: Minimum and Maximum (MIN(i), MAX(i)) Uniform Distributions Used to Model Percentages of Gross Weight Distributed on Axle Groups by Truck Categories

<table>
<thead>
<tr>
<th>Truck Categories</th>
<th>1st Axle Group</th>
<th>2nd Axle Group</th>
<th>3rd Axle Group</th>
<th>4th Axle Group</th>
<th>5th Axle Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>220000</td>
<td>(37.5%, 44.5%) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>230000</td>
<td>(35.5%, 46.5%) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>322000</td>
<td>(21.5%, 26.5%) (33.0%, 37.0%) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>332000</td>
<td>(16.5%, 21.5%) (41.0%, 45.0%) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>333000</td>
<td>(14.0%, 20.0%) (37.0%, 41.0%) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>337000</td>
<td>(16.5%, 19.5%) (39.5%, 42.5%) (20.5%, 23.5%) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>521200</td>
<td>(14.5%, 17.5%) (22.5%, 25.5%) (21.5%, 24.5%) (17.0%, 19.0%) *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* The last (kth) axle group percentage is calculated as: \[ PW(k) = 1 - \sum_{i=1}^{k-1} PW(i) \]

where \( PW(i) \) is the percentage of the ith axle group

Table 8: Percentages of Empty Truck Gross Weight Distributed on Axle Groups by Truck Categories

<table>
<thead>
<tr>
<th>Truck Categories</th>
<th>1st Axle Group</th>
<th>2nd Axle Group</th>
<th>3rd Axle Group</th>
<th>4th Axle Group</th>
<th>5th Axle Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>220000</td>
<td>51%</td>
<td>49%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>230000</td>
<td>49%</td>
<td>51%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>322000</td>
<td>28%</td>
<td>40%</td>
<td>32%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>332000</td>
<td>30%</td>
<td>42%</td>
<td>28%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>333000</td>
<td>21%</td>
<td>43%</td>
<td>36%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>337000</td>
<td>29%</td>
<td>43%</td>
<td>14%</td>
<td>14%</td>
<td></td>
</tr>
<tr>
<td>521200</td>
<td>28%</td>
<td>25%</td>
<td>16%</td>
<td>18%</td>
<td>13%</td>
</tr>
</tbody>
</table>
Table 9: Axle Spacing Data In Inches for Different Truck Categories

<table>
<thead>
<tr>
<th>Truck Categories</th>
<th>Vehicle Length</th>
<th>1st Axle Spacing</th>
<th>2nd Axle Spacing</th>
<th>3rd Axle Spacing</th>
<th>4th Axle Spacing</th>
<th>5th Axle Spacing</th>
</tr>
</thead>
<tbody>
<tr>
<td>220000</td>
<td>212</td>
<td>162</td>
<td>45</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>230000</td>
<td>247</td>
<td>152</td>
<td>45</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>322000</td>
<td>516</td>
<td>126</td>
<td>294</td>
<td>45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>332000</td>
<td>602</td>
<td>144</td>
<td>45</td>
<td>318</td>
<td>45</td>
<td></td>
</tr>
<tr>
<td>333000</td>
<td>578</td>
<td>146</td>
<td>45</td>
<td>251</td>
<td>42</td>
<td>41</td>
</tr>
<tr>
<td>337000</td>
<td>633</td>
<td>163</td>
<td>45</td>
<td>274</td>
<td>101</td>
<td></td>
</tr>
<tr>
<td>521200</td>
<td>696</td>
<td>122</td>
<td>209</td>
<td>95</td>
<td>219</td>
<td></td>
</tr>
</tbody>
</table>

Table 10: List of Truck Attributes in the Computer Simulation

<table>
<thead>
<tr>
<th>ATTRIBUTE NUMBER</th>
<th>TRUCK ATTRIBUTES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truck Attribute (1)</td>
<td>Arrival Time</td>
</tr>
<tr>
<td>Truck Attribute (2)</td>
<td>Truck Category</td>
</tr>
<tr>
<td>Truck Attribute (3)</td>
<td>The 1st Axle-Group Weight</td>
</tr>
<tr>
<td>Truck Attribute (4)</td>
<td>The 2nd Axle-Group Weight</td>
</tr>
<tr>
<td>Truck Attribute (5)</td>
<td>The 3rd Axle-Group Weight</td>
</tr>
<tr>
<td>Truck Attribute (6)</td>
<td>The 4th Axle-Group Weight</td>
</tr>
<tr>
<td>Truck Attribute (7)</td>
<td>The 5th Axle-Group Weight</td>
</tr>
<tr>
<td>Truck Attribute (8)</td>
<td>0/1 Indicator of Overweight/Legally Laden</td>
</tr>
<tr>
<td>Truck Attribute (9)</td>
<td>0/1 Indicator of Screening Result</td>
</tr>
</tbody>
</table>
Figure 6: Modeled Truck Arrival Rates on Weekdays, Saturdays, and Sundays
Figure 7: An illustration of Modeled Triangular Truck Gross Weight Distribution
EVENT 1: assign attributes to a truck
EVENT 2: check if the weigh station is open
EVENT 3: check if the waiting queue is full
EVENT 4: add truck length to the queue
EVENT 5: subtract truck length from the queue
EVENT 6: calculate fines and offload an overweight truck
EVENT 7: calculate ESAL

ACT 1: Screening
ACT 2: Weight Enforcement Check

Figure 8: Network Presentation of the Weight Station Simulation Model
CHAPTER IV

Formulating and Approximating the Multi-Attribute Disutility Function

In Chapter 3, we predicted the attribute levels. The next steps in the MAEU evaluation process are to assess the disutility function and to calculate the expected utility of the alternatives. In this chapter, we first formulate the multi-attribute disutility function in Section 4.1. The two components of the MAEU, the scaling parameters and the single-attribute disutility functions, are also discussed. Scaling parameters are those parameters which scale the single-attribute disutility functions into the multi-attribute utility scale. A single-attribute disutility function is a function which describes one's degree of satisfaction toward a specific attribute level. Finally, in Section 4.2, we discuss how to calculate the multi-attribute disutility of an alternative and how we approximate it for this study.

4.1 Formulating the Multi-Attribute Disutility Function

In MAEU evaluation, a multi-attribute disutility function is used to represent one's preferences toward a set of attributes. The mathematical expression of a multi-attribute disutility function consists of a series of individual single-attribute disutility functions and scaling parameters (Keeney, 1980). With this expression, the function indicates which combinations of attributes are considered better than others.
We use an additive form of disutility function because of simplicity. The conditions leading to this form of disutility function can be found in de Neufville (1990) and Keeney and Raiffa (1976), for example. Here the main point to be considered is that a change in attribute \( j \) does not affect how the single-attribute disutility for attribute \( i \) contributes to the overall disutility.

We defined attributes \( Y_1, Y_2, Y_3, \) and \( Y_4 \) as the government revenue generated from fines, weigh enforcement system costs, number of ESAL's, and number of bridge formula violation truck trips in Chapter 2. With the additive property, we can formulate the disutility function of the government agencies as:

\[
U_g = k_1 u_1 + k_2 u_2 + k_3 u_3 + k_4 u_4
\]

(4-1)

where \( u_1, u_2, u_3, \) and \( u_4 \), respectively, are the single-attribute disutilities associated with attributes at the levels \( Y_1 = y_1, Y_2 = y_2, Y_3 = y_3, \) and \( Y_4 = y_4 \), that is, \( u_1 = u_1(y_1), u_2 = u_2(y_2), u_3 = u_3(y_3), \) and \( u_4 = u_4(y_4) \). In (4-1) \( k_1, k_2, k_3, \) and \( k_4 \) are, respectively, the scaling parameters for the disutilities of revenue from fines, weigh system costs, number of ESAL’s, and number of bridge formula violation truck trips. In an additive formulation, the scaling parameters sum to one. Therefore, we can write:

\[
k_4 = 1 - k_1 - k_2 - k_3.
\]

(4-1b)

In Chapter 2, we defined the attributes \( Y_5, Y_6, \) and \( Y_7 \) as fine assessed to a random truck, offloading penalty for a random truck, and time delay for a random truck at the weigh station in Chapter 2. The additive disutility function form would allow us to formulate the disutility function of the private motor carriers as:

\[
U_c = k_5 u_5 + k_6 u_6 + k_7 u_7
\]

(4-2)

where \( u_5, u_6, \) and \( u_7 \) respectively, are the single-attribute utilities associated with attribute levels \( Y_5 = y_5, Y_6 = y_6, \) and \( Y_7 = y_7; \) that is, \( u_5 = u_5(y_5), u_6 = u_6(y_6), \) and \( u_7 = u_7(y_7) \). In (4-2)
$k_5$, $k_6$, and $k_7$ are, respectively, the scaling parameters for the disutilities of fine, offloading penalty, and truck time delay. These scaling parameters sum to one. Therefore, we can write:

$$k_7 = 1 - k_5 - k_6.$$  \hspace{1cm} (4-2b)

To combine the concerns of these two interest groups, let us act as if there is a decision maker who balances the concerns of the government agencies and the private motor carriers. We further model the problem as if this decision maker's disutility function is a "weighted" sum of the government agencies' disutility function and the private motor carriers' disutility function. In this study, we call the weights of the interest groups the group tradeoff parameters. We let $K_g$ be the group tradeoff parameter (weight) of the government agencies. Since there are only two interest groups, the value of the group tradeoff parameter for the private motor carriers would be $(1-K_g)$. Therefore, combining (4-1) and (4-2), the "decision maker's" disutility function $U$ can be formulated as:

$$U = K_g[u_1 + k_2 u_2 + k_3 u_3 + (1 - k_1 - k_2 - k_3) u_4] + (1 - K_g)[k_5 u_5 + k_6 u_6 + (1 - k_5 - k_6) u_7]$$

(4-3)

In our study it seems reasonable to consider that system costs, number of ESAL's, number of bridge formula violation truck trips, fine assessed to a random truck, offloading penalty for a random truck, and time delay for a random truck are negative impacts. That is, when all other things are equal, less of each attribute is preferred to more. The only positive impact is the revenues from fines for the government agencies. That is, when all other things are equal, the government would prefer more revenue to less. Since most of our attributes in this evaluation are negative impacts, we model all the single attribute functions as disutility functions.
Consistent with multi-attribute utility theory, we scale the single-attribute disutility functions $u_i(y_i)$, $i=1,2,...,7$, so that the most and the least preferred attribute levels have disutility 0.0 and 1.0, respectively. That is, if we assume the most preferred level of attribute $Y_i$ to be $y_i^0$ and the least preferred attribute level to be $y_i^\wedge$, then we have $u_i(y_i^0) = 0.0$ and $u_i(y_i^\wedge) = 1.0$. With this scaling we can show that the MAEU function of government agencies, the MAEU of private motor carriers, and the MAEU of the evaluation are also scaled from one to zero.

As a first cut, we formulate the single-attribute disutility functions of government revenue from fines, system costs, number of ESAL's, number of bridge formula violation truck trips, and fines assessed to the a random truck as linear. This implies that the effect on preferences of an extra unit of any of these attributes is the same, no matter how much of this attribute is obtained. Compared to the annual government revenue, the revenue generated by a weigh station is only a small amount. Also, compared to the annual government budget, the weight enforcement system cost is only a small amount. Therefore, we can approximate the single-attribute disutility functions of revenue and system cost with linear functions. That is, an extra dollar collected in revenue is of equal importance to the first dollar collected and an extra dollar spent in system cost is of equal importance to the first dollar spent. In our study, we measure the nonlinear pavement damage with ESAL's which transform pavement damage into a linear scale. It is reasonable to approximate the single-attribute disutility function of number of ESAL's as a linear function. That is, an extra ESAL is of equal importance to the first ESAL. In this research, we measure bridge damage with the number of bridge formula violation truck trips. We argue that each bridge violation trip is of equal importance to the first bridge formula violation truck trip. Therefore, we formulate the single-attribute disutility function
of number of bridge formula violation truck trips as a linear function. Finally, compared to a trucking company's revenue, the fine collected from a random truck is only a small amount. Therefore, we can approximate the single-attribute disutility function of fines assessed to a random truck as a linear function. That is, an extra dollar in fines is of equal importance to the first dollar in fines.

In this study, offloading penalty for a random truck is formulated as a binary (0/1) variable. The outcome is either 0 or 1, therefore, we do not have to assume any form of single-disutility function for offloading penalty.

Recall that we scale the single disutility functions from zero to one (zero is most preferred and one is least preferred). Using the notation that $u_i(.)$ is a single disutility function, $y_i$ is the attribute level of attribute $Y_i$, and $y_i^\wedge$ and $y_i^0$ are the least preferred level and the most preferred level of $y_i$, the single-attribute disutility functions of revenues from fines, system costs, number of ESAL's, number of bridge formula violation truck trips, fine assessed to a random truck, and offloading penalty for a random truck can, therefore, be expressed as (4-4a), (4-4b), (4-4c), (4-4d), (4-4e), and (4-4f), respectively:

\[
\begin{align*}
    u_1(y_1) &= 1 - \frac{y_1 - y_1^\wedge}{y_1^0 - y_1^\wedge}, \\
    u_2(y_2) &= \frac{y_2 - y_2^0}{y_2^\wedge - y_2^0}, \\
    u_3(y_3) &= \frac{y_3 - y_3^0}{y_3^\wedge - y_3^0}, \\
    u_4(y_4) &= \frac{y_4 - y_4^0}{y_4^\wedge - y_4^0}, \\
\end{align*}
\]

(4-4a), (4-4b), (4-4c), (4-4d), (4-4e), and (4-4f)
For truck time delays, delaying a hundred trucks for one minute each might not be equal to delaying one truck for a hundred minutes. That is, the time delay disutility for the trucks might not be linear. In this study, we use a power function (de Neufville, 1990) with coefficient $\alpha$ to capture this nonlinearity. Using the notation that $u_7(.)$ is the single disutility of time delays, $y_7$ is the attribute level of $Y_7$, and $y_7^\wedge$ and $y_7^0$ are the least preferred level and the most preferred level of $y_7$ and recalling that we scale the single disutility function of time delays from zero to one (zero is most preferred and one is least preferred), the disutility for truck delays can be expressed as:

$$u_7(y_7) = \left( \frac{y_7 - y_7^0}{y_7^\wedge - y_7^0} \right)^{\alpha} .$$

(4-4g)

To define the most and least preferred levels of our attribute ranges-- $y_i^0$, $y_i^\wedge$, we use the existing data and our simulation pilot runs. Specifically, for the government agencies, the bounds $(y_i^0, y_i^\wedge)$ are ($20,000,000$, $0$) for revenues from fines; ($0$, $5,000,000$) for weigh system costs; (0 ESAL, 4,000,000 ESAL's) for number of ESAL's; and (0 violation truck trip, 1,000,000 violation truck trips) for number of bridge formula violation truck trips. For the private motor carriers, the bounds $(y_i^0, y_i^\wedge)$ are ($0$, $1,500$) for fine assessed to a random truck, (0 offloading, 1 offloading) for offloading penalty for a random truck,
(0 minute, 60 minute) for time delay for a random truck. These bounds can be found in Table 11. With these bounds, equations (4-4a-g) become:

\[ u_i(y_i) = 1 - \frac{y_i}{20,000,000}, \quad (4-5a) \]

\[ u_2(y_2) = \frac{y_2}{5,000,000}, \quad (4-5b) \]

\[ u_3(y_3) = \frac{y_3}{4,000,000}, \quad (4-5c) \]

\[ u_4(y_4) = \frac{y_4}{1,000,000}, \quad (4-5d) \]

\[ u_5(y_5) = \frac{y_5}{1,500}, \quad (4-5e) \]

\[ u_6(y_6) = \frac{y_6}{1}, \quad \text{and} \]

\[ u_7(y_7) = \left(\frac{y_7}{60}\right)^a. \quad (4-5g) \]

The single-attribute disutility functions are summarized in Table 12.

To evaluate the truck weight enforcement technologies, we also need values for the scaling parameters. We obtain what we call a set of benchmark scaling parameter and then perform sensitivity of the evaluation to the values of these scaling parameters. Approaches like lottery-based utility questions (McCord and de Neufville, 1986) and the strength of preference questions (McCord and de Neufville, 1985) can be used to obtain the scaling
parameters. However, experience has shown that to assessing the preference parameters is a difficult task (McCord et al., 1993). Moreover, these approaches would required interaction with a decision maker. In this study, we propose to use data on preference tradeoffs that appear in literature and other sources to approximate the benchmark scaling parameters. We use this approach, which we call a Marginal Rates of Substitution (MRS) approach, to estimate the benchmark data in Chapter 5.

### 4.2 Calculating Expected Disutilities

After formulating the multi-attribute utility function, the last step in our multi-attribute expected utility evaluation process is to calculate the expected utility of each alternative. In our weight enforcement technologies evaluation problem, the attribute levels that would result when an alternative is implemented are uncertain.

According to the expected disutility theory, the related measure used to rank alternatives is the excepted disutility of the alternative (de Neufville, 1990; Keeney and Raiffa, 1976). The expected disutility function for an alternative weight enforcement technology $X_i$ can be expressed as:

$$E(U(Y/X_i)) = \int \int \int \int f_{Y/X_i}(y_1, y_2, y_3, y_4, y_5, y_6, y_7/X_i) U_Y(y_1, y_2, y_3, y_4, y_5, y_6, y_7) dy_1 dy_2 dy_3 dy_4 dy_5 dy_6 dy_7$$

where $U_Y$ is the disutility function for the seven-attribute vector $Y = (Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7)$, and the $f_{Y/X_i}$ is the joint probability density function over the seven attribute vectors, given that alternative $X_i$ is chosen. The underlying expected utility function
implies that an alternative with lower expected disutility value $E(U(Y/X_j))$ should be preferred to one with higher expected disutility value.

Substituting (4-3) for $U(Y/X_j)$ and (4-5a-g) for the $u_i$'s in (4-3), (4-6) can be written as:

$$E[U(Y/X_j)] = E[K_g k_1 (1-y_1/y_1) + k_2 (y_2/y_2) + k_3 (y_3/y_3) + (1-k_1-k_2-k_3) (y_4/y_4)]$$

$$+(1-K_g) (k_4 (y_4/y_4) + k_5 (y_5/y_5) + k_6 (y_6/y_6) + (1-k_5-k_6) (y_7/y_7)^α) \tag{4-7}$$

Taking the expectation of this expression, (4-7) can be written as:

$$E[U(Y/X_j)] = E[K_g k_1 (1-y_1/y_1)] + E[K_g k_2 (y_2/y_2)] + E[K_g k_3 (y_3/y_3)] + E[K_g (1-k_1-k_2-k_3) (y_4/y_4)]$$

$$+ E[(1-K_g) k_4 (y_4/y_4)] + E[(1-K_g) k_5 (y_5/y_5)] + E[(1-K_g) k_6 (y_6/y_6)] + E[(1-K_g) (1-k_5-k_6) (y_7/y_7)^α] \tag{4-8}$$

This shows that we only need the expected values of the marginal attribute level distribution for attributes 1, 2, 3, 4, 5, and 6. In this study, we use simulation to approximate the joint probability density function $f_{Y/X_i}$ by a joint mass function $p_{Y/X_i}$. Specifically, we generate $n$ attribute vectors $Y$, each occurring with probability $1/n$. With this approximation of $f_{Y/X_i}$ by $p_{Y/X_i}$, the expected attribute levels of the marginal distribution become:

$$E[y_i] = \frac{1}{n} \sum_{j=1}^{n} y_j \quad \text{for } i=1,2,3,...,6 \tag{4-9}$$

Equation (4-8) also shows that we cannot approximate time delay disutility by using the expected time delays. To approximate $E[(y_7/y_7^α)$, we generate our simulation output of the truck time delays in terms of the number of trucks that would be delayed in two-minute time intervals. Trucks in the same time interval are assumed to have the same time delay which is represented by the mid-point of the time interval. We let $TD_j$ be the mid-point of time delays of the $j$th two-minute time interval where $TD_1=1$ and $TD_j=TD_{j-1}+2$. 
for \( j = 2, \ldots, 30 \). We define the time interval to include the upper bound of the interval but not the lower bound of the interval. Then the \( j \)th time interval can be represented as \((T_{Dj-1}, T_{Dj+1}]\) for \( j = 1, 2, \ldots, 30 \). We also let \( OBS_j \) be the number of trucks observed in the \( j \)th two-minute time interval for \( j = 1, 2, \ldots, 30 \). In addition, those trucks which have no time delay are collected separately. We let \( OBS_0 \) be the number of trucks which have no time delays. Also, we use \( T_{D0} \) to represent 0 time delay. Then we have:

\[
E\left[\frac{y_j}{y_j^*}\right]^\alpha = \left(\frac{1}{\sum_{j=0}^{30} OBS_j}\right) \left(\sum_{j=0}^{30} OBS_j \left(\frac{T_{Dj}}{y_j^*}\right)^\alpha\right)
\]

(4-10)

where \( y_j^* \) is the upper bound of time delays--namely, 60 minutes in this study--and \( \alpha \) is the power function coefficient.
Table 11: The Upper and Lower Bounds of the Attributes Used to Scale Single-Attribute Disutility Functions

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Lower Bound ((y_i^0))</th>
<th>Upper Bound ((y_i^*))</th>
<th>Unit of Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Government Agencies</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Y_1): Revenue from Fines in a typical year</td>
<td>0</td>
<td>20,000,000</td>
<td>Dollars</td>
</tr>
<tr>
<td>(Y_2): Weight Enforcement System Costs in a typical year</td>
<td>0</td>
<td>5,000,000</td>
<td>Dollars</td>
</tr>
<tr>
<td>(Y_3): Number of ESAL's in a typical year</td>
<td>0</td>
<td>4,000,000</td>
<td>ESAL's</td>
</tr>
<tr>
<td>(Y_4): Number of bridge formula violation truck trips in a typical year</td>
<td>0</td>
<td>1,000,000</td>
<td>Number of violation truck trip</td>
</tr>
<tr>
<td><strong>The Private Motor Carriers</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Y_5): Fine assessed to a random truck</td>
<td>0</td>
<td>1,500</td>
<td>Dollars</td>
</tr>
<tr>
<td>(Y_6): Binary variable indicating whether a random truck is offloaded</td>
<td>0</td>
<td>1</td>
<td>Binary value (0/1)</td>
</tr>
<tr>
<td>(Y_7): Time delay for a random truck</td>
<td>0</td>
<td>60</td>
<td>Minute</td>
</tr>
</tbody>
</table>
TABLE 12: List of the Single-Attribute Utility Functions and Preference Scaling Parameters

<table>
<thead>
<tr>
<th>ATTRIBUTE</th>
<th>SINGLE-ATTRIBUTE UTILITY FUNCTION</th>
<th>PREFERENCE SCALING PARAMETER</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Government Agencies</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Y_1$: Revenues from fines in a typical year</td>
<td>$u_1(y_1) = \frac{y_1}{20,000,000}$</td>
<td>$k_1$</td>
</tr>
<tr>
<td>$Y_2$: Weigh system costs in a typical year</td>
<td>$u_2(y_2) = \frac{y_2}{5,000,000}$</td>
<td>$k_2$</td>
</tr>
<tr>
<td>$Y_3$: Number of ESAL's in a typical year</td>
<td>$u_3(y_3) = \frac{y_3}{4,000,000}$</td>
<td>$k_3$</td>
</tr>
<tr>
<td>$Y_4$: Number of bridge formula violation truck trip in a typical year</td>
<td>$u_4(y_4) = \frac{y_4}{1,000,000}$</td>
<td>$k_4 = 1 - k_1 - k_2 - k_3$</td>
</tr>
<tr>
<td><strong>Private Motor Carriers</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Y_5$: Fines assessed to a random truck</td>
<td>$u_5(y_5) = \frac{y_5}{1,500}$</td>
<td>$k_5$</td>
</tr>
<tr>
<td>$Y_6$: Binary variable indicating whether a random truck is offloaded</td>
<td>$u_6(y_6) = \frac{y_6}{1}$</td>
<td>$k_6$</td>
</tr>
<tr>
<td>$Y_7$: Time delay for a random truck</td>
<td>$u_7(y_7) = \frac{y_7}{60}$</td>
<td>$k_7 = 1 - k_5 - k_6$</td>
</tr>
</tbody>
</table>
CHAPTER V

Estimating Benchmark Scaling Parameters

As mentioned in Chapter 4, we need preference data to analyze the truck weight technology evaluation problem with our MAEU approach. In this study, we use Marginal Rates of Substitution (MRS) to assess benchmark parameters for the utility functions. We discuss the MRS methodology and calculate the benchmark scaling parameters for the various attributes and the tradeoff parameter that represent the tradeoff between the government agencies and the private motor carriers in this chapter. In Section 5.1, we present the Marginal Rate of Substitution (MRS) approach and the mathematical expressions to which it leads. Using the mathematical expressions we derive in Section 5.1 and data obtained from various sources, we calculate the benchmark scaling parameters of the attributes of the government agencies in Section 5.2. In Section 5.3, we calculate the benchmark scaling parameters of the attributes of the private motor carriers. Finally, in Section 5.4, we calculate the benchmark parameter that represents the tradeoff between the government agencies and the private motor carriers.

5.1 The Marginal Rate of Substitution (MRS) Approach

We use an approach based on the concept of the Marginal Rate of Substitution (MRS) to estimate the scaling parameters of the attributes we use in the truck weight technology
evaluation problem. The MRS indicates by how much one attribute should change to compensate for the change of another attribute in order to keep a constant preference level when all other attributes are held at constant levels.

With the MRS approach, we can derive a mathematical equation that relates the values of scaling parameters of two attributes as a function of the MRS. We obtain data from literature and other sources on how much an attribute should be substituted for a change in another attribute to keep preferences constant, i.e., on the MRS. Using this information, the equations then become such that the value of the scaling parameter of one attribute can be expressed as a constant times the value of the scaling parameter of another attribute. We obtain enough independent equations to allow a solution for the attribute scaling parameters. We can then use this solution as our benchmark preference data. The mathematical formulation is presented in the following.

In equation (4-3), we expressed the multi-attribute disutility function U as:

\[
U(y_1, y_2, y_3, y_4, y_5, y_6, y_7) = K_g[k_1 u_1(y_1) + k_2 u_2(y_2) + k_3 u_3(y_3) + k_4 u_4(y_4)]
+ (1 - K_g)[k_5 u_5(y_5) + k_6 u_6(y_6) + k_7 u_7(y_7)],
\]  

(5-la)

where the \(k_i\)'s are scaling parameters, the \(K_g\) represents the tradeoff between the government agencies and the motor carriers, and the \(u_i\)'s are single-attribute disutility functions \((i=1,2,\ldots,7)\). These single-attribute disutility functions are given in equations (4-5a-g). If we let \(y_i\) be the specific levels of attribute \(Y_i\), and \(y_i^\text{^}\) be the upper bound of this attribute, we have:

\[
U(y_1, y_2, y_3, y_4, y_5, y_6, y_7) = K_g[k_1 (1 - (y_1/y_1^\text{^}))+ k_2 (y_2/y_2^\text{^})+ k_3(y_3/y_3^\text{^})
+ k_4(y_4/y_4^\text{^})] + (1 - K_g)[k_5(y_5/y_5^\text{^})+ k_6(y_6/y_6^\text{^})+ k_7(y_7/y_7^\text{^})].
\]  

(5-1b)

Consider the derivative of (5-1a). We obtain:
\[
\frac{dU}{dy_i} = \sum_{i=1}^{n} \frac{\partial U}{\partial y_i} dy_i.
\]  

(5-2)

The MRS considers variations in only two attributes at one time. The other attribute levels remain constant. That is, if we make \( Y_j \) and \( Y_k \) the pair of analyzed attributes and \( y_j \) and \( y_k \) their attribute levels, we have \( dy_i = 0 \) for \( i \neq j, k \). In this way, (5-2) becomes:

\[
dU = \frac{\partial U}{\partial y_j} dy_j + \frac{\partial U}{\partial y_k} dy_k.
\]  

(5-3)

The change in \( y_j \) and \( y_k \) are to be such that the decision maker feels no change in preferences between the situations represented by the attributes before and after the changes. Therefore, the disutility should remain constant, and we have:

\[ dU = 0. \]  

(5-4)

Substituting (5-3) into (5-4) and rearranging, we have:

\[
\frac{dy_j}{dy_k} = \frac{-\partial U/\partial y_k}{\partial U/\partial y_j}.
\]  

(5-5)

The attributes can be considered to fall in one of two groups. Group 1 includes the attributes of the government agencies. Group 2 includes the attributes of the private motor carriers. That is, Group 1 includes attributes 1, 2, 3, 4, and Group 2 includes attributes 5, 6, 7.

Consider first the case where both attributes \( j \) and \( k \) considered are in Group 1 and neither is the revenue attribute \( Y_1 \). Substituting (5-1b) into (5-5), we have:

\[
\frac{dy_j}{dy_k} = \frac{-K_g (k_j/y_j^\wedge) - k_j/y_j^\wedge}{K_g (k_j/y_j^\wedge)} = \frac{k_j/y_j^\wedge}{k_j/y_j^\wedge}, \text{ or}
\]
Thus, if we know how much \( y_j \) should be substituted for a change in \( y_k \) to keep the same preference level, we know \( dy_j/dy_k \). Since \( y_k^\wedge \) and \( y_j^\wedge \) are the already determined upper bounds (see Section 4.2), we obtain \( k_k \) as a constant times \( k_j \).

Consider next the case where both attributes \( j \) and \( k \) considered are in Group 1 and one is the revenue attribute \( Y_1 \). Substituting (5-1b) into (5-5), we have:

\[
ky_k = \frac{k_k}{y_k^\wedge} \left( \frac{dy_j}{dy_k} \right) k_j .
\]

The difference between (5-6) and (5-7) is a change in sign. Thus, if we know how much \( y_j \) should be substituted for a change in \( y_k \) to keep the same preference level, we know \( dy_j/dy_k \). Since \( y_k^\wedge \) and \( y_j^\wedge \) are the already determined upper bounds (see Section 4.2), we obtain \( k_k \) as a constant times \( k_j \).

Consider next the case where both attributes \( j \) and \( k \) considered are in Group 2 and neither is the time delay attribute \( Y_7 \). Substituting (5-1b) into (5-5), we have:

\[
ky_k = \frac{k_k}{y_k^\wedge} \left( \frac{dy_j}{dy_k} \right) k_j .
\]

We obtain the same result as the first case. Thus, if we know how much \( y_j \) should be substituted for a change in \( y_k \) to keep the same preference level, we know \( dy_j/dy_k \). Since \( y_k^\wedge \) and \( y_j^\wedge \) are the already determined upper bounds (see Section 4.2), we obtain \( k_k \) as a constant times \( k_j \).
Consider next the case where both attributes \( j \) and \( k \) considered are in Group 2 and one of them is the time delay attribute \( Y_7 \). Substituting (5-1b) into (5-5), we have:

\[
\frac{dy_j}{dy_k} = \frac{- (1 - K_g) (k_j/y_j^\wedge)}{\alpha (1 - K_g)(k_j/y_j^\wedge)(y_j/y_j^\wedge)^\alpha - 1}, \quad \text{or}
\]

\[
k_k = - \alpha (y_k^\wedge/y_j^\wedge)(y_j^\wedge/y_j^\wedge)^\alpha - 1 (dy_j/dy_k) k_j.
\]

In the base case, we shall assume \( \alpha = 1 \). Then (5-9a) becomes:

\[
k_k = - (y_k^\wedge/y_j^\wedge)(dy_j/dy_k) k_j.
\]

We obtain the same result as the first case. Thus, if we know how much \( y_j \) should be substituted for a change in \( y_k \) to keep the same preference level, we know \( dy_j/dy_k \). Since \( y_k^\wedge \) and \( y_j^\wedge \) are the already determined upper bounds (see Section 4.2), we obtain \( k_k \) as a constant times \( k_j \).

Finally, consider the case where attribute \( j \) considered is in Group 1 but not the revenue attribute and attribute \( k \) considered is the time delay attribute in Group 2. Substituting (5-1b) into (5-5), we have:

\[
\frac{dy_j}{dy_k} = \frac{- K_g (k_j/y_j^\wedge) (y_k/y_k^\wedge)^\alpha - 1}{(1 - K_g)(k_j/y_j^\wedge)}, \quad \text{or}
\]

\[
K_g/(1 - K_g) = - \alpha (y_k^\wedge/y_j^\wedge)(dy_j/dy_k)(y_j^\wedge/k_j) (k_k/y_k^\wedge).
\]

In the base case, we shall assume \( \alpha = 1 \). Then (5-10a) becomes:

\[
K_g/(1 - K_g) = - (dy_j/dy_k)(y_j^\wedge/k_j) (k_k/y_k^\wedge), \quad \text{or}
\]

\[
(1 - K_g)/K_g = - (y_k^\wedge/y_j^\wedge)(dy_j/dy_k)(k_k/k_k).
\]

Thus, if we know how much \( y_j \) should be substituted for a change in \( y_k \) to keep the same preference level, we know \( dy_j/dy_k \). Both \( y_k^\wedge \) and \( y_j^\wedge \) are the already determined upper bounds.
bounds (see Section 4.2). If we can calculate benchmark values for scaling parameters $k_j$ and $k_k$, then we can obtain the value of $K_g$.

So far, we have derived mathematical equations that relate the values of two attribute scaling parameters as a function of their upper bounds and their MRS of one for the other. In the following, we estimate the MRS, $dy/dy_k$, i.e., by how much the increase of one attribute should be substituted for an increase in another to keep the preference the same. We estimate the MRS from literature and other sources so that we can get a set of independent equations and solve for the scaling parameters.

5.2 Relationship between Pairs of Government Agency Attributes

Our evaluation model uses four scaling parameters for the government agencies: $k_1$, $k_2$, $k_3$, and $k_4$. Since we have modeled the utility function so that the scaling parameters sum to one, we need data for three independent equations to calculate those parameters.

System costs are probably the most understandable of the government agency attributes. Therefore, in this research, we propose to calculate relationships between the scaling parameter of system costs and the scaling parameters of the other three government agency attributes. We estimate the relationship between the scaling parameter of system costs and the scaling parameter of revenues from fines first. Then we estimate the relationship between the scaling parameter of system costs and the scaling parameter of number of ESAL's. After that, we estimate the relationship between the scaling parameter of system costs and the scaling parameter of number of bridge formula violation truck trips. Finally, we use this set of equations to calculate the benchmark values of the scaling parameters of the government agencies.
5.2.1 System Costs and Revenues from Fines

To approximate the MRS between the scaling parameter of system costs and the scaling parameter of revenues from fines, we conducted an interview at a meeting of the Commercial Vehicle Operations sub-committee of the Ohio Intelligent Transportation Society. We asked approximately ten representatives from trucking industries or state governments how much they were willing to pay for a weigh system which can generate $100,000 in fines in order to keep preferences the same while other things were held constant. The result was that the respondents were willing to trade approximately $50,000 in system costs ($Y_2$) for $100,000 fines ($Y_1$) to keep the utility constant. Therefore, we have:

$$\frac{dy_2}{dy_1} = \frac{50,000}{100,000} = 0.5. \quad (5-11)$$

Substituting (5-11) into (5-7), with the upper bounds on revenues and system costs (see Section 4.2) -- namely, $y_1^\wedge = 20,000,000; y_2^\wedge = 5,000,000$ -- we can obtain:

$$k_1 = \frac{(20,000,000/5,000,000)(0.5)}{k_2} = 2.0 k_2. \quad (5-12)$$

5.2.2 System Costs and Number of ESAL's

To calculate the relationship between the scaling parameter of system costs and the scaling parameter of number of ESAL's, we first define an overweight truck and calculate the pavement damage in ESAL's caused by this truck from the AASHTO ESAL model (AASHTO, 1986). Next, we estimate the average length of a truck trip and also calculate the overweight permit fees that state governments would collect from this defined truck to compensate for pavement damage. To obtain benchmark data, we assume that those fees
collected by the government agencies are used to pay for the pavement damage repair. In addition, we also assume that all cost items are equally important to the government agencies. That is, a dollar spent in pavement repair has the same value as a dollar spent in weigh system costs. This allows us to use the overweight truck permit fees to estimate the equivalent system costs and calculate the relationship between the scaling parameter of number of ESAL's and the scaling parameter of system costs.

We assume all overweight trucks are the FHWA defined TYPE-9 trucks which have 3-axle tractors plus 2-axle semitrailers with a gross weight of 100,000 lb. (FHWA, 1980). In order to distinguish this particular type of TYPE-9 truck from the other kind of Type-9 trucks which have a spread tandem configuration, we call the former category of truck TYPE-9A trucks in this study. In addition, to obtain the percentages of truck gross weight on each axle group, we use the average data from the ODOT data set. This gives average weight loading percentages on the axle groups of 19%, 43%, and 38% for the first, second, and third axle groups, respectively. With the axle loads and the AASHTO's flexible pavement ESAL model (AASHTO, 1986), we estimate that the number of ESAL's generated by this truck is 5.72 ESAL--1.26 ESAL by the first axle group, 2.76 ESAL by the second axle group, and 1.70 ESAL by the third axle group.

To estimate pavement damage costs from these 5.72 ESAL's, we need an average truck trip length and the costs imposed by an ESAL. To the best of our knowledge, there is no average truck trip data available in the Ohio state government agencies. Therefore, we calculate this information indirectly from the Ohio Trucking Association's (OTA) data based on average yearly truck mileage and average yearly truck trips.

According to OTA, a two cents per mile tax was added to the carrier taxes on January 1, 1991. This generated an average per truck mileage tax of $543 annually (Ohio Trucking
Association, 1991). From this data, we calculate that an average Ohio-registered truck traveled 27,150 miles in the year. An independent study supports this number— an average Michigan-registered tractor traveled about 25,500 miles in 1989 (Lyles et al., 1991). Note that this is very close to what we estimate for the Ohio-registered trucks.

To obtain benchmark data for this study, we assume that a truck goes on duty every two days, leading to approximately 182.5 trips per year. Dividing this 182.5 trips per year into 27,150 miles per year yields an average truck trip of approximately 150 miles. In this study, we will use 150 miles as the average truck trip length to calculate the related data.

To determine the pavement damage costs for a 5.72 ESAL truck traveling 150 miles, we calculate the fees which different state governments would charge our truck. Different state governments charge different permit fees for this 150-mile, 5.72-ESAL trip. The states' fee structure for overweight truck permits is listed in Table 13 (Moses, 1992). Here, we only list the fees for those states which use a ton or ton-mileage concept. We do not include fees of those states using flat surcharges. We use the structures in Table 13 to calculate the fees of the various charges for our 150-mile, 5.72-ESAL truck trip. The fees range from $15 to $165 for the 5.72 ESAL damage on 150 miles of pavement. This leads to between $2.62/ESAL and $28.85/ESAL for the 150 miles of pavement. For our base case study, we use the average value— namely, $13.19 per ESAL— for 150 miles of pavement damage. This information is listed in Table 14.

As previously mentioned, we assumed that all cost items are equally important to the government agencies. This means that a dollar spent in pavement repair has the same value as a dollar spent in weigh system costs. The $13.19 per ESAL on a 150-mile trip can be thought of as increasing costs by $13.19 for every ESAL on the average trip, and one should be willing to increase weigh system costs \( Y_2 \) (i.e., \( dy_2 > 0 \)) by $13.19 to decrease an
ESAL $y_3$ (i.e. $dy_3 < 0$) on an average trip. That is, to keep preference levels constant, we have:

$$\frac{dy_2}{dy_3} = -\frac{13.19}{\text{ESAL}}$$ on a violation trip. \hfill (5-13)

Substituting (5-13) into (5-6), with the upper bounds on number of ESAL's and system costs (see Section 4.2) -- namely, $y_3^\wedge = 4,000,000$ ESAL; $y_2^\wedge = 5,000,000$ -- we can obtain:

$$k_3 = -\frac{(4,000,000/5,000,000)(-13.19)k_2}{k_2} = 10.552 k_2.$$ \hfill (5-14)

5.2.3 System Costs and Number of Bridge Formula Violation Truck Trips

We also use the same TYPE-9A trucks we defined previously to estimate the relationship between the scaling parameter of number of bridge formula violation truck trips and the scaling parameter of system costs. First, we estimate the average number of bridges on an average truck trip. Then, we obtain the damage costs of each single bridge to calculate the total bridge damage costs in a truck trip. To obtain benchmark data, we assume the bridge damage costs are the costs to pay for the bridge damage repair. In addition, to obtain benchmark data, we also assume that all cost items are equally important to the government agencies. That is, a dollar spent in bridge repair has the same value as a dollar spent in weigh system costs. This would allow us to use the bridge repair costs to estimate the equivalent system costs and calculate the relationship between the scaling parameter of number of bridge formula violation trips and the scaling parameter of system costs.

We also need data concerning the number of bridges on an average truck trip so that the total bridge damage caused by an overweight truck can be calculated. We use two approaches to estimate the number. First, we sampled the number of bridges on 100 miles
of I-70 west from Ohio State Route 315 to the Indiana and Ohio state border. The total number of bridges counted was 34, that is, 0.34 bridges per mile. Then, we used data from the Ohio Department of Transportation (ODOT). From an interview with ODOT officials, we learned that there are 42,844 bridges on the 117,000 miles of state owned highway in the state of Ohio (Ohio DOT, 1991), that is, 0.366 bridges per mile. These two estimated numbers are very close. We use a rough average of 0.35 bridges per mile in this research. This gives us roughly 52 bridges for our average truck trip (150 miles).

From the literature, we determine that the defined TYPE-9A truck will cause an average of $0.13 in damage on a single bridge (Moses, 1992). Since there are 52 bridges on an average truck trip, the bridge damage costs for a weight violating truck trip is estimated as $6.76.

As mentioned previously, we also assumed that all cost items are equally important to the government agencies. That is, a dollar spent in bridge repair has the same value as a dollar spent in weigh system costs. The $6.76 per bridge formula violation trip can be thought of as increasing costs by $6.76 for an average truck trip, and one should be willing to increase system costs $Y_2$ (i.e., $dy_2 > 0$) by $6.76 to decrease a bridge formula violating truck trip $Y_4$ (i.e., $dy_3 < 0$). That is, to keep preference levels constant, we have:

$$dy_2/dy_4 = -$6.76/bridge formula violating truck trip.$$  \hfill (5-15)

Substituting (5-15) into (5-6), with the upper bounds on number of bridge formula violation truck trips and system costs (see Section 4.2) -- namely, $y_4^\wedge = 1,000,000$ bridge formula violating truck trips; $y_2^\wedge = 5,000,000$-- we can obtain:

$$k_4 = - (1,000,000/5,000,000)( -6.76) k_2 = 1.352 k_2.$$ \hfill (5-16)

Finally, the scaling parameters of the government agencies sum to one, that is,

$$k_1 + k_2 + k_3 + k_4 = 1.$$ \hfill (5-17)
From (5-12), (5-14), (5-16), and (5-17), we obtain:

\[ k_1 = 0.134, \]  
\[ k_2 = 0.067, \]  
\[ k_3 = 0.708, \]  
\[ k_4 = 0.091. \]  

(5-18a)  
(5-18b)  
(5-18c)  
(5-18d)

5.3 Relationship between Pairs of Private Motor Carrier Attributes

Our evaluation model uses three scaling parameters for the private motor carriers: \( k_5, k_6, \) and \( k_7. \) Since we have modeled the utility function so that the scaling parameters sum to one, we need data for two independent equations to calculate those parameters.

Fines are probably the most understandable of the private motor carrier attributes. Therefore, in this research, we calculate relationships between the scaling parameter of fines and the scaling parameters of the other attributes. We estimate the relationship between the scaling parameter of fines and the scaling parameter of offloading penalties first. Then we estimate the relationship between the scaling parameter of fines and the scaling parameter of time-delays. Finally, we use this set of equations to calculate the benchmark values of the scaling parameters of the private motor carriers.

5.3.1 Fines and Offloading Penalties

To calculate the relationship of the scaling parameter of fines and the scaling parameter of offloading penalties, we first estimate the average costs of an offloading penalty. To obtain benchmark data, we assume that all cost items are equally important to the private motor
carriers. That is, a dollar spent in offloading penalties has the same value as a dollar spent in fines. This would allow us to use the estimated offloading costs to estimate the equivalent fines and calculate the relationship of the scaling parameter between offloading penalties and the scaling parameter of fines.

We first estimate the cost of an offloading to the carriers. At a meeting of the Commercial Vehicle Operations sub-committee of the Ohio Intelligent Transportation Society, motor carriers representatives agreed that the cost of an offloading could be thought of as the sum of extra costs to remove the offloaded cargo, the time delay of the offloadings and the reputation-damage of late delivery. Here extra costs to ship the offloaded cargo can be estimated by the time needed to ship the cargo times the unit shipping cost. Time delay costs can be estimated as time value times the time delay at the weigh station. If we let OFFCT be an offloading cost, we have:

\[ \text{OFFCT} = \text{CT1} \times \text{WH} + \text{TV} \times \text{D1} + \text{RPM}. \]  

(5-19)

where
- OFFCT: an offloading cost
- CT1: unit cost of hiring trucks to ship the offloaded cargo ($/hour)
- WH: average time to ship the unloaded cargo (hour)
- TV: time value ($/minute)
- D1: cargo time delay due to offloading (minute)
- RPM: monetary equivalence of reputation.

To obtain a set of benchmark data, we use data from literature and interviews. The HELP/Crescent project used a time value of $0.83/minute and performer sensitivity analysis with bounds of $0.50/minute and $1.00/minute (Castle Rock Consultant, 1994). Other research (Waters, et al., 1995) recently claimed a result that the time value for commercial trucks was between $24.94/hour to $35.82/hour-- i.e., $0.42/minute to $0.60/minute. In addition, the weighed average is $30.76/hour-- i.e., $0.51/minute. In this research, we use the average time value of $0.83/minute from the HELP project to
calculate benchmark data (Castle Rock Consultant, 1994). Later in sensitivity analysis, we shall set the range of the time value to include all those values. Then our benchmark assumption is:

\[ TV = \$0.83/\text{minute}. \] \hspace{1cm} (5-20a)

At a meeting of the Commercial Vehicle Operations sub-committee of the Ohio Intelligent Transportation Society, motor carrier representatives stated that the cost of hiring a company to ship the offloaded cargo might be as high as \$100 per hour. That is:

\[ CT1 = \$100/\text{hour}. \] \hspace{1cm} (5-20b)

An interview with a truck dispatcher in Hilliard, Ohio, informed us that the average time to ship the offloaded cargo is about 15 hours. We also verify the time by our assumptions and calculation.

We assume that when a truck is offloaded the carrier has to arrange to hire a truck to come to the weigh station to pick up the offloaded goods. We assume the total time for arranging to hire a truck, driving to the weight station, and loading the offloaded goods is 2 to 4 hours.

As we estimated previously, an average truck trip is about 150 miles. We assume that 100 miles of the trip are on interstate highways on which trucks can travel at a speed of 55 MPH and the other 50 miles are on local routes or city streets on which trucks can only travel at a speed of 35 MPH. Therefore, it roughly takes 3.5 hours for the truck to ship the offloaded goods.

At the destination, we assume that it takes 1 to 2 hours to unload the goods. Finally, the hired truck has to go back to its company. We assume that it takes 3.5 hours for the truck to travel the 150-mile trip. In addition, we assume that it will take additional thirty
minutes for the truck to get back to its company. That is, it takes the hired truck about
four hours total to return to its company. Therefore, it takes the hired truck 10.5 to 13.5
hours in total to ship the offloaded goods.

The number we calculated is not too different from the number was given by the
dispatcher. Therefore, we feel more confident in using the dispatcher's 15 hours to
calculate the benchmark data. That is:

\[ WH = 15 \text{ hours.} \] (5-20c)

For the time delay at the station due to the offloading, we interviewed station personnel
in Cambridge, Ohio. They estimated the delay time at the weight station to be around 2 to
4 hours. We use 4 hours for this study. That is:

\[ D_1 = 4 \text{ hours.} \] (5-20d)

Finally, we assume that there is no reputation damage in our study. That is, RPM is 0% of
the sum of the extra moving costs and the time delay costs. We perform sensitivity
analysis to include the reputation damage later in our study. Using equation (5-19) with
values presented in (5-20a-d), we have:

\[ \text{OFFCT} = -$1699.2. \] (5-21)

We assume that every dollar spent is equally important to the trucking companies. That
is, a dollar spent in fines has the same value as a dollar spent in offloading penalties. This
allows us to use the offloading costs as an equivalent of the costs in fines. The $1699.2
per offloading can be thought of as increasing costs by $1699.2, and one should be willing
to increase fines \( Y_5 \) (i.e., \( dy_5 > 0 \)) by $1699.2 to decrease an offloading penalty \( Y_6 \) (i.e.
\( dy_6 < 0 \)). That is, to keep preference levels constant:

\[ dy_5 / dy_6 = -$1699.2. \] (5-22)
Substituting (5-22) into (5-8) with the upper bounds on offloading penalties and fines (see Section 4.2) -- namely, $y_6^\wedge = 1$ offloadings per truck; $y_5^\wedge = $1,500 per truck-- we can obtain:

$$k_6 = -\frac{1}{1,500}(-1699.2) k_5 = 1.1328 k_5.$$  \hfill (5-23)

5.3.2 Fines and Time Delays

To calculate the relationship of the scaling parameter of fines and the scaling parameter of time delay, we use the data from the HELP project (Castle Rock Consultant, 1994). The time value is $0.83$ per minute. The $0.83$ per minute can be thought of as increasing costs by $0.83$, and one should be willing to increase fines $Y_5$ (i.e., $dy_5>0$) by $0.83$ to decrease a minute of time delays $Y_7$ (i.e. $dy_7<0$). That is, to keep preference levels constant, we have:

$$\frac{dy_5}{dy_7}=-0.83 /\text{minute.} \hfill (5-24)$$

Substituting (5-24) into (5-9b) with the upper bounds on time delays and fines (see Section 4.2) -- namely, $y_7^\wedge = 60$ minutes per truck; $y_5^\wedge = $1,500 per truck-- we can obtain:

$$k_7 = -\frac{60}{1,500}(-0.83) k_5 = 0.0332 k_5.$$  \hfill (5-25)

Finally, the scaling parameters of the private motor carriers sum to one, that is:

$$k_5 + k_6 + k_7 = 1.$$  \hfill (5-26)

From (5-23), (5-25), and (5-26), we obtain:

$$k_5 = 0.462,$$  \hfill (5-27a)

$$k_6 = 0.523,$$  \hfill (5-27b)

$$k_7 = 0.015.$$  \hfill (5-27c)
5.4 Calculating the Tradeoff Parameter that Represent the Relative Importance between the Interest Groups (K_g)

We can calculate the value of the tradeoff parameter that represents the relative importance of the government agencies and the private motor carriers by using equation (5-10b). In this study, we estimate the group tradeoff by using the MRS of system costs (Y_2) of the government agencies and the time delays (Y_7) of the private motor carriers. We let j=2 and k=7, and equation (5-10b) becomes:

\[
\frac{1 - K_g}{K_g} = - (y_7^\gamma / y_2^\gamma) \left( \frac{dy_2}{dy_7} \right) \left( \frac{k_2}{k_7} \right).
\]  

Equation (5-28)

By using the upper bounds on system costs and time delays (see Section 4.2) -- namely, $y_2^\gamma = 5,000,000$; $y_7^\gamma = 60$ minutes per truck-- we get:

\[
\frac{1 - K_g}{K_g} = - \left( \frac{60}{5,000,000} \right) \left( \frac{dy_2}{dy_7} \right) \left( \frac{0.067}{0.015} \right) = -0.0000536(dy_2/dy_7).
\]  

Equation (5-29)

Equation (5-29) shows that if we know how much a change in time delay ($y_7$) can compensate for the change of system costs ($y_2$) such that the utility would hold constant, we can obtain the value of group tradeoff.

In our study, the government agency attributes are estimated as an annual total, and the private motor carrier attributes are estimated based on a random truck concept. To be able to calculate $dy_2/dy_7$, we must transform the private motor carriers' attributes from 'random truck measurement' to 'annual total sum'. This can be accomplished by multiplying the expected value of a random truck by the expected annual truck traffic volume.

We estimate the annual truck traffic volume by using our ODOT data set. That is, the truck volumes for a weekday and weekend day are 4,400 trucks/day and 1,600 trucks/day,
respectively. This gives us an annual truck traffic volume of 1,504,000. That is, if we save a minute for a random truck, we save roughly 1,504,000 minutes annually in total for private motor carriers.

In addition, we continue to use the time value used in HELP project evaluation (Castle Rock Consultant, 1994)—namely, $0.83/minute. If we let TTSC be the total time saving cost, we have:

\[ TTSC = \$0.83/\text{minute} \times 1,504,000 \text{ random minutes} = \$1,248,320. \quad (5-30) \]

We further assume that $1 in costs for the government is equal to $1 in costs for the private motor carriers. The $1,248,320 per minute can be thought of as increasing costs by $1,248,320 and one should be willing to increase system costs \( Y_2 \) (i.e., \( dy_2 > 0 \)) by $1,248,320 to decrease a minute of delay per truck \( Y_7 \) (i.e., \( dy_7 < 0 \)). That is, to keep preference levels constant, we have:

\[ \frac{dy_2}{dy_7} = -\frac{1,248,320}{\text{ random minute}}. \quad (5-31) \]

Using (5-31), (5-29) becomes:

\[ (1 - K_g)/K_g = -0.0000536 (-1,248,320). \quad (5-32) \]

That is,

\[ K_g = 0.015, \quad \text{and} \]

\[ 1 - K_g = 0.985. \quad (5-33a) \]

The benchmark scaling parameters for the attributes and for the parameter that represents the relative importance between the government agencies and the private motor carriers are listed in Table 15.
Table 13: Different States' Permit Fee Structures for Overweight Trucks  
(Source: Moses, 1992)

<table>
<thead>
<tr>
<th>STATE</th>
<th>FEE STRUCTURE</th>
</tr>
</thead>
<tbody>
<tr>
<td>AL</td>
<td>$20 + $10 if GW &lt; 80,000 lb., $30 if GW &lt; 125,000 lb., $60 if GW &lt; 150,000 lb.</td>
</tr>
<tr>
<td>DE</td>
<td>$10 + $5/8,000 lb. for GW over 80,000 lb.</td>
</tr>
<tr>
<td>FL</td>
<td>$24 if GW &lt; 95,000 lb., $28 if GW &lt; 112,000 lb., ..., $36 if GW &lt; 145,000 lb., $38 if GW &lt; 150,000 lb.</td>
</tr>
<tr>
<td>MS</td>
<td>$0.05 per mile per thousand pounds of GW overweight</td>
</tr>
<tr>
<td>NJ</td>
<td>$10 + $5 per ton over 80,000 lb.</td>
</tr>
<tr>
<td>OK</td>
<td>$10 + $5 for each 1,000 pounds when load exceeds the bridge formula</td>
</tr>
<tr>
<td>OR</td>
<td>$8 + $0.05 per ton mile of GW overweight</td>
</tr>
<tr>
<td>PA</td>
<td>$15 + overweight fees computed at $0.03 per ton mile over 80,000 lb.</td>
</tr>
<tr>
<td>SD</td>
<td>$20 + $0.05 per ton mile</td>
</tr>
<tr>
<td>TN</td>
<td>$15 + $0.10 per ton mile</td>
</tr>
<tr>
<td>VA</td>
<td>$0.10 per mile</td>
</tr>
<tr>
<td>WV</td>
<td>$20 + $0.04 per ton mile</td>
</tr>
<tr>
<td>WY</td>
<td>$0.04 per tone with minimum of $15 * GW - Gross Weight</td>
</tr>
</tbody>
</table>

*G.W. - Gross Weight

Table 14: Calculated States' ESAL Fee on a Truck Trip

<table>
<thead>
<tr>
<th>State</th>
<th>Fee Collected for 5.72 ESAL's on a Truck Trip</th>
<th>Dollars per ESAL on a Truck Trip</th>
</tr>
</thead>
<tbody>
<tr>
<td>AL</td>
<td>50</td>
<td>8.74</td>
</tr>
<tr>
<td>DE</td>
<td>25</td>
<td>4.37</td>
</tr>
<tr>
<td>FL</td>
<td>28</td>
<td>4.90</td>
</tr>
<tr>
<td>MS</td>
<td>150</td>
<td>26.22</td>
</tr>
<tr>
<td>NJ</td>
<td>60</td>
<td>10.49</td>
</tr>
<tr>
<td>OK</td>
<td>110</td>
<td>19.23</td>
</tr>
<tr>
<td>OR</td>
<td>83</td>
<td>14.51</td>
</tr>
<tr>
<td>PA</td>
<td>60</td>
<td>10.49</td>
</tr>
<tr>
<td>SD</td>
<td>95</td>
<td>16.61</td>
</tr>
<tr>
<td>TN</td>
<td>165</td>
<td>28.85</td>
</tr>
<tr>
<td>VA</td>
<td>15</td>
<td>2.62</td>
</tr>
<tr>
<td>WV</td>
<td>80</td>
<td>13.99</td>
</tr>
<tr>
<td>WY</td>
<td>60</td>
<td>10.49</td>
</tr>
<tr>
<td>Average</td>
<td>75.46</td>
<td>13.19</td>
</tr>
</tbody>
</table>
Table 15: Benchmark Data for Preference Scaling Parameters

<table>
<thead>
<tr>
<th>Preference Scaling Parameter</th>
<th>Benchmark Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_1$</td>
<td>0.134</td>
</tr>
<tr>
<td>$k_2$</td>
<td>0.067</td>
</tr>
<tr>
<td>$k_3$</td>
<td>0.708</td>
</tr>
<tr>
<td>$k_4$</td>
<td>0.091</td>
</tr>
<tr>
<td>$k_5$</td>
<td>0.462</td>
</tr>
<tr>
<td>$k_6$</td>
<td>0.523</td>
</tr>
<tr>
<td>$k_7$</td>
<td>0.015</td>
</tr>
</tbody>
</table>
CHAPTER VI

ANALYSIS

In this chapter, we use the predicted attribute levels, the defined MAEU function, and the benchmark scaling parameter values obtained in Chapter 5 to analyze the truck weight technology evaluation problem. In Section 6.1, we present our base case analysis. In section 6.2, we present analyses that investigate the sensitivity of the base case results to changes in selected base case parameters.

6.1 Base Case Studies

For the base case studies, we first define the truck volume levels which we will investigate. Here the truck volumes we defined are the daily truck volumes. Then we use the simulation models to predict the attribute levels for each of the five weight enforcement systems under these chosen truck volumes. We then discuss the performances for the five weight enforcement systems in terms of their predicted single-attribute levels as a function of truck volume in Section 6.1.1. In Section 6.1.2, we present and discuss the optimal weight enforcement system solution as a function of the truck volume and the group tradeoff parameter that represents the relative importance of the government agencies and the private motor carriers.

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In this study, we classify the truck volume into three levels: low, medium, and high. To define the truck volume levels, we use the observed highest truck volume at weigh station sites in the HELP/Crescent project—6,770 trucks/day—as the upper bound of truck volume (Castle Rock Consultant, 1994). We also use 0 trucks/day as the lower bound. Then we use from 0 trucks/day to 6,770 trucks/day as the truck volume's range and select three equally spaced volumes—namely, 1,690 trucks/day, 3,380 trucks/day, and 5,100 trucks/day—to represent the low traffic volume condition, medium truck volume condition, and high truck volume condition, respectively.

In addition to these three truck volume levels, for this base case study, we also investigate two additional truck traffic levels—very low and very high truck volumes—so that the trend of the optimal weight enforcement system as a function of truck volume can be investigated. In this study, we use the highest observed traffic volume in HELP/Crescent project—6,770 trucks/day—as the very high truck traffic condition. We use 720 trucks/day to represent the very low truck volume condition. This is greater than one third of the distance from 0 trucks/day to the low truck volume point and is smaller than one half of the distance from 0 trucks/day to the low truck volume point.

We use 150 weekday computer simulation runs to estimate average attribute levels of a weekday for each of the five alternative weight enforcement systems. We also use 150 weekend—including a Saturday and a Sunday—simulation runs to estimate average attribute levels of a weekend for each of the five alternative weight enforcement systems. Then we use the average weekday and weekend data to calculate the attribute levels of each of the five alternative weight enforcement systems for a typical year. Since we need more than the average for time delays, we collected them in two-minute intervals (see Chapter 4). We accumulate the number of trucks in each two-minute interval for the 150
weekday simulations. Then we divide the numbers by 150 to get the average number of trucks in each interval. Since the weigh station is closed on the weekends, there are no time delays for trucks on the weekends. We use the average weekday and weekend data to estimate the number of trucks in each two-minute interval in a year for the five alternative weight enforcement systems. The results of the base case studies are presented in Section 6.1.1 and Section 6.1.2.

6.1.1 Weight Enforcement System Single-Attribute Performance Analysis

In this section we analyze the weight enforcement system performance in terms of each individual attribute as a function of truck volume. Specifically, we discuss the expected revenue from fines in a typical year, the expected number of ESAL's in a typical year, the expected number of bridge formula violation truck trips in a typical year, the expected fines for a random truck, the expected number of offloadings for a random truck, and the expected time delay for a random truck. In this section, we do not discuss the weight enforcement system cost, since weight enforcement system costs are constant for different truck volume conditions in this study. For each of the five weight enforcement systems we plot the expected revenue from fines in a typical year, the expected number of ESAL's in a typical year, the expected number of bridge formula violation truck trips in a typical year, the expected fines for a random truck, the expected number of offloadings for a random truck, and the expected time delay for a random truck as a function of truck volume in Figure 9, Figure 10, Figure 11, Figure 12, Figure 13, and Figure 14, respectively.
As shown in Figure 9, the expected revenues from fines in a typical year increase when the truck volume increases for all the weight enforcement systems. Among the five alternative systems, the HSWIM-ONLY system collects the least revenue and the MSWIM-ONLY system collects the second least revenue for all truck volume conditions. The STATIC-with-HSWIM and STATIC-with-MSWIM systems collect roughly the same amount of revenues, which are the highest under all truck volume condition. Under the very-low, low and medium truck volume conditions, the STATIC-ONLY system collects roughly the same amount of revenue as the STATIC-with-HSWIM and STATIC-with-MSWIM systems. Under the high and very-high truck volume conditions, however, the increase in revenue for the STATIC-ONLY system begins to decrease with respect to truck volume. As a result, the expected revenues for the STATIC-ONLY system drops to third place under the high and very-high truck volume conditions.

As shown in Figure 10, the expected number of ESAL's in a typical year increases when truck volume increases for all the weight enforcement systems. Among the five alternative systems, the HSWIM-ONLY system results in the highest number of ESAL's, and the MSWIM system results in the second highest number of ESAL's under all truck volume conditions. The STATIC-with-HSWIM and STATIC-with-MSWIM systems result in roughly the same number of ESAL's, which are the lowest under all truck volume conditions. Under the very-low, low and medium truck volume conditions, the STATIC-ONLY system roughly results in the same number of ESAL's as the STATIC-with-HSWIM and STATIC-with-MSWIM systems. Under the high and very-high truck volume conditions, however, the increase of ESAL's for the STATIC-ONLY system begins to increase with respect to truck volume. As a result, the ESAL's for the STATIC-ONLY system become the third highest under the high and very-high truck volume conditions.
As shown in Figure 11, the expected number of bridge formula violation truck trips in a typical year increases when truck volume increases for all the weight enforcement systems. Among the five alternative systems, the HSWIM-ONLY system has the highest number of bridge formula violation truck trips and the MSWIM-ONLY system has the second highest number of bridge formula violation truck trips under all truck volume conditions. The STATIC-with-HSWIM and STATIC-with-MSWIM systems have roughly the same number of bridge formula violation truck trips, which are the lowest under all truck volume conditions. Under the very-low, low and medium truck volume conditions, the STATIC-ONLY system roughly has the same number of bridge formula violation truck trips as the STATIC-with-HSWIM and STATIC-with-MSWIM systems. Under the high and very-high truck volume conditions, however, the increase in the number of bridge formula violation truck trips for the STATIC-ONLY system begins to increase with respect to truck volume. As a result, the ESAL's for the STATIC-ONLY system become the third highest under the high and very-high truck volume conditions.

As shown in Figure 12, the expected fines for a random truck are almost constant under different truck volume conditions for all the weight enforcement systems except for the STATIC-ONLY system. Among the five alternative systems, the HSWIM-ONLY system has the least expected fines for a random truck and the MSWIM-ONLY system has the second least expected fines for a random truck under all truck volume condition. The STATIC-with-HSWIM and STATIC-with-MSWIM systems have roughly the same amount of expected fines for a random truck, which are the highest under all truck volume conditions. Under the very-low, low and medium truck volume conditions, the STATIC-ONLY system has roughly the same amount of expected fines for a random truck as the STATIC-with-HSWIM and STATIC-with-MSWIM systems. Under the high and very-
high truck volume conditions, however, the expected fines for a random truck for the STATIC-ONLY system begin to decrease with respect to the truck volume. As a result, the expected fines for a random truck for the STATIC-ONLY system become the third highest under the high and very-high truck volume conditions.

As shown in Figure 13, the expected number of offloadings for a random truck are almost constant under different truck volume conditions for all the weight enforcement systems except for the STATIC-ONLY system. Among the five alternative systems, the HSWIM-ONLY system has the least expected number of offloadings for a random truck and the MSWIM-ONLY system has the second least expected number of offloadings for a random truck under all truck volume conditions. The STATIC-with-HSWIM and STATIC-with-MSWIM systems have roughly the same amount of expected number of offloadings for a random truck, which are the highest under all truck volume conditions. Under the very-low, low and medium truck volume conditions, the STATIC-ONLY system has roughly the same amount of expected number of offloadings for a random truck as the STATIC-with-HSWIM and STATIC-with-MSWIM systems. Under the high and very-high truck volume conditions, however, the expected number of offloadings for a random truck for the STATIC-ONLY system begins to decrease with respect to truck volume. As a result, the expected number of offloadings for a random truck for the STATIC-ONLY system becomes the third highest under the high and very-high truck volume conditions.

We also analyze the time delays for the weight enforcement systems in expected values—i.e., $\alpha=1$. As shown in Figure 14, the expected time delays for a random truck are almost constant under different truck volume conditions for all the weight enforcement systems except for the STATIC-ONLY system. Among the five alternative systems, the HSWIM-
ONLY system has the least expected time delays for a random truck and the HSWIM-ONLY system has the second least expected time delays for a random truck under all truck volume conditions. The STATIC-with-HSWIM and STATIC-with-MSWIM systems have roughly the same expected time delays for a random truck, which are the third lowest under all truck volume conditions. When truck volume is higher—e.g., medium, high, and very high—the STATIC-with-MSWIM systems have slightly higher expected time delays for a random truck. Under the very-low and low truck volume conditions, the STATIC-ONLY system has roughly the same expected time delays for a random truck as the STATIC-with-HSWIM and STATIC-with-MSWIM systems. Under the medium, high, and very-high truck volume conditions, however, the expected time delays for a random truck for the STATIC-ONLY system begin to increase with respect to truck volume. As a result, the expected time delays for a random truck for the STATIC-ONLY system become the highest under the medium, high and very-high truck volume conditions. We note that the expected time delay for a random truck stays constant when truck volumes exceed 5,100 trucks/day. We cannot explain this phenomena. Therefore, results should be considered cautiously.

The results show that the HSWIM-ONLY system has the least amount of expected revenues from fines, the highest expected number of ESAL's, the highest expected number of bridge formula violation truck trips, the least expected fines for a random truck, the least expected number of offloadings for a random truck, and the least expected time delays for a random truck. Also, the MSWIM-ONLY system has the second least amount of expected revenues from fines, the second highest number of ESAL's, the second highest expected number of bridge formula violation truck trips, the second least expected fines for a random truck, the second least expected number of offloadings for a random truck,
and the second least expected time delays for a random truck. In addition, the STATIC-with-MSWIM and STATIC-with-HSWIM systems have the highest expected revenue from fines, the least expected number of ESAL's, the least expected number of bridge formula violation truck trips, the highest expected fines for a random truck, the highest expected number of offloadings for a random truck, and higher expected time delays for a random truck than those of the HSWIM-ONLY and MSWIM-ONLY systems.

From this analysis, we found other interesting results. Under the very-low, low, and medium truck volume conditions, the performance of the STATIC-ONLY system is roughly the same as those of the STATIC-with-HSWIM and STATIC-with-MSWIM systems. However, under the high and very-high truck volume conditions, the performance of the STATIC-ONLY system begins to decline as the truck volume increases. This shows that the STATIC-ONLY system faces capacity limitations when truck volume is higher than medium truck volume conditions. Especially in very-high truck volume conditions, the performance of the STATIC-ONLY system is very close to those of the MSWIM-ONLY system. We speculate that as truck volume increases, the STATIC-ONLY system eventually will have the least expected revenues from fines, the highest expected number of ESAL's, the highest expected number of bridge formula violation truck trips, the least expected fines for a random truck, the least expected number of offloadings for a random truck, and the highest expected time delays for a random truck.

The simulation results show that the performance of the STATIC-with-MSWIM and STATIC-with-HSWIM systems are roughly the same. However, the STATIC-with-MSWIM systems have slightly higher expected revenues from fines, a fewer expected number of ESAL's, a fewer expected number of bridge formula violation truck trips,
higher expected fines for a random truck, and a higher expected number of offloadings for a random truck under the very-high truck volume conditions. We speculate that when truck volume increases, the differences in these attributes between the STATIC-with-MSWIM and STATIC-with-MSWIM systems will become larger.

From our single-attribute analysis, we found that the traditional STATIC-ONLY weight enforcement system is a good enforcement system for the government agencies under the very-low, low, and medium truck volume conditions. However, the STATIC-ONLY system has capacity limitation problems when truck volume increases to between 3,380 trucks/day and 5,100 trucks/day. Because of its capacity limitation, as truck volume increases, more overweight trucks can escape being fined and offloaded and those trucks in the waiting queue experience long delays. Therefore, under the high truck traffic volume and very-high truck traffic volume conditions, the STATIC-ONLY system not only causes the highest average time delays of all the systems, its performance in protecting pavement and bridges also drops dramatically. Therefore, from the government agencies' point of view, we recommend that traditional STATIC-ONLY systems should not be used in high volume and very-high volume highway sites as weight enforcement systems.

6.1.2 Optimal Weight Enforcement System Solutions

In this analysis, we combine the attributes levels with the MAEU function and the set of benchmark scaling parameters we calculated in Section 5.2 to find the optimal weight enforcement system solution of the evaluation problem. Here, an optimal weight enforcement system is the one which has the lowest disutility. We investigate the solution
as a function of truck volumes and the group tradeoff parameter that represents the relative importance of the concerns of the government agencies and the private motor carriers.

There is an error term in calculating the Multi-Attribute disutility, however. In our case, the error comes from rounding off the calculations of the attribute levels and the scaling parameters. In this study, we round off the scaling parameters to the third digit after the decimal point. We round off the predicted attribute levels of the government agency attributes to the first digit before the decimal point. We round off the predicted attribute levels of the motor carrier attributes to the fifth digit after the decimal point. The combined round-off error can contribute as much as 0.0015 in disutility.

To acknowledge the possible effect of the round-off error, we let the round-off error—i.e., 0.0015—be the threshold in the study. That is, if the difference of the disutility of two alternatives is less than 0.0015, we assume that we are not able to specify whether one disutility is really bigger than the other. Therefore, we would specify the two alternatives as indifferent; that is, one alternative is as good as the other.

To portray the results, we construct an optimal weight enforcement system solution diagram as a function of traffic volume and the group tradeoff parameter $K_g$ (see Figure 15). Along the left side of the diagram, we list truck volumes from very-low (at the top) to very-high (at the bottom). In the horizontal direction, we show the group tradeoff parameter $K_g$ from 0 to 1. For each truck volume condition, we calculate by increments of 0.001 the disutilities of the five weight enforcement systems for $K_g$ values from 0 to 1. Then we specify the weight enforcement system which has the least disutility as the optimal. We mark this optimal weight enforcement system with "•••". To recognize the existence of the round-off error, those weight enforcement systems whose disutilities are
not bigger than the disutility of the optimal system plus the defined threshold—e.g., 0.0015—are also listed as optimal solutions. The optimal weight enforcement systems under different truck volume conditions and $K_g$ values are shown in Figure 15.

To illustrate how to read Figure 15, consider the very high truck volume conditions and the group tradeoff parameter $K_g = 0.8$. The results of very-high truck volume conditions are at the very bottom of Figure-15. For $K_g = 0.8$, the diagram shows that the optimal solutions under the very-high truck volume condition are alternatives 4 and 5—i.e., the STATIC-with-HSWIM and STATIC-with-MSWIM systems. That is, under the very-high truck volume with $K_g= 0.8$, we can not specify which of the STATIC-with-HSWIM and STATIC-with-MSWIM systems is better, but we can say that they are better then the other three alternatives. Also, at $K_g= 0.8$ alternative 5—i.e., the STATIC-with-MSWIM system—has a lower calculated disutility then alternative 4 under the very-high volume condition. Therefore, it is marked with "•••", while alternative 4—i.e., the STATIC-with-HSWIM system—is not.

6.1.2.1 Examining Optimal Solutions for $K_g$ Values

Group tradeoff parameter represents the "weight" between the two interest groups. In this study, $K_g$ is specified as the weight parameter of the government agencies. That is, a bigger $K_g$ means putting more weight on the government agency attributes and, therefore, the private motor carrier attributes get less weight. If we move toward the left on the optimal weight enforcement system diagram, the attributes of the motor carriers will be weighed more. On the other hand, if we move toward the right of the diagram, the attributes of the government agencies would have more weight.
Therefore, when $K_g$ is smaller, the optimal solutions should be those systems which have less negative impacts on the motor carriers. When $K_g$ becomes bigger, the optimal solutions should be those systems which have less negative impacts for the government agencies.

We consider the optimal solutions in Figure 15 for all truck volume conditions with $K_g$ increasing from 0 to 1-- i.e., from left to right. The HSWIM-ONLY system is the optimal weight enforcement system under all truck volume conditions for values of $K_g$ near 0. As we move toward the right of the diagram, the MSWIM-ONLY system becomes one of the optimal weight enforcement systems under all truck volume conditions. As $K_g$ increases, the STATIC-ONLY system becomes one of the optimal weight enforcement systems in the diagram. Finally, the STATIC-with-HSWIM and STATIC-with-MSWIM systems appear in the diagram almost at identical values of $K_g$ under the various truck volume conditions.

As $K_g$ increases, there are not only some alternatives which become the optimal weight enforcement systems, but some alternatives drop out of the optimal weigh system diagram. From examining the diagram, we conclude that the systems that are optimal for lower values of $K_g$ will no longer be optimal for higher values. In Figure 15, the HSWIM-ONLY system first drops out of the diagram, the MSWIM-ONLY system second, the STATIC-ONLY system third if it drops out the diagram, and the STATIC-with-HSWIM systems fourth if it drops out of the diagram. However, not every weigh system will drop out of the diagram. The STATIC-with-MSWIM systems stay in the diagram to the end-- e.g., $K_g = 1$. 

6.1.2.2 Optimal Solutions for Different Truck Volumes

Now let us examine Figure 15 across different truck volumes. Generally speaking, we find that the STATIC-ONLY loses its competitiveness when the truck volume increases. As the volume increases, this alternative appears in the diagram for a smaller range of $K_g$. On the other hand, the STATIC-with-HSWIM and STATIC-with-MSWIM systems become more preferred as the truck volume increases. There is not too much difference between the STATIC-with-HSWIM and STATIC-with-MSWIM systems in terms of disutilities. However, the results in Figure 9 through Figure 14 show that when truck volume increases, the STATIC-with-MSWIM system seems to outperform the STATIC-with-HSWIM system.

Now, let us examine the optimal weight enforcement system solutions for fixed values of the group tradeoff parameter. Consider the benchmark value—i.e., $K_g = 0.015$. Figure 15 indicates that the HSWIM-ONLY system is always the optimal alternative under every truck traffic condition.

We also investigate two other interesting $K_g$ values—namely, $K_g = 0$ and $K_g = 1$. When $K_g = 0$ we only address the optimal weight enforcement system solutions from the motor carriers' point of view. Figure 15 indicates that the HSWIM-ONLY system is always the optimal alternative for the carriers under every truck traffic condition.

When $K_g = 1$ we only address the weight enforcement systems solution from the government agencies' point of view. Under the very-low, low, and medium truck volume conditions, the STATIC-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems are the optimal weight enforcement systems. Under the high truck volume condition, only the STATIC-with-HSWIM and STATIC-with-MSWIM systems are the
optimal weight enforcement systems. Under the very-high truck volume condition, the STATIC-with-MSWIM system is the only optimal weight enforcement system.

From the motor carriers' point of view, we conclude that the HSWIM-ONLY system is the only system that is optimal under all truck volume conditions. This is because of its limited scale accuracy. Since the HSWIM-ONLY system has the biggest weight scale measurement error, the greatest tolerance has to be set in weight law enforcement (see Chapter 3). Therefore, with the HSWIM-ONLY system, more overweight trucks can escape from being fined and offloaded.

However, we speculate that when truck volume becomes higher, the private motor carriers would prefer the STATIC-ONLY system over the HSWIM-ONLY system. Under higher truck volume conditions, more trucks can skip the weight enforcement procedure due to the static scale's capacity limitations. As indicated in Figure 12 and Figure 13 the expected fines for a random truck and the expected number of offloadings for a random truck would continue to decrease. The expected time delay of the STATIC-ONLY system is expected to decrease as truck volume increases, but will be greater than 0. Therefore, we speculate that up to a certain truck volume, the STATIC-ONLY system would surpass the HSWIM-ONLY system and become the most preferred weigh system to the motor carriers.

The government agencies would want to catch more overweight trucks so that there are fewer ESAL's, fewer bridge formula violation truck trips, and more revenue from fines. In lower volume conditions—namely, the very-low, low, and medium truck volume conditions, static systems do not face problems in capacity limitation. Most trucks that pass the station can be weighed. Therefore, adding a WIM scale as a screening device to a static station is not very helpful for the government agencies in terms of the increasing
revenues and protecting pavement and bridges. When the truck volume increases to between 1,690 trucks/day and 3,380 trucks/day, the government agencies prefer to put a screening device to sort out those trucks which are most likely to be weight law violators. In this way, a certain percentage of the legally laden trucks can by-pass the station without entering the waiting queue so that the static scale can be used more efficiently in terms of catching overweight trucks. In addition, if the screening scale is more accurate, the static scale can be used more efficiently in terms of catching overweight trucks. Under the high truck volume, almost all the trucks which fail the screening can be weighed by the static scale. However, as truck volume increases to between 5,100 trucks/day and 6,770 trucks/day, a higher percentage of trucks which fail the screening can escape from being weighed because of the capacity limitations of static scales. If the screening device is more accurate, those trucks in the waiting queue are more likely to be overweight. Therefore, the government agencies would prefer a STATIC-with-MSWIM over a STATIC-with-HSWIM system as truck volume grows higher.

Note that, in this study, we assume that if a truck is overloaded, offloading is required even if it is a small amount. However, in the real world, this is not the case. A truck dispatcher in Hilliard, Ohio, informed us that when the overloading is not excessive, some weigh stations might just take the fines and not require the offloading. In this way, the predicted number of ESAL's and number of bridge formula violation truck trips will increase while the offloadings for a random truck will decrease. This might change the optimal weigh system in Figure 15. The change depends on the contribution to the disutility by the number of ESAL's, the number of bridge formula violation truck trips, and the offloading for a random truck. We suggest that following studies can investigate this.
6.2 Sensitivity Analysis

In this section, we investigate which parameters and variables can affect these optimal solutions in the base case under different conditions. We describe the general design of our sensitivity studies in Section 6.2.1 and present the results of the sensitivity analysis in Section 6.2.2.

6.2.1 General Design of Sensitivity Studies

For our study, the sensitivity analysis studies are designed as five-step procedures: 1) changing input parameters by a given amount; 2) re-running the analysis; 3) examining whether the new optimal solution is different from that of the base case; 4) repeating the process for different values of inputs; 5) summarizing the change of the optimal weight enforcement system as a function of the inputs.

In this study, we call the parameters which we vary in the sensitivity analysis the studied parameters. The studied parameters in this research can be classified into two categories: prediction parameters and preference parameters. The prediction parameters are those parameters used in predicting weight enforcement system performances. The preference parameters we refer to are those parameters used to calculate the scaling parameters in the multi-attribute disutility function.

For prediction parameter analysis, we use the weigh scale measurement error, the percentage of overweight trucks in the truck traffic stream, the fraction of TYPE-9A trucks in the truck traffic stream, the weight enforcement system costs, and the number of ESAL's predicted by the ESAL model. We are interested in the fraction of TYPE-9A
trucks in the traffic stream because we were informed by an official at ODOT that this
category of trucks has the highest percentage of overweight trucks. We use the notation
SP1, SP2, SP3, SP4, and SP5 to represent weigh scale measurement error, the percentage
of overweight trucks in the truck traffic stream, and the percentage of TYPE-9A trucks in
the truck traffic stream, weight enforcement system costs, and the number of predicted
ESAL’s from the ESAL model. Also, we set the preference parameters at their benchmark
levels.

In Chapter 5, we used the MRS approach to calculate benchmark parameter values. In
the MRS approach, the marginal rates of substitution—e.g., $dy_i/dy_j$—are the elements
which decide the benchmark scaling parameters. Note that if we change any of the MRS's
for an interest group, all of the calculated scaling parameters for that interest group will
change (see Section 5.2 and 5.3). In this study, we use the marginal rates of substitution as
the preference parameters for the sensitivity analysis. We use notation PP1, PP2, PP3,
PP4, and PP5 to represent $dy_2/dy_1$, $dy_2/dy_3$, $dy_2/dy_4$, $dy_5/dy_6$, and $dy_5/dy_7$. In addition, we
analyze the sensitivity of the coefficient of time delay utility power function $\alpha$. We use
notation PP6 to represent $\alpha$. Also, we set the prediction parameters at their benchmark
levels. The studies parameters are listed in Table 16.

For our sensitivity analysis, we analyze the studied parameters on an equal footing. In
this study, we change the studied parameters by 50% of their benchmark values. To
analyze weigh scale measurement errors, we define a reduction in weigh scale
measurement error as a reduction of the measurement errors of all the three type of scales—
namely, the static, HSWIM, and MSWIM scales. The existing measuring errors for static
scales, HSWIM scales, and MSWIM scales are 0%, 5%, 10% respectively (see Chapter
3). In the case that the system measurement errors are reduced by 50%, the scale
measurement errors for the static scale, MSWIM scale, and HSWIM scale become 0%, 2.5%, 5% respectively. We do not consider the case that weight enforcement systems are inferior to the current technologies in this research. That is, we do not consider increases in weigh scale measurement error.

To analyze the percentage of overweight trucks in the truck traffic stream, we assume that increases or decreases in the percentage of overweight trucks in the traffic stream will only cause shifts of the triangular truck gross weight distributions (defined in Chapter 3) and not changes in the shape of the distributions. Since truck gross weights are modeled with triangular distributions, we can calculate the needed shifts for each of the seven categories of trucks to increase or decrease the percentages of overweight trucks to the proposed levels. We detail the calculations in Appendix-F. Here, to simplify the problem, we assume that all categories of trucks increase or decrease by the same percentage.

Truck gross weight limit is 80,000 lb. in our study. When the percentage of overweight trucks increase by 50%, the triangular distribution of truck category i can be described as:

\[
\begin{align*}
\text{NMAX}(i) &= 1.22 \times \text{MAX}(i) - 17,600 \\
\text{NMOD}(i) &= 1.22 \times \text{MOD}(i) - 17,600 \\
\text{NMIN}(i) &= 1.22 \times \text{MIN}(i) - 17,600
\end{align*}
\]

for \(i = 1, 2, 3, 4, 5, 6, 7\) \(\text{(6-1a)}\)

where \(i\) is the category number of a truck category defined in Table 5, MAX(i) and NMAX(i) are the base case maximum bound and new maximum bound of the gross weight triangular distribution of truck category \(i\), respectively; MIN(i) and NMIN(i) are the base case minimum bound and new minimum bound of the gross weight triangular distribution of truck category \(i\); and MOD(i) and NMOD(i) are the base case mode and new mode of the gross weight triangular distribution of truck category \(i\).
In the case that the percentage of overweight truck decreases by 50%, the triangular distribution of truck category i can be described as:

\[
\begin{align*}
N\text{MAX}(i) &= 0.71 \times \text{MAX}(i) + 23,200 \quad \text{for } i = 1, 2, 3, 4, 5, 6, 7. \quad (6\text{-}2a) \\
N\text{MOD}(i) &= 0.71 \times \text{MOD}(i) + 23,200 \quad \text{for } i = 1, 2, 3, 4, 5, 6, 7. \quad (6\text{-}2b) \\
N\text{MIN}(i) &= 0.71 \times \text{MIN}(i) + 23,200 \quad \text{for } i = 1, 2, 3, 4, 5, 6, 7. \quad (6\text{-}2c)
\end{align*}
\]

where \( i \) is the category number of a truck category defined in Table 5, \( \text{MAX}(i) \) and \( N\text{MAX}(i) \) are the base case maximum bound and new maximum bound of the gross weight triangular distribution of truck category \( i \), respectively; \( \text{MIN}(i) \) and \( N\text{MIN}(i) \) are the base case minimum bound and new minimum bound of the gross weight triangular distribution of truck category \( i \); and \( \text{MOD}(i) \) and \( N\text{MOD}(i) \) are the base case mode and new mode of the gross weight triangular distribution of truck category \( i \).

To analyze the fraction of TYPE-9A trucks in the traffic stream, we assume that a change in the percentage of TYPE-9A trucks will be proportionally shared by other truck types. In the benchmark value, the percentage of TYPE-9A trucks is 73.25%. If we decrease the percentage of TYPE-9A trucks by 50%, the new percentage of TYPE-9A trucks is 36.625%. The percentage of the all types of trucks can be expressed as:

\[
\begin{align*}
N\text{PT}(4) &= 36.625, \quad (6\text{-}3a) \\
N\text{PT}(i) &= \frac{\text{PT}(i)}{1 - \text{PT}(4)} \quad \text{for } i = 1, 2, 3, 5, 6, 7. \quad (6\text{-}3b)
\end{align*}
\]

where \( i \) is the category number of a truck category defined in Table 5, \( N\text{PT}(i) \) is the new percentage of the trucks in the \( i \)th category after the decrease, \( \text{PT}(i) \) is the benchmark percentage of the trucks in the \( i \)th category, and \( \text{PT}(4) \) and \( N\text{PT}(4) \) are the benchmark and new percentage of TYPE-9A trucks, respectively—namely 73.25% and 36.625%.
In the case that the percentage of TYPE-9A trucks increases by 50%, the percentage of TYPE-9A trucks will be more than 100%. We assume that all the trucks in the traffic stream are TYPE-9A. That is,

\[ NPT(4) = 100\% , \quad \text{for } i = 1, 2, 3, 5, 6, 7. \]  

where \( i \) is the category number of a truck category defined in Table 5, \( NPT(i) \) is the new percentage of the trucks in the \( i \)th category after the decrease, and \( PT(4) \) and \( NPT(4) \) are the benchmark and new percentage of TYPE-9A trucks, respectively.

In this study, we also define that a percentage increase or decrease in weight enforcement system costs means that all the five enforcement systems increase or decrease by the same percentage. The system costs for the STATIC-ONLY, HSWIM-ONLY, and MSWIM-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems are $20,000, $33,375, $33,375, $90,107, and $90,107 respectively. After an increase of 50%, the new system costs for the STATIC-ONLY, HSWIM-ONLY, and MSWIM-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems are $30,000, $50,063, $50,063, $135,161, and $135,161 respectively. In the case of a 50% decrease, the new system costs for the STATIC-ONLY, HSWIM-ONLY, and MSWIM-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems are $10,000, $16,688, $16,688, $45,054, and $45,054 respectively.

To analyze the accuracy of the ESAL model, we assume an extreme case that the prediction errors from the ESAL model will cause a shift (increase or decrease) of 50% of the total predicted number of ESAL's. In the case the ESAL's are overestimated by 50%, the predicted number of ESAL's is:

\[ NNESAL(X_i) = NESAL(X_i) \times (150\%) \quad \text{for } i = 1, 2, 3, 4, 5. \]  

(6-5a)
where $X_i$ is the $i$th weight enforcement system defined in Table 1, $NNESAL(X_i)$ is the new predicted number of ESAL's after the change for weight enforcement system $X_i$, $NESAL$ is the predicted number of ESAL's before the change for weight enforcement system $X_i$.

In the case the ESAL's are underestimated by 50%, the predicted number of ESAL's is:

$$NNESAL(X_i) = NESAL(X_i) * (50\%)$$

for $i=1,2,3,4,5$. (6-5b)

where $X_i$ is the $i$th weight enforcement systems defined in Table 1, $NNESAL(X_i)$ is the new predicted number of ESAL's after the change for weight enforcement $X_i$, $NESAL$ is the predicted number of ESAL's before the change for weight enforcement system $X_i$.

We repeat the computer simulations with all the possible combinations of the prediction parameters and calculate the MAEU with the benchmark scaling parameters for the five weight enforcement systems. In this research, we consider two values--namely, reducing by 0% and by 50%-- for weight scale measurement error; we consider three values--namely, increasing by 0%, by 50%, and decreasing by 50% for the fraction of overweight trucks in the truck traffic stream, the percentage of TYPE-9A trucks in the traffic stream, weight enforcement system costs, and the number of predicted ESAL's. From each replication, we obtain a sample observation. Therefore, we have $2^4\cdot 3^4$--i.e., 162-- samples in our prediction parameter analysis.

For the preference parameters, we do not need to re-run the computer simulations. However, we have to change the MRS's to calculate the new scaling parameters. In our base case analysis, the MRS between fines for a random truck and the offloading for a random truck--i.e., $dy_5/dy_6$-- is set at a lower bound (see Section 5.2.2) . Therefore, we only consider increasing by 0% and by 50% for $dy_5/dy_6$ (PP4). Also we only study $a$ (PP6) at the values of 1 and 2. That is, we only consider increasing $a$ by 0% and by 100%. When $a$ equals 1, a thirty-minute delay is only twice as bad as a fifteen-minute delay. When $a$
equals 2, a thirty-minute delay is four times as bad as a fifteen-minute delay. For the rest of
the four studies parameters—namely, \( \frac{dy_2}{dy_1} \) (PP1), \( \frac{dy_2}{dy_3} \) (PP2), \( \frac{dy_2}{dy_4} \) (PP3), and
\( \frac{dy_5}{dy_7} \) (PP5), we consider the case of both an increase percentage and a decrease
percentage from the benchmark value—i.e., increasing by 0%, by 50%, and decreasing by
50%. The calculated values for preference parameters are summarized in Table 17. We
repeat the calculation of the new scaling parameters for all combinations of the preference
values. Then we use the base case simulation results and calculate the MAEU of the five
weight enforcement systems. In our research, we have \( 3^4 \times 2^2 \) —i.e., 324 samples in the
preference parameter analysis.

By comparing the calculated MAEU of the five weight enforcement systems, the new
optimal weight enforcement system can be determined. Here, the optimal weight
enforcement system is defined as the alternative which has the lowest calculated disutility.

As mentioned previously, round-off errors are involved in our disutility calculation.
Therefore, as in the base case study, we introduce the same "threshold" of 0.0015 in the
comparison of the new optimal and the base case optimal solution. Only in the case that
the disutility of the new optimal weight enforcement system is less than that of the base
case optimal minus 0.0015 do we consider that sample to have changed from the base
case; otherwise, we consider the sample not to have changed. We let "0" represent the
"NO-CHANGE" situation; that is, after the change in parameters, the optimal weight
enforcement system is still the same as the base case. We let "1" represent the "CHANGE"
situation; that is, after a change in parameters, the optimal weight enforcement system
switches to another system instead of the base case optimal.

We had planned to use Binary (0/1) LOGIT models to summarize the change of the
optimal weight enforcement system solution. As we shall see, however, there were no
changes, and we did not need a model to summarize the results. Before running the
sensitivity analysis, we had defined the independent variables in the LOGIT model as the
percentage changes of the studied parameters or their interaction terms. In addition, we
believed that the effect of the increase of a parameter might not be the same as that of its
decrease. That is, if increasing a parameter can cause changes in the optimal weight
enforcement system, it does not necessary imply that a decrease of the same parameter
should also cause changes in the optimal weight enforcement system solutions. Therefore,
we planned to use two variables—namely, one variable marked as the percentage increase
of a parameter and the other variable marked as the percentage decrease of a parameter.

For prediction parameter analysis, we let variable VAR11 represent the percentage
decrease of scale measurement error. We let VAR21 and VAR22 represent the percentage
increase and decrease of the percentage of overweight trucks, respectively. We let VAR31
and VAR32 represent the percentage increase and decrease of the percentage of TYPE-
9A trucks in the truck traffic stream. We let VAR41 and VAR42 represent the percentage
increase and decrease of weight enforcement system costs. Finally, we let VAR51 and
VAR52 represent the percentage increase and decrease of the predicted number of ESAL's
from the ESAL model.

For preference parameter analysis, we let variables UVAR11 and UVAR12 represent
the percentage increase and the decrease of \( \frac{dy_2}{dy_1} \) (PP1). We let variables UVAR21 and
UVAR22 represent the percentage increase and the decrease of \( \frac{dy_3}{dy_1} \) (PP2). We let
variables UVAR31 and UVAR32 represent the percentage increase and the decrease of
\( \frac{dy_3}{dy_4} \) (PP3). We let variable UVAR41 represent the percentage increase of \( \frac{dy_5}{dy_6} \)
(PP4). We let variables UVAR51 and UVAR52 represent the percentage increase and
decrease of $dy_5/dy_7$ (PP5). We let variable UVAR61 represent the percentage increase of $\alpha$ (PP6).

With a Binary LOGIT Model, which has two alternatives $i$ and $j$, the probability of choosing alternative $i$ can be modeled as (6-6a) (Ben-Akiva and Lerman, 1985). Here, alternative $i$ would represent changes in the optimal weight enforcement system solution and alternative $j$ would represent no change in the optimal weight enforcement system solution.

$$P_n(i) = \frac{e^{\beta_0 + \sum_{k=1}^{m} \beta_k x_{ki}}}{e^{\beta_0 + \sum_{k=1}^{m} \beta_k x_{ki}} + e^{\sum_{k=1}^{m} \beta_k x_{kj}}}$$

where
- $P_n(i)$: the probability of an observation $n$ having a "Change",
- $\beta_0$ is alternative specific coefficient,
- $\beta_k$ is the coefficient of $k$th independent variable,
- $x_{ki}$ are the value of the $k$th independent variable for alternative $i$,
- $x_{kj}$ are the value of the $k$th independent variable for alternative $j$, and
- $m$ is the number of independent variables.

Since there are only two alternatives--namely, change and no-change, the probabilities must sum to one. We have:

$$P_n(j) = 1 - P_n(i).$$

(6-6b)

We planned to use LIMDEP (Greene, 1991) to do the LOGIT discrete choice analysis. We would have used an $F$ test with 0.05 level of significance to test the null hypothesis that all the coefficients of the LOGIT model are zero (Ben-Akiva and Lerman, 1985), in
which case the model can not give us any information about the change of the optimal weight system solution. We also would have used an asymptotic t test with 5% level of significance to test the null hypothesis that a specific coefficient is zero (Ben-Akiva and Lerman, 1985), in which case the specific variable does not influence the change of the optimal weight system solution.

In such a formulation, a LOGIT model would give us the probability of changing from the base case optimal to other weight enforcement systems. In the final LOGIT model, those variables which are not in the model would not influence the probability of change of the weight enforcement system optimal solution. Positive signs on variables would mean that increasing such variables will increase the probability of changing the base case optimal to other weight enforcement systems. On the other hand, negative signs on variables would mean that increasing such variables will decrease the probability of changing the base case optimal to other weight enforcement systems.

6.2.2 Analysis Results

In the preference parameter sensitivity analysis, our purpose is to specify those preference parameters which will tend to cause the optimal solutions to change from the base case results or to remain as these results. We perform the sensitivity analysis for the preference parameters for three truck volume conditions—namely, low, medium, and high truck volume conditions.

Under the low, medium, and high truck volume conditions, all optimal weight enforcement system solutions of the samples remain the same as the base case solution for all of the 324 combinations of input parameters. Therefore, we conclude that the base case
results are very insensitive to changes in the preference parameters. Moreover, since there were no changes, there was no need to use the LOGIT model to summarize the results.

The results gives us great confidence on our base case results. In the case that the preference parameters are different from our base case values but within the ranges we defined, the base case results can still apply.

In the prediction parameter sensitivity analysis, our purpose is to specify those prediction parameters which will tend to cause the optimal solutions to change from the base case results or to remain as these results. We perform the sensitivity analysis for the prediction parameters under three truck volume conditions-- namely, the low, medium, and high truck volume conditions.

Under the low, medium, and high truck volume conditions, all optimal weight enforcement system solutions of the samples remain the same as the base case solution for all of the 162 combinations of input parameters. Therefore, we conclude that the base case results are very insensitive to changes in the prediction parameters. Moreover, since there were no changes, there was no need to use the LOGIT model to summarize the results.

This result gives us confidence on our base case results. Under the low and high truck volume conditions, when the prediction parameters are different from our base case values but within the ranges we defined, the base case solutions can still apply.
### TABLE 16: List of Studied Parameters in Sensitivity Analysis

<table>
<thead>
<tr>
<th>STUDIED PARAMETERS</th>
<th>VARIABLES USED IN LOGIT ANALYSIS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prediction Parameters</strong></td>
<td></td>
</tr>
<tr>
<td>SP1: weigh scale measurement error</td>
<td>VAR11: percentage decrease of SP1</td>
</tr>
<tr>
<td>SP2: percentage of overweight trucks</td>
<td>VAR21: percentage increase of SP2</td>
</tr>
<tr>
<td>SP3: percentage of TYPE-9A trucks in the truck traffic stream</td>
<td>VAR22: percentage decrease of SP2</td>
</tr>
<tr>
<td>SP4: weight enforcement system costs</td>
<td>VAR31: percentage increase of SP3</td>
</tr>
<tr>
<td>SP5: number of predicted ESAL's from ESAL model</td>
<td>VAR32: percentage decrease of SP3</td>
</tr>
<tr>
<td></td>
<td>VAR41: percentage increase of SP4</td>
</tr>
<tr>
<td></td>
<td>VAR42: percentage decrease of SP4</td>
</tr>
<tr>
<td></td>
<td>VAR51: percentage increase of SP5</td>
</tr>
<tr>
<td></td>
<td>VAR52: percentage decrease of SP5</td>
</tr>
<tr>
<td><strong>Preference Parameters</strong></td>
<td></td>
</tr>
<tr>
<td>PP1: dy&lt;sub&gt;2&lt;/sub&gt; / dy&lt;sub&gt;1&lt;/sub&gt;</td>
<td>UVAR11: percentage increase of PP1</td>
</tr>
<tr>
<td>PP2: dy&lt;sub&gt;2&lt;/sub&gt; / dy&lt;sub&gt;3&lt;/sub&gt;</td>
<td>UVAR12: percentage decrease of PP1</td>
</tr>
<tr>
<td>PP3: dy&lt;sub&gt;2&lt;/sub&gt; / dy&lt;sub&gt;4&lt;/sub&gt;</td>
<td>UVAR21: percentage increase of PP2</td>
</tr>
<tr>
<td>PP4: dy&lt;sub&gt;5&lt;/sub&gt; / dy&lt;sub&gt;6&lt;/sub&gt;</td>
<td>UVAR22: percentage decrease of PP2</td>
</tr>
<tr>
<td>PP5: dy&lt;sub&gt;5&lt;/sub&gt; / dy&lt;sub&gt;7&lt;/sub&gt;</td>
<td>UVAR31: percentage increase of PP3</td>
</tr>
<tr>
<td>PP6: α (coefficient of time delay power function)</td>
<td>UVAR32: percentage decrease of PP3</td>
</tr>
<tr>
<td></td>
<td>UVAR41: percentage increase of PP4</td>
</tr>
<tr>
<td></td>
<td>UVAR42: percentage decrease of PP4</td>
</tr>
<tr>
<td></td>
<td>UVAR51: percentage increase of PP5</td>
</tr>
<tr>
<td></td>
<td>UVAR52: percentage decrease of PP5</td>
</tr>
<tr>
<td></td>
<td>UVAR61: percentage increase of PP6</td>
</tr>
<tr>
<td></td>
<td>UVAR62: percentage decrease of PP6</td>
</tr>
</tbody>
</table>
Table 17: List of Preference Parameter Values in Sensitivity Analysis

<table>
<thead>
<tr>
<th>Preference Parameter</th>
<th>Base Case Value</th>
<th>Increase 50% (%)</th>
<th>Decrease 50% (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PP1 (dy₂/dy₁)</td>
<td>0.5</td>
<td>0.75</td>
<td>0.25</td>
</tr>
<tr>
<td>PP2 (dy₂/dy₃)</td>
<td>-13.19</td>
<td>-19.785</td>
<td>-6.595</td>
</tr>
<tr>
<td>PP3 (dy₂/dy₄)</td>
<td>-6.76</td>
<td>-10.14</td>
<td>-3.38</td>
</tr>
<tr>
<td>PP4 (dy₅/dy₆)</td>
<td>-1699.2</td>
<td>-2548.8</td>
<td>—</td>
</tr>
<tr>
<td>PP5 (dy₅/dy₇)</td>
<td>-0.83</td>
<td>-1.245</td>
<td>-0.415</td>
</tr>
<tr>
<td>PP6 (α)</td>
<td>1.0</td>
<td>2.0</td>
<td>—</td>
</tr>
</tbody>
</table>
Figure 9: Expected Revenues from Fines in a Typical Year for Different Weigh Technologies Under Different Truck Traffic Conditions

Figure 10: Expected Number of ESAL's in a Typical Year for Different Weigh Technologies Under Different Truck Traffic Conditions
Figure 11: Expected Number of Bridge Formulas Violation Truck Trips in a Typical Year for Different Weigh Technologies Under Different Truck Traffic Conditions

Figure 12: Expected Fines for a Random Truck for Different Weigh Technologies Under Different Truck Traffic Conditions
Figure 13: Expected Number of Offloadings for a Random Truck for Different Weigh Technologies Under Different Truck Traffic Conditions

Figure 14: Expected Time Delays for a Random Truck for Different Weigh Technologies Under Different Truck Traffic Conditions
Figure 15: Optimal Weigh System as a Function of Group Tradeoff Parameter Under Different Truck Traffic Volumes
Figure 15: (Continue)

CHAPTER VII

Summary and Conclusions

This study investigates the desirability of truck weight enforcement technologies under various conditions. Because of the nature of the truck weight enforcement technology evaluation problem, we use Multi-Attribute Expected Utility (MAEU) to address the problem. MAEU evaluation, which is arguably the most attractive means of analyzing problems with multi-attributes and uncertainties, includes five steps: identifying alternatives, identifying the involved interest groups and attributes, predicting the attribute levels for a given alternative, specifying the utility function over the attributes, and calculating the expected disutility of the alternatives.

In Chapter 2, we specify the alternatives as various weight enforcement systems. We also specify the involved interest groups and the attributes to be used in this evaluation. We consider a single weigh station in this study and investigate five truck weight enforcement systems as exclusive alternatives for this station. We formulate the problem as upgrading the single station from a static scale. One alternative is to retain the static scale for weight enforcement. We consider replacing the static scale with a high-speed weigh-in-motion scale and replacing the static scale with a medium-speed weigh-in-motion scale. In addition to the single enforcement scale used at the weigh station, we investigate the option of adding a high-speed weigh-in-motion scale on the mainline as a screening
device to sort out trucks most likely to be violating weight regulations; such trucks would later be checked by a static scale. Finally, we investigate the addition of a medium-speed weigh-in-motion scale as a screening device to screen truck traffic in by-pass lanes.

We define the interest groups as the government agencies and private motor carriers. We also define the concerns of the interest groups as attributes (criteria). The concerns of the government agencies are revenue, weight system costs, pavement damage, and bridge damage. For revenue, we use the dollar amount of fines collected in a typical year. For weight enforcement system costs, we use the upgrading costs of a traditional static system to other weight enforcement systems. The weight enforcement system costs are estimated by the sum of discounted yearly weight station remodeling costs, equipment purchase and installation costs, and maintenance costs. For pavement damage, we use the number of ESAL's (equivalent single axle load) in a typical year. For bridge damage, we use the number of bridge formula violation truck trips in a typical year.

The concerns of the private motor carriers are fines, offloadings, and time delays at the weigh station. We predict private motor carrier attributes for a truck chosen at random from the population of trucks passing the weigh station. For fines, we use the fines collected from a random truck. For offloadings, we use a 0/1 binary indicator to represent if a random truck is offloaded. Specifically, 0 represents no offloading and 1 represents offloading. For time delays, we use the minutes of time delays for a random truck at the weigh station.

We predict the attribute levels for each of the five alternatives in Chapter 3. Weight enforcement system costs are estimated from existing data. To predict the other attribute levels, we use computer simulation. We model the weigh station operation in our study in the following manner. When the weigh station is closed, trucks by-pass the weigh station
without been checked of. On the other hand, if the weigh station is open and if it is equipped with a screening device, a truck must go through the screening device. In the case that a truck "fails the screening", it has to wait in the line to be weighed by a static scale; otherwise, it by-passes the weigh station. In the case that a weigh station is not equipped with a screening device, trucks are sent to the end of the waiting line to be weighed by the weigh scale. If the waiting lane is full, trucks can by-pass the weigh station without being weighed. When a truck is weighed, if it is legally laden, it can also leave the station and continue its trip. On the other hand, if an overweight truck is caught, it will be fined and asked to rectify its weight problem—i.e., to offload the cargo. Only after being fined and offloaded will these trucks be able to continue their trips.

We base the truck characteristics on a set of data we obtained from the Ohio Department of Transportation (ODOT). The computer simulation is coded in SLAM II. The linear, additive specification of the utility functions (see below) allows us to use mean attribute levels for six of the attributes. We use 150 weekday computer simulation runs and 150 weekend computer simulation runs to estimate average attribute levels of a weekday and a weekend for each of the five alternative weight enforcement systems, respectively. Then we use the average weekday and weekend data to calculate the attribute levels of each of the five alternative weight enforcement systems for a typical year. The nonlinear utility specification on time delays (see below) require us to use more than the average for time delays. We collect a distribution of time delays in two-minute intervals.

In Chapter 4, we formulate the multi-attribute disutility function. We assume an additive form of the disutility function. We also use linear disutility functions for the four attributes of the government agencies—namely, revenue from fines in a typical year,
yearly weight enforcement system costs, number of ESAL's in a typical year, and number of bridge violation truck trips in a typical year. We also use linear disutility functions for the first two attributes of the private motor carriers -- namely, fines for a random truck and offloading for a random truck. The linear disutility function implies that an extra unit of an attribute is of equal importance to the first unit of the attribute. Finally, we think that the time delay disutility might not be linear. Therefore, we want to investigate the effect of potential nonlinearity in the time, we specify this disutility function as a power function.

In Chapter 5, we discuss how we obtain a set of benchmark scaling parameters for the multi-attribute disutility function. In this research, we calculate a set of benchmark data based on Marginal Rates of Substitution (MRS) and data from literature and other sources. The MRS indicates by how much one attribute should change to compensate for the change of another attribute in order to keep a constant preference level when all other attributes are held at constant levels. The marginal rate of substitution is estimated as $0.5 of weight enforcement system costs for $1 of revenues from fines. The marginal rate of substitution is estimated as $13.19 of weight enforcement system costs for an ESAL on a violation truck trip. The marginal rate of substitution is estimated as $6.76 of weight enforcement system costs for a bridge formula violation truck trip. The marginal rate of substitution is estimated as $1699.2 in fines for a random truck for an offloading of a random truck. The marginal rate of substitution is estimated as $0.83 in fines for a random truck for a one-minute time delay for a random truck (assuming a linear delay disutility function). Using these marginal rates of substitution, we can calculate the scaling parameters of the government agency attributes, the scaling parameters of private motor carrier attributes, and the tradeoff parameter that represents the relative importance between the two interest groups.
In Chapter 6, we analyze the truck weight technology evaluation problem with the formulated MAEU function and the set of benchmark data. We call this the base case study. In the base case study, we analyze the weight enforcement system performance in terms of the single-attributes as a function of truck volume. We also analyze the optimal weight enforcement systems as a function of truck volume and the tradeoff parameter that represents the relative importance of the government agencies' and the motor carriers' concerns ($K_g$). We construct an optimal weight enforcement system solution diagram as a function of different truck volumes and the group tradeoff parameter $K_g$ (see Figure 15).

We investigate our base case study under five truck volume conditions. Specifically, we use mean arrival rates of 720 trucks/day, 1,690 trucks/day, 3,380 trucks/day, 5,100 trucks/day, and 6,770 trucks/day and define these as the very-low, low, medium, high, and very-high truck volume conditions, respectively.

From the single-attribute analysis in our base case study, we found that the traditional STATIC-ONLY weight enforcement system is a good enforcement system under the very-low to medium truck volume conditions. However, the STATIC-ONLY system has capacity limitation problems when truck volumes increase to between 3,380 trucks/day and 5,100 trucks/day. Because of its limited capacity, as truck volumes increase, more overweight trucks can escape being fined and offloaded, and those trucks in the waiting queue experience long delays. Therefore, when truck volumes become sufficiently large, the STATIC-ONLY system not only causes the highest average time delays of all the systems, its performance in protecting pavement and bridges also drops dramatically. Therefore, we recommend that the traditional STATIC-ONLY system should not be used as a weight enforcement system when truck traffic is heavy.
When we calculate the multi-attribute disutility, we round off the attribute levels and the scaling parameters. The combined round-off error can contribute as much as 0.0015 in disutility. To acknowledge the possible effect of the round-off error, we let the round-off error—i.e., 0.0015—be the threshold in the study. That is, if the difference of the disutility of two alternatives is less than 0.0015, we assume that we are not able to specify whether one disutility is really bigger than the other. Therefore, we specify the two alternatives as indifferent; that is, one alternative is as good as the other.

From the motor carriers' point of view, we conclude that the HSWIM-ONLY is the only system that is optimal under all truck volume conditions. This is because of its limited scale accuracy. With the HSWIM-ONLY system, more trucks can escape being fined and offloaded. However, we speculate that when truck volume becomes higher, the STATIC-ONLY system will be the optimal solution for the motor carriers. This is because of their limitations in waiting lane capacity. Under higher truck volume conditions than analyzed in this study, a large number of trucks can by-pass the static station without being checked.

Concerning the government agencies' point of view, the analysis leads to several conclusions. Under the very-low to medium truck volumes, the STATIC-ONLY, STATIC-with-HSWIM, and STATIC-with-MSWIM systems are equally good. Any of the three systems can be deployed in weight enforcement. Under high truck volume, the STATIC-with-HSWIM and STATIC-with-MSWIM systems are equally good. Both of these two systems can be deployed in weight enforcement. Under very-high truck volume condition, the STATIC-with-MSWIM system is the only optimal system for the government agencies.

The results show that adding a screening device to a static scale is not very helpful in terms of collecting fines and protecting pavements and bridges under the very-low to
medium truck volume conditions. Under higher truck volume conditions, adding a screening device can screen out and statically weigh those trucks mostly likely to be overweight. This does help in collecting more revenue from fines and protecting pavements and bridges. As truck volume continues to increase, a more accurate screening device helps collect revenue and protect pavements and bridges. Therefore, the STATIC-with-MSWIM systems are preferred by the government agencies over the STATIC-with-HSWIM systems when truck volume increases to between 5,100 trucks/day and 6,770 trucks/day.

When balancing government agency and private motor carrier concerns, we conclude that the HSWIM-ONLY is the only system that is optimal under all truck volume conditions.

As formulated in this research, there are two categories of parameters that would affect the optimal truck weight enforcement technology alternative, namely, the prediction parameters and preference parameters. The prediction parameters are those which we use to predict the performance of the weight enforcement technologies. The scaling parameters are those which we use to describe the preference for the attributes. We use sensitivity analysis to analyze the influence of those parameters.

We conduct our sensitivity analysis under three truck volumes—namely, the low, medium, and high truck volume conditions. Specifically, we specify 1,690 trucks/day, 3,380 trucks/day, and 5,100 trucks/day as the low, medium, high truck volume conditions, respectively. We had planned to summarize the change and no-change in optimal solutions with a LOGIT Binary choice model. With this model, we can input the percentage change of the independent variables in the LOGIT model to predict the probability of change in the optimal solution. Based on the predicted probability, state governments can decide
whether they want to use the base case results or to conduct their own study for the specific situation.

The sensitivity analysis shows that even over fairly large changes in the preference parameters, the optimal solutions do not change from the base case solution under the three truck volume conditions. Therefore, we conclude that the base case results are very insensitive to changes in the preference parameters.

The sensitivity analysis shows that even over fairly large changes in the prediction parameters, the optimal solutions do not change from the base case solution under the three truck volume conditions. Therefore, we conclude that the base case results are very insensitive to changes in the prediction parameters.

Our analysis also leads us to make some suggestions for future studies. From our study, we conclude that time values, preference parameters, weight enforcement systems costs, and ESAL model accuracy do not seem to be important factors in determining the optimal solutions in our evaluation. Therefore, future studies related to these issues in the context of the weight enforcement system evaluation problems should not be listed as a first priority.

On the other hand, there are two factors which we originally thought were unimportant and, therefore, did not investigate in our sensitivity analysis. Based on insights gained from this analysis, we now feel that they might have great influence on the optimal solutions. They are the waiting lane capacity and safety issues. In this study, we used a waiting lane length from an existing weigh station. If the waiting lane length is increased, fewer trucks would be able to by-pass the weigh station without being weighed statically. In this way the differences in collected revenue, number of ESAL's, number of bridge formula violation truck trips, fines assessed to a random truck, and the offloading penalty for a
random truck among the STATIC-with-HSWIM, STATIC-with-MSWIM, and the STATIC-ONLY systems would be smaller. We speculate that these three systems will tie as optimal for a wider range of \( K_g \) values in the optimal solution diagram in Figure 15. In sensitivity analysis, we also speculate that a smaller percentage of samples will change from the base case optimal under the medium truck volume condition in the prediction parameter analysis. For the rest of the sensitivity analysis, they will still be insensitive to the changes.

In our evaluation, we consider safety issues as secondary. However, if we consider these secondary issues in the evaluation, the optimal solution diagram might be different. Those alternatives which require less separating and merging maneuvers will be more likely to be in the optimal weight enforcement system diagram. That is, the alternatives which weigh trucks or screen trucks in mainline traffic with HSWIM scales—namely, the HSWIM-ONLY and STATIC-with-HSWIM systems—are more likely to tie with other systems as optimal weight enforcement systems in Figure 15. Therefore, we speculate that HSWIM-ONLY and STATIC-with-HSWIM systems will stay in the optimal weight enforcement diagram for a wider range of \( K_g \) values.

In addition, as described in Chapter 6, we think the policy in offloading will also affect our base case results. In this study, we assume that if a truck is overloaded, offloading is required even if it is a small amount. In reality, when the overloading is not excessive, some weigh stations might just fine the trucker and not require the offloading. Therefore, the predicted number of ESAL's and number of bridge formula violation truck trips will increase while the expected offloadings for a random truck will decrease. This might change the optimal weight enforcement system in Figure 15. The change depends on the contribution to the disutility by the number of ESAL's, the number of bridge formula
violation truck trips, and the expected offloadings for a random truck. We suggest that following studies can investigate this.

We also think that it would be useful to be able to specify the performance of the five weight enforcement systems as a function of truck volume. To be able to do that, we suggest that following studies run more simulations to predict the performance of the five weight enforcement systems under more truck volume conditions so that enough sample points can be obtained. Then we can use linear or non-linear regression techniques to specify the relationship between the performance of the weight enforcement systems and truck volume. With these relations, additional analysis can be performed without running simulations.

Finally, our study only offers insight into a single weight enforcement system deployment problem. Eventually, the implementation of the new weight technologies should be considered on a state-wide, region-wide, or even nation-wide basis. Considering the deployment of weight enforcement systems on a transportation network would be more complicated and challenging. In this case, we cannot use our single weigh station results to estimate the results on a network, since when an overweight truck is fined and offloaded, it will not be stopped again. Therefore, if we use the single weigh station results to estimate the results on a network, we will overestimate revenue from fines, number of ESAL's, number of bridge formula violation truck trips, fines for a random truck, and offloading for a random truck. To analyze the weight system deployment problem on a transportation network, multiple weigh station operations would have to be simulated simultaneously instead of one. Also, the issues we ignored when evaluating a single weigh station operation may no longer be ignored. The safety issues at a single weigh station are secondary. However, the safety issues might no longer be ignored when we consider the
potential benefit of reducing 13% of the total truck related accidents at all weigh station sites around the country (see Chapter 2). This is also true for fuel conservation and air pollution issues. If new technologies are deployed nationwide, we may no longer be able to ignore the savings in energy consumption and the reduction of air pollution. Therefore, we must include the non-truck road users and non-road users in the evaluation.
REFERENCES


Moses, F., 1992. *Assessments of Bridge and Structure Related Costs for an Ohio Truck Weight and Fee System*, Ohio Department of Transportation, Columbus, Ohio.


The Ohio Department of Transportation, 1991. *FACTS*, Columbus, Ohio.


APPENDIX A

Truck Arrival Data in ODOT Data Set
Figure 16: Truck Arrival Data at Weigh Station Site on I-70 West-Bound Near Columbus, Ohio (July 21, 1993 and July 25, 1993)
APPENDIX B

Truck Weight Data in ODOT Data Set
Table 18: Truck Gross Weight Data at Weigh Station Site on I-70 West-Bound Near Columbus, Ohio (Sunday, July 25, 1993)

<table>
<thead>
<tr>
<th>GROSS WEIGHT</th>
<th>2200</th>
<th>2300</th>
<th>3220</th>
<th>3320</th>
<th>3330</th>
<th>3370</th>
<th>5212</th>
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</thead>
<tbody>
<tr>
<td>under 100</td>
<td>33.65%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>15.95%</td>
<td>1.67%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>150</td>
<td>20.00%</td>
<td>21.67%</td>
<td>8.57%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>17.57%</td>
<td>38.33%</td>
<td>14.29%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>250</td>
<td>8.11%</td>
<td>6.67%</td>
<td>5.71%</td>
<td>0.72%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>300</td>
<td>3.38%</td>
<td>3.33%</td>
<td>17.14%</td>
<td>2.07%</td>
<td>0.68%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>350</td>
<td>1.34%</td>
<td>11.67%</td>
<td>8.57%</td>
<td>7.55%</td>
<td>1.38%</td>
<td>3.23%</td>
<td></td>
</tr>
<tr>
<td>400</td>
<td>10.00%</td>
<td>8.57%</td>
<td>6.74%</td>
<td>28.57%</td>
<td>2.05%</td>
<td>2.42%</td>
<td></td>
</tr>
<tr>
<td>450</td>
<td>1.67%</td>
<td>14.29%</td>
<td>7.73%</td>
<td>0.00%</td>
<td>0.68%</td>
<td>3.23%</td>
<td></td>
</tr>
<tr>
<td>500</td>
<td>1.67%</td>
<td>14.29%</td>
<td>8.00%</td>
<td>7.14%</td>
<td>2.74%</td>
<td>7.26%</td>
<td></td>
</tr>
<tr>
<td>550</td>
<td>3.32%</td>
<td>5.71%</td>
<td>8.18%</td>
<td>7.14%</td>
<td>4.80%</td>
<td>7.26%</td>
<td></td>
</tr>
<tr>
<td>600</td>
<td></td>
<td></td>
<td>0%</td>
<td>8.63%</td>
<td>0.00%</td>
<td>4.80%</td>
<td>12.10%</td>
</tr>
<tr>
<td>650</td>
<td></td>
<td></td>
<td>2.86%</td>
<td>9.70%</td>
<td>7.14%</td>
<td>6.85%</td>
<td>13.71%</td>
</tr>
<tr>
<td>700</td>
<td></td>
<td></td>
<td>9.07%</td>
<td>0.00%</td>
<td>16.44%</td>
<td>20.97%</td>
<td></td>
</tr>
<tr>
<td>750</td>
<td></td>
<td></td>
<td>13.75%</td>
<td>14.29%</td>
<td>21.23%</td>
<td>19.35%</td>
<td></td>
</tr>
<tr>
<td>800</td>
<td></td>
<td></td>
<td>12.22%</td>
<td>14.29%</td>
<td>26.03%</td>
<td>8.87%</td>
<td></td>
</tr>
<tr>
<td>850</td>
<td></td>
<td></td>
<td>4.40%</td>
<td>21.43%</td>
<td>7.53%</td>
<td>1.60%</td>
<td></td>
</tr>
<tr>
<td>900 &amp; above</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.24%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
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</tbody>
</table>
Table 19: Truck Gross Weight Data at Weigh Station Site on I-70 West-Bound Near Columbus, Ohio (Wednesday, July 21, 1993)

<table>
<thead>
<tr>
<th>GROSS WEIGHT</th>
<th>2200</th>
<th>2300</th>
<th>3220</th>
<th>3320</th>
<th>3330</th>
<th>3370</th>
<th>5212</th>
</tr>
</thead>
<tbody>
<tr>
<td>under 100</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>25.40%</td>
<td>1.88%</td>
<td></td>
<td>0.03%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>150</td>
<td>36.10%</td>
<td>12.03%</td>
<td>6.06%</td>
<td>0.09%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>24.33%</td>
<td>23.13%</td>
<td>3.79%</td>
<td>0.16%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>250</td>
<td>7.76%</td>
<td>19.12%</td>
<td>7.58%</td>
<td>2.70%</td>
<td></td>
<td>0.33%</td>
<td></td>
</tr>
<tr>
<td>300</td>
<td>2.67%</td>
<td>15.12%</td>
<td>23.48%</td>
<td>5.24%</td>
<td>2.08%</td>
<td>1.67%</td>
<td>1.06%</td>
</tr>
<tr>
<td>350</td>
<td>0.53%</td>
<td>10.16%</td>
<td>24.24%</td>
<td>7.68%</td>
<td>9.58%</td>
<td>3.33%</td>
<td>4.96%</td>
</tr>
<tr>
<td>400</td>
<td>0.53%</td>
<td>4.80%</td>
<td>14.39%</td>
<td>10.12%</td>
<td>17.71%</td>
<td>5.00%</td>
<td>7.09%</td>
</tr>
<tr>
<td>450</td>
<td>0.00%</td>
<td>4.38%</td>
<td>7.58%</td>
<td>8.86%</td>
<td>10.94%</td>
<td>2.00%</td>
<td>8.16%</td>
</tr>
<tr>
<td>500</td>
<td>0.27%</td>
<td>3.75%</td>
<td>6.82%</td>
<td>7.61%</td>
<td>4.17%</td>
<td>2.33%</td>
<td>8.51%</td>
</tr>
<tr>
<td>550</td>
<td>2.43%</td>
<td>4.55%</td>
<td>6.93%</td>
<td>2.08%</td>
<td>5.67%</td>
<td>9.93%</td>
<td></td>
</tr>
<tr>
<td>600</td>
<td>1.15%</td>
<td></td>
<td>6.25%</td>
<td>0.00%</td>
<td>4.33%</td>
<td>10.99%</td>
<td></td>
</tr>
<tr>
<td>650</td>
<td>0.63%</td>
<td>0.76%</td>
<td>7.25%</td>
<td>3.65%</td>
<td>5.00%</td>
<td>15.96%</td>
<td></td>
</tr>
<tr>
<td>700</td>
<td>0.00%</td>
<td>0.76%</td>
<td>8.25%</td>
<td>7.49%</td>
<td>10.00%</td>
<td>16.31%</td>
<td></td>
</tr>
<tr>
<td>750</td>
<td>0.00%</td>
<td>0.76%</td>
<td>8.25%</td>
<td>7.49%</td>
<td>10.00%</td>
<td>16.31%</td>
<td></td>
</tr>
<tr>
<td>800</td>
<td>0.00%</td>
<td></td>
<td>9.92%</td>
<td>8.85%</td>
<td>28.00%</td>
<td>9.57%</td>
<td></td>
</tr>
<tr>
<td>850</td>
<td>0.16%</td>
<td></td>
<td>11.60%</td>
<td>10.42%</td>
<td>24.00%</td>
<td>6.74%</td>
<td></td>
</tr>
<tr>
<td>900 &amp; above</td>
<td>1.26%</td>
<td></td>
<td>6.16%</td>
<td>8.86%</td>
<td>7.00%</td>
<td>0.72%</td>
<td></td>
</tr>
<tr>
<td>TOTAL</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
</tbody>
</table>
APPENDIX C

Federal Bridge Formula
The federal bridge formula (Johnson, 1980):

\[ W = 500 \left[ \frac{L \times N}{N - 1} + 12N + 36 \right] \]  

where \( W \): maximum weight in pounds carried on any group of two or more axles, including any and all weight tolerances,

\( L \): distance in feet between the extremes of any group of two or more consecutive axles

\( N \): number of axles under consideration.
APPENDIX D

Functions and Subroutines of the Simulation Program
I. FUNCTIONS

USERF(1): This function records the arrival time of each truck at the weigh station.

USERF(2): This function calculates the time and decides whether the weigh station is open or close.

USERF(3): This function calculate truck arrival rates according to the time.

USERF(4): This function check if the weigh station waiting lane is full at when a truck arrives at the station.

II. SUBROUTINES

SUBROUTINE ASSIGN: This subroutine is a truck characteristics (attributes) assigning mechanism. When a truck is generated, this subroutine assigns the truck with truck type, gross weight, and a set of weight percentage parameters of its axle-groups. With the data, the generated truck will be equipped with attributes 1 through 7.

SUBROUTINE EVENT: In process oriented simulation of SLAM II, those project specialized events have to be scheduled through this EVENT subroutine.

SUBROUTINE WCHECK: This subroutine functions as a weigh station. It will call the related subroutines to execute the process.

SUBROUTINE SCREEN: This subroutine functions as a screening device to screen out those most likely overweight trucks. The result will be assigned as the truck's 9th attribute.

SUBROUTINE CALVIO: This subroutine checks the bridge formula.

SUBROUTINE CALFIN: This subroutine assesses the weight regulation violation fines.
SUBROUTINE ADDLNG: This subroutine adds an arriving truck's vehicle length to the waiting queue.

SUBROUTINE SUBLNG: This subroutine subtracts a truck's vehicle length from the queue when its weighing process begins.

SUBROUTINE TEST: This subroutine checks a truck and determines if it really is a legally laden or overloaded truck. The result will be assigned as the truck's 8th attribute.

SUBROUTINE SGLCHK: This subroutine compares single axle weights and the weight regulation limit for single axles to determine if they are overweight.

SUBROUTINE TAMCHK: This subroutine compares a truck's tandem axle weight and the weight regulation limit to determine if they are overweight.

SUBROUTINE CEASL: This subroutine calculates the pavement damage in EASL's.
APPENDIX E

Comparison of the Computer Simulation Results and the ODOT Data Set
Table 20: Summary of Weigh Station Simulation Model Validation

<table>
<thead>
<tr>
<th>ITEMS</th>
<th>SUNDAY</th>
<th>WEDNESDAY</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Simulation</td>
<td>Simulation</td>
</tr>
<tr>
<td>Total Number of Trucks</td>
<td>1,650</td>
<td>4,400</td>
</tr>
<tr>
<td></td>
<td>1,650</td>
<td>4,432</td>
</tr>
<tr>
<td>Number of Gross Weight Violation Trucks</td>
<td>187</td>
<td>406</td>
</tr>
<tr>
<td></td>
<td>173</td>
<td>390</td>
</tr>
<tr>
<td>Fines Collected</td>
<td>$43,229</td>
<td>$89,319</td>
</tr>
<tr>
<td></td>
<td>$37,599</td>
<td>$90,364</td>
</tr>
<tr>
<td>Number of ESAL's</td>
<td>1,761</td>
<td>4,726</td>
</tr>
<tr>
<td></td>
<td>1,812</td>
<td>4,284</td>
</tr>
</tbody>
</table>
APPENDIX F

Shift of Truck Gross Weight
Triangular Distributions
CASE 1: Overweight Trucks Increase 50%

In Figure 17, fb is parallel to ae. Therefore,

$$\frac{W}{T} = \frac{(a-80,000)}{(b-80,000)}$$

(F-1)

To increase the area above 80,000 lb. by 50%, \( \Delta bdf = 1.5 \Delta ade \). Then we get:

$$0.5 * (b-80,000) * T = 1.5 * 0.5 * (a-80,000) * W,$$

or

$$(b-80,000)^2 = 1.5 *(a-80,000)^2,$$

(F-2)

That is,

$$b-80,000 = 1.22 * (a-80,000),$$

or

$$b=1.22a - 17,600$$

(F-3)

CASE-2: Overweight Trucks Decrease 50%

In Figure 18, fb is parallel to ae. Therefore,

$$\frac{W}{T} = \frac{(a-80,000)}{(b-80,000)}$$

(F-4)

To decrease the area above 80,000 lb. by 50%, \( \Delta bdf = 0.5 \Delta ade \). Then we get:

$$0.5 * (b-80,000) * T = 0.5 * 0.5 * (a-80,000) * W,$$

or

$$(b-80,000)^2 = 0.5 *(a-80,000)^2,$$

(F-5)

That is,

$$b-80,000 = 0.71 * (a-80,000),$$

or

$$b= 0.71a + 23,200$$

(F-6)
Figure 17: An Illustration of a Shift of a Truck Gross Weight Triangular Distribution When the Percentage of Overweight Trucks Increases.

Figure 18: An Illustration of a Shift of a Truck Gross Weight Triangular Distribution When the Percentage of Overweight Trucks Decreases.