FEM BASED INTERDISCIPLINARY APPROACHES TO OPTIMIZATION OF MULTI-STAGE METAL FORMING PROCESSES

Dissertation

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By

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* * * *

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ABSTRACT

Timely response to customer needs is extremely important, at the same time, the internal and external qualities of the product need to be ensured. A good process design and control technique could lower the production cost, at the same time, reduce the scrap rate. However, the non-linear nature of the manufacturing, the close coupling between the thermal, mechanical and material phenomena, and the multi-step nature of optimization make the process difficult to formulate and solve. Advances in the numerical analysis tools have made it possible to model the metal flow in non-isothermal metal forming processes. However, the calculations often become time and computer resource intensive. Process optimizations become very difficult and unstable limiting the numerical tools to trial and error approaches.

In this dissertation, interdisciplinary approaches to optimization of multi-stage metal forming are investigated for application to different aspects of the metal forming processes. These approaches utilize the numerical efficiency and accuracy of the finite element method, fast processing and decision making ability of AI (Artificial Intelligence) techniques, and the strong planning function of the Design of
Experiment (DOE) method. The inverse technique is examined for its efficiency in
determining the thermomechanical processing history of the rolling mill for the
desired final product attributes in roll pass and mill design. Moreover, a virtual soft
sensor is developed for the metal forming process, and is applied to the hot forging of
a wheel hub process. Finally, a roll pass design approach with minimum sensitivity is
presented to accommodate the variance in the rolling process. In this dissertation, the
interdisciplinary approaches are investigated, including Finite Element Method (FEM),
ANN, Simulated Annealing (SA), and DOE and other statistical techniques.
Dedicated to my parents
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# TABLE OF CONTENTS

ABSTRACT ....................................................................................................................... ii
ACKNOWLEDGMENTS................................................................................................. v
VITA ................................................................................................................................. vii
LIST OF TABLES........................................................................................................... xii
LIST OF FIGURES........................................................................................................ xiv

CHAPTERS:

1. INTRODUCTION AND BACKGROUND ......................................................... 1
   1.1 Introduction ........................................................................................................... 1
   1.2 Challenges in the metal forming process design .............................................. 2
      1.2.1 Inverse problems ........................................................................................... 2
      1.2.2 Minimum sensitivity design problems ...................................................... 4
   1.3 Objective of research .......................................................................................... 6
   1.4 Approach used and Research significance .................................................... 7
   1.5 Dissertation Outline ......................................................................................... 10

2. LITERATURE SEARCH FOR DIFFERENT APPROACHES ..................... 11
   2.1 Literature search for inverse problems ......................................................... 11
      2.1.1 Introduction ................................................................................................. 11
      2.1.2 Inverse problems ....................................................................................... 16
   2.2 Literature Search for Minimum sensitivity Design Problems ....................... 22
   2.3 Approach and methodology of the research ............................................... 25
3. HOT BAR ROLLING PROCESS DESIGN AND EVALUATION ................. 32
3.1 Problem statement .................................................................................. 32
3.2 Introduction to rolling process ................................................................. 34
3.3 Process modeling tool ROLPAS ............................................................... 37
3.4 Introduction to Artificial Neural Network (ANN) ..................................... 43
3.5 Inverse agent architecture ..................................................................... 46
3.6 Verification: square-to-round bar rolling .............................................. 50
   3.6.1 Hot bar rolling process used ............................................................. 50
   3.6.2 Implementations details ................................................................. 52
   3.6.3 Results discussion ........................................................................ 55
4. INFERENCE CONTROL: SOFT SENSOR FOR THE METAL FORMING
   PROCESS.................................................................................................... 62
4.1 Introduction ............................................................................................. 62
4.2 Development of virtual soft sensor for hot forging .................................. 66
4.3 Process modeling tool FORGE3 .............................................................. 68
4.4 Simulated annealing ............................................................................... 71
4.5 Soft sensing approach .......................................................................... 74
4.6 Application: wheel hub forging .............................................................. 81
   4.6.1 Process modeling ............................................................................. 84
   4.6.2 Procedures for seeking the relationship for soft sensors ................. 89
   4.6.3 Determining accuracy of soft sensors ............................................ 92
4.7 Discussion .............................................................................................. 95
5. MINIMUM SENSITIVITY ROLL PASS DESIGN..................................... 96
5.1 Need for a roll pass design with a minimum sensitivity ......................... 96
5.2 Minimum roll pass design strategy ....................................................... 101
5.2.1 Seam formation mechanism and seam recognition criteria....................... 101
5.2.2 Problem formulation.................................................................................. 103
5.2.3 Approach implementation ....................................................................... 105
5.3 Approach applied to an actual hot bar rolling process .................................. 110
  5.3.1 Select noise-sensitive parameters ......................................................... 111
  5.3.2 Knowledge preparation for the minimal sensitivity roll pass design ....... 115
  5.3.3 Seek the roll pass design with minimum sensitivity .............................. 119
  5.3.4 Verification ............................................................................................ 121
6. SUMMARY OF CONCLUSIONS AND FUTURE WORK ............................... 126
  6.1 Conclusion .................................................................................................. 126
  6.2 Future work ................................................................................................. 128
BIBLIOGRAPHY ..................................................................................................... 130
## LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 2.1 Classification of inverse problems</td>
<td>18</td>
</tr>
<tr>
<td>Table 3.1 Comparison of inverse agent and ROLPAS verification (850°C/35 microns target, method one)</td>
<td>56</td>
</tr>
<tr>
<td>Table 3.2 Comparison of forward neural solver and ROLPAS results using method one (first design)</td>
<td>58</td>
</tr>
<tr>
<td>Table 3.3 Comparison of forward neural solver and ROLPAS results using method one (second design)</td>
<td>58</td>
</tr>
<tr>
<td>Table 3.4 Comparison of direct inverse NN and inverse agent (1000°C/55 microns target) (method two)</td>
<td>59</td>
</tr>
<tr>
<td>Table 3.5 Comparison of direct inverse NN and inverse agent (1060°C/60 microns target) (method two)</td>
<td>60</td>
</tr>
<tr>
<td>Table 3.6 Direct inverse model results (970°C/48 microns target) (method two)</td>
<td>61</td>
</tr>
<tr>
<td>Table 4.1 Process parameters and their levels for the Kurimoto DOE</td>
<td>86</td>
</tr>
<tr>
<td>Table 4.2 The correlation coefficient of $D_4$, $D_5$, $D_6$, and $D_7$</td>
<td>90</td>
</tr>
<tr>
<td>Table 4.3 The result for target state $D_4$ and $D_5$ are ($77.4998$, $32.1797$)</td>
<td>94</td>
</tr>
<tr>
<td>Table 4.4 The best process design for target state $D_4$ and $D_5$ are ($77.4998$, $32.1797$)</td>
<td>94</td>
</tr>
<tr>
<td>Table 5.1 Data from hot rolling process NN (Jin et al. (2004))</td>
<td>98</td>
</tr>
<tr>
<td>Table 5.2 Underfill values for pass 1 to 7 with nominal and perturbations</td>
<td>113</td>
</tr>
</tbody>
</table>
Table 5.3 Normalized Sensitivity of underfills to perturbations at pass 1 to 7 ....... 114
Table 5.4 Design array for FEM simulations and results of seams recognition .... 116
Table 5.5 Underfill values for pass 1 to 7 with safe design and perturbations .... 123
LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fig. 1.1 Objective for minimum sensitivity design for process with high uncertainty</td>
<td>6</td>
</tr>
<tr>
<td>Fig. 1.2 Objective for minimum sensitivity design using soft sensors</td>
<td>8</td>
</tr>
<tr>
<td>Fig. 2.1 A flow chart for soft sensor approach</td>
<td>13</td>
</tr>
<tr>
<td>Fig. 2.2 Inverse problem: (a) Inverse design problem (b) Soft sensor Problem</td>
<td>17</td>
</tr>
<tr>
<td>Fig. 2.3 The overall strategy for minimum sensitivity metal forming design</td>
<td>31</td>
</tr>
<tr>
<td>Fig. 3.1 Mechanics of the rolling process (Kalpakjian, 1995)</td>
<td>35</td>
</tr>
<tr>
<td>Fig. 3.2 Configuration of a hot strip mill (Lenard et al., 1999)</td>
<td>37</td>
</tr>
<tr>
<td>Fig. 3.3 Flow diagram of the integrated hot rolling model (Pauskar 1998)</td>
<td>39</td>
</tr>
<tr>
<td>Fig. 3.4 The architecture of a three-layer ANN (Hertz et al., 1991)</td>
<td>44</td>
</tr>
<tr>
<td>Fig. 3.5 Development of forward and inverse neural solvers</td>
<td>46</td>
</tr>
<tr>
<td>Fig. 3.6 Inverse agent with error-feedback corrector</td>
<td>49</td>
</tr>
<tr>
<td>Fig. 3.7 FEM meshes in the roll bites</td>
<td>51</td>
</tr>
<tr>
<td>Fig. 3.8 Forward neural network solver (method one)</td>
<td>53</td>
</tr>
<tr>
<td>Fig. 3.9 Inverse neural network solver (method one)</td>
<td>53</td>
</tr>
<tr>
<td>Fig. 3.10 Forward neural network solver (method two)</td>
<td>54</td>
</tr>
<tr>
<td>Fig. 3.11 Inverse neural network solver (method two)</td>
<td>54</td>
</tr>
<tr>
<td>Fig. 3.12 Sensitivity analysis of control variables in method one</td>
<td>57</td>
</tr>
</tbody>
</table>
Fig. 4.1 Typical forging process. (Courtesy Woodheaven forging plant) ..................... 63
Fig. 4.2 Flowchart of measurement system using “soft sensing” ................................. 64
Fig. 4.3 Development criteria of virtual soft sensors .................................................. 66
Fig. 4.4 Graphical illustration of the simulated annealing search of the global minimum (Tarng, 1995) ................................................................. 72
Fig. 4.5 Soft Sensor approach architecture ................................................................. 76
Fig. 4.6 The Initialization Procedures ........................................................................ 79
Figure 4.7. Workpiece configuration during forging (a) Before upset operation (B) 
After upset operation (c) After blocker operation (d) After finisher operation ...... 82
Figure 4.8 Fourteen dimensional locations on the part used for quality control purposes (Courtesy Meteldyne Corp) .................................................................. 84
Figure 4.9 Output attributes $D_4$, $D_5$, $D_6$, and $D_7$. ................................ 88
Figure 4.10 Correlation of output attributes $D_4$, $D_5$, $D_6$, and $D_7$. .................. 88
Figure 4.11 The architecture of forward ANN ............................................................... 91
Figure 4.12 The architecture of backward ANN .......................................................... 91
Figure 4.13 The generalization result for $D_4$ ............................................................. 92
Figure 4.14 The generalization result for $D_5$ ............................................................. 93
Figure 4.15 The training process of inverse ANN ......................................................... 93
Fig. 5.1 Rolling Seam Defect Leads to “End Cracks” in the Long Shafts Cold Extruded. ................................................................. 97
Fig. 5.2 Components of a four-high rolling mill or stand (Kalpakjian, 1995) ............... 99
Fig. 5.3 Schematic illustrating the formation of underfill in rolled bars that result in potential seams in the future................................................................. 102

Fig. 5.4 (a) Two rolls revolving in opposite directions to reduce thickness, (b) Rolls and parts deflection caused by the variation of roll separation force .................. 107

Fig. 5.5 The overall strategy for the robust roll pass design process. ...................... 108

Fig. 5.6 FEM meshes in the roll bites................................................................. 111

Fig. 5.7 Sensitivity analysis for reduction perturbations at all 6 passes...................... 115

Fig. 5.8 Profiles of the bar after the final pass................................................... 118

Fig. 5.9 Simulation results for underfills.......................................................... 118

Fig. 5.10 Illustration of selection of minimum sensitivity design.......................... 119

Fig. 5.11 2D contours for underfills for different roll pass design.......................... 121

Fig. 5.12 Profiles of recrystallized grain size of the nominal and minimum sensitivity design................................................................................................................. 122

Fig. 5.13 Profiles of the roll pass design with perturbation to the minimum sensitivity design................................................................................................................. 122

Fig. 5.14 Comparison of the normalized sensitivity to perturbations for both initial nominal design and safe insensitivity design. .................................................. 124

Fig. 5.15 Effect of different roll pass design on final average grain size................. 125
CHAPTER 1

INTRODUCTION AND BACKGROUND

1.1 Introduction

Manufacturing has been practiced for several thousand years. It is also a human activity that pervades all phases of our life. All the products of manufacturing are around us. Manufacturing process is very important to the world. In the broad sense, manufacturing is the process of converting raw materials into products with desired shapes (Creese, 1999). Various materials can be used in the manufacturing process, such as metals, polymers, ceramics, and wood.

One of the most important manufacturing processes is metal forming, which deforms metals to the desired shapes. It is also called deformation processing or metal working. Metals are important engineering materials because of their strength and toughness. Though various new materials have emerged, metals are still the most generally employed engineering materials, and the growth of their production has often been taken as an indicator of industrial development (Schey, 2000). Metal forming process involve conservation of mass and extensive plastic deformation (Creese, 1999). Plastic
deformation means that only the shape of the workpiece is changed without a change in volume or melting of the material (Schey, 2000).

**1.2 Challenges in the metal forming process design**

With the development of the manufacturing technology and equipment, a large amount of significant changes have been made in the way manufacturing systems are configured and operated. It has been widely recognized that the patterns of customer demands in a global economy are changing rapidly. New products are emerging frequently. This has caused a significant number of industries to shift from the traditional mass-production type of manufacturing system to a more flexible and agile system (Schrader, 2000). Therefore, it is extremely important to give quick response whenever a “new” product is needed by the customers. In a competitive market nowadays, steel companies have already realized this trend and have shown interest in developing a tool which can assist the metal forming process design and reduce the using of trial and error approach to achieve the goal, and reduce the scrap rate.

**1.2.1 Inverse problems**

Often a major goal in metal forming process and mill design is to determine the settings for the process and material conditions to obtain the final product with desired
final properties. For example, during the hot bar rolling process, the average finishing temperature and the average final grain size could be critical as they in turn determine the post-cooling final properties of the product. Determination of process variables for target attributes are classified as “inverse problem” as they are basically a backward simulation procedure.

Furthermore, in process control of metal forming processes, as a result of the limitation incurred by process technology or measurement techniques, some important process variables and material properties of the initial billet are very difficult or impossible to monitor, or adjust promptly. These variables could affect the properties of the final product significantly. It is critical to guarantee them in the proper settings for improved product reliability and reduced scrap rates. These variables are normally obtained by the off-line sample analyses in laboratory. There are several drawbacks associated to this approach (Yan, 2004):

- It is often expensive, and requires frequent and high cost maintenance.
- Significant delay (often several hours) will be incurred in laboratory testing such that the measured signals cannot be used as feedback signals for quality control systems.

Those limitations can have a severe influence on the quality of product and safety in production. Then the need from the actual production urges the researchers to seek a more efficient approach to determine these variables in an on-line manner. Can they can be inferred from the easily monitored parameters? This is also can be thought as
an “inverse problems”, the unknown critical parameters need to be determined from the easily monitored parameters in the control process. The relationship between these variables need to be dug out and utilized to achieve the goal.

To solve the “inverse problems” proposed above, the implicit relationship needs to be discovered. However, metal forming process is very complicated, many variables are involved; they affect the final product in different ways. Trial and error methods are usually used to determine the process settings and materials to be used for a specific desired product. Some of the problems faced by a designer include: design of proper mill for new product, design of dies for new product, selection of proper initial structure of initial billets, the determination of the thermomechanical deformation history of the current billet, the predictive die wear etc.

1.2.2 Minimum sensitivity design problems

During the metal forming process, as a result of the variability of metal forming processes, the properties of final products may vary; sometimes they go beyond the acceptable limits. Moreover, defects are formed which include flow-related defects and material related defects etc. in the final products. These defects in the workpiece can often lead to failure of the parts in the subsequent cold or hot metalworking applications. Hence it is important to guarantee high tolerance on the shape as well as
a close control of final properties. Therefore, it is necessary to analyze all the design parameters from the processing history, and then adjust them to appropriate settings to ensure a satisfied product.

The expenditures involved in the metal forming facilities are easily over several million dollars. Changing or adjusting equipments is also expensive. The determination of initial billet size is very important to ensure a fine final product. For example, in the rolling process, a slightly oversize bar would press hard against the sides and would lead to pinching of the bars and assist in the formation of fins. Fins can be lapped over causing defect in the final bar. If the roll pass design is so robust, such that a small variation in the billet size won’t lead the process to failure or defects. Several papers have discussed the techniques to improve the product quality. Most of final product defects may be removed if there is an opportunity for conditioning the initial billets before processing, or carrying on other techniques. However, those techniques are only focused to control and reduce the variability in the control parameters. This variability can not be eliminated completely. Therefore, a robust design, which is insensitive to the presence of variability in the actual working environment, is extremely important.

A robust metal forming process design, which is insensitive to the presence of variability in the actual working environment, is extremely important. A robust design is needed to accommodate the variance in the metal forming process. As shown in figure 1.1, the metal forming process with the minimum sensitivity will lead to a final
part with required properties, with regard to the variance in the billet size, temperature change etc.

![Diagram showing billet size change, temperature change, and other process variations leading to a final part with acceptable properties through a process with minimum sensitivity.](image)

**Fig. 1.1 Objective for minimum sensitivity design for process with high uncertainty**

From the above discussion, it can be seen that a large number of issues and challenges need to be solved in the metal forming process and that they all have to be addressed for a metal forming sequence.

### 1.3 Objective of research

A major goal in metal forming process and mill design is to determine the settings for the process and material conditions to obtain the final product with desired final properties online, for example, average finishing temperature and the average grain size as they in turn determine the post-cooling final properties of the product. These
classes of problems are just “inverse problem” as they are basically a backward procedure.

The objective here in this research is to find a method that can efficiently determine the process design parameters and the corresponding materials needed, which generate the required product. This can be used in both design process or as a soft sensor for the manufacturing process control.

The process with a minimum sensitivity to process variances would be desired to ensure a final rolled part with required final properties, with regard to the variance in the billet size, temperature change etc. Controlling and reducing the variability of the control parameters during the production process would be costly, and the variability can not be eliminated completely. Therefore, a roll pass design, which is insensitive to the presence of variability in the actual working environment, is extremely important. A robust design is needed to accommodate the variance in the rolling process.

1.4 Approach used and Research significance

With the development of the computer science and numerical modeling techniques, Finite Element Method (FEM) has been popular and efficient in solving metal forming problems. However, the process uncertainty is not included in the deterministic FEM,
and the design is still a trial-error process based on FEM. Artificial Neural Networks (ANN) are used widely nowadays, they have the following advantages:

- Fast and Adaptive (easy to be used online)
- Ability to handle non-linear relationships
- More tolerant to the data points (noise or limited information)

But the performance of ANN strongly relies on the distribution of training patterns available in the design space. Design of Experiment (DOE) is efficient for the collection of engineering data, but the actual DOE is difficult to conduct in the real production process.

Figure 1.2 shows the interdisciplinary approaches used in my approach. In this hybrid approach:
• The inverse process design and the soft sensor problems are the integrated approach based on: ANN, DOE, FEM and Simulated annealing algorithms.

• Minimum sensitivity process design is based on FEM, DOE, Sensitivity analysis, statistical method and optimization techniques.

This research presents interdisciplinary approaches for inverse and robust process design, and also soft sensor approach for the real time on-line process control. These approaches will help in improving process capability and reduction of scrap rate, and will also ensure a more tolerant production system. This technique is a hybrid integration of different disciplines, FEM, AI, and statistical methods. This technique for design and monitoring will also have great utility in the evaluation of existing production processes and for new process development.

The proposed system consisting of interdisciplinary approaches would significantly contribute to:

• The design of a metal forming process without undergoing the trial-and-error procedures traditionally used.

• Obtaining the best metal forming process design and material selection that is robust, considering the inevitable process variances.

• Reduce the scrap rate in the design stage, which would make the process control easier.
• Improve the quality in the final products.

• Offer a fast real-time monitoring means for process control.

1.5 Dissertation Outline

Chapter 1 outlines the motivation behind this work along with the objectives and research approach. Chapter 2 presents a literature search on the approaches used by the other researchers. Chapter 3 presents ANN technique applied in the inverse design problem of the hot bar rolling process design and evaluation. Chapter 4 discusses the soft sensor problem based on the inverse technique, and applied in the hot forging process. Chapter 5 introduces the minimum sensitivity design for the hot bar rolling process. Finally, Chapter 6 summarizes the conclusions of this work and discusses the scope for future work.
CHAPTER 2

LITERATURE SEARCH FOR DIFFERENT APPROACHES

2.1 Literature search for inverse problems

2.1.1 Introduction

Both process design and soft sensor problems can be treated as “inverse problems”. The detailed information is described below in this section.

**Process design problems:**

Often a major goal in metal forming process and mill design is to determine the mill settings for the process and material conditions to obtain the final product with desired final properties online. For example, average finishing temperature and the average grain size as they in turn determine the post-cooling final properties of the product. These classes of problems are just “inverse problem” as they are basically a backward simulation procedure.

**Soft sensor problems:**

It is quite often that some important variables are very difficult to measure in a timely manner. Traditionally, these variables are normally determined by off-line sample
analysis in laboratory. It is generally expensive and needs frequent maintenance; also due to significant delay, by the time these variables are available, the processing conditions have been changed. Hence, they can not be used for the on-line quality control of the changing metal forming conditions.

**Some soft sensors used by others:**

Joseph and Brosillow (Joseph, 1978) presented “inference control of processes” as an approach to monitor these variables, which is also known as “soft sensing”. Here, if some process variables (primary variables) can not be monitored online directly, then some easily measured variables (secondary variables) are measured first, and then the secondary variables can be correlated to the primary variables by empirical or mathematical models to monitor the primary variables.
As can be seen from the flowchart of measurement system using “soft sensing” in figure 2.1, after direct sensors measure the measurable secondary variables, by adopting “soft sensing” technology, the virtual soft sensor are used to create a virtual measurement for unmeasurable primary variables, which would then be used to as a reference for the on-line adjustment corresponding to the optimized the forging process, thus improving process reliability and reduce scrap rates.

The core of a soft sensor approach is the soft sensing model of a plant, which generates a virtual measurement to replace a real sensor measurement. Models based on first principles are called phenomenological models. However, a phenomenological model is often not available due to the complexity of industrial processes. As a result, empirical models are the most popular ones to develop soft sensors. The problem of
empirical modeling is to find a model with the best generalization and prediction performance, given the empirical data. Currently, soft sensing modeling techniques based on empirical models include:

1. multivariate statistics, Kalman filters (KF)
2. artificial neural networks (ANN)
3. regression based on model
4. fuzzy logic
5. hybrid methods.

Yan and his colleagues (Yan, 2004) proposed soft sensing modeling based on support vector machine, and applied soft sensors to the estimation of the freezing point of light diesel oil in distillation column. Here a soft sensing model based on SVM is a black-box model, which based only on input–output measurements of an industrial process. In the modeling procedure, the relationship between the input and output of the plant can be emphasized while the sophisticated inner structure is ignored. The secondary variables are employed to act as the inputs of the soft sensing model, and they are mapped the output as the primary variable. Mapping relationship of the secondary variables to the primary variable is implemented by SVM.

Su (Su, 1998) used a recurrent neural network as a soft sensor for monitoring the process of curing of epoxy/graphite fiber composites. At the outset, the prototype soft sensor, i.e., RNN, was configured through a series of repeated and rapid simulations.
of an analogous model system with known performance equations for learning and testing. Subsequently, this prototype RNN was tuned and validated through a minimum number of laborious experiments, so that the resultant soft sensor is capable of effectively monitoring on-line the DOC of a commercial epoxy/graphite fiber composite in a bag-molding process.

Assis and Filho (Assis, 2000) developed soft sensors for on-line bioreactor state estimation. During a fermentation process, variables such as concentrations are determined by off-line laboratory analysis, making this set of variables of limited use for control purposes. However, these variables can be on-line estimated using soft sensors. It is shown that software based state estimation is a powerful technique that can be successfully used to enhance automatic control performance of biological systems as well as in system monitoring and on-line optimization.

All above papers show successful results for different applications. It has been demonstrated that soft sensors is a powerful technique that can be used to enhance automatic control performance, as well as in system monitoring and on-line optimization. However, “soft sensing” applied hot forging process has not been reported in literature.
2.1.2 Inverse problems

Inverse problems are prominent in science and engineering where often an effect is measured with the cause unknown. Scientists and engineers observe the response of a system and desire to know the particulars of the system that elicited such a response (Karr, 2000). Therefore, the purpose of inverse engineering is often to find an efficient method to obtain the unknown causes based on the observation of their effects. This is in contrast to the corresponding direct problem, whose solution involves finding effects based on known causes.

As shown in the figure 2.2, the inverse design problem is to seek the mapping relationship from the desired final properties to the proper process settings. In essence the soft sensor problem is to map the measurable variables to the unmeasurable variables. Therefore, the technique used for both problems are similar, and both of them can be treated as the inverse problems.
Inverse problem: (a) Inverse design problem (b) Soft sensor Problem

According to the type of information desired in the solution procedure, inverse problems can be classified as backward inverse problem, coefficient inverse problems and boundary inverse problems (Inverse problems, 2002). Table 2.1 shows the difference between above three kinds of inverse problems.

Moreover, Dulikravich (Dulikravich, 1999) classified inverse problems into five categories as following:

1. Shape determination inverse problems
2. Boundary/initial value determination inverse problems
3. Sources and forces determination inverse problems
4. Material properties determination inverse problems

5. Governing equation(s) determination inverse problems.

<table>
<thead>
<tr>
<th>Backward inverse problem</th>
<th>The initial conditions are to be found</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient inverse problem</td>
<td>The classical parameter estimation problem where a constant multiplier in a governing equation is to be found</td>
</tr>
<tr>
<td>Boundary inverse problem</td>
<td>Some missing information at the boundary of a domain is to be found. Note this can be a function estimation problem when this boundary condition changes with time</td>
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**Table 2.1 Classification of inverse problems** (Dulikravich, 1999)

The first sort of inverse problem defined by Dulikravich seems like a formidable problem, while it is the most common problem. Moreover, many quantities can be generated by different sources. They might be very difficult to distinguish. Thus determination of the correct sources is often of significant practical interest. For many applications, it is not allowed to destroy the workpiece in order to extract the physical properties, such as thermal conductivity, specific heat, thermal diffusivity, viscosity, electric conductivity etc. Thus, inverse determination of the physical properties from other available variables is very popular research area.

Inverse engineering aims to solve inverse problems. It actually forms a new research paradigm. In the mathematical formulation of the inverse problem, unknown causes are determined given knowledge regarding the desired solution. Various approaches
for solving inverse problems have been explored. Different types of inverse problems may adopt different methods for their convenience. For example, in the paper by Greywall and his colleagues (Greywall, 1994), they divided the previous works on the inverse problem into two categories broadly. Firstly, the inverse problem is solved by writing the flow equations in a form that does not use the flow boundary as one of the independent variables. In the second category, the wall geometry is first assumed and the pressure distribution using direct flow solvers for the assumed geometry. The wall geometry is then iteratively corrected to reduce the difference between the calculated and the prescribed pressure distribution. Rodic and Gresvonik (Rodic, 1998) claimed that a wide variety of inverse and optimization problems can be solved by minimization of objective function with respect to investigated parameters. A constraint minimization problem is then reduced to an unconstrained problem by a transformational approach. Ko and his colleagues (Ko, 1999) also minimize the objective function in the preform design in metal forming processes.

Trial and error is a method, in which a user starts from some initial value, compares the computed value with the observed value, and appeals to his physical intuition to guess a new value. The procedure is iterated until successive updatings of the value do not significantly lower the difference between the observed and the computed one. If the number of the dimensions of the work space is large, it is difficult to obtain the answers with iterative trial and error method even a result is obtained. It would be very time consuming and expensive.
Least square method is also a commonly adopted technique to solve inverse problems as a result of easy computations. Their only drawback is their lack of robustness, their strong sensitivity to a small number of large errors in a data set (Tarantola, 1994). The least-squares methods can be modified by the addition of regularization terms that impose additional restrictions on admissible solutions and the conjugate gradient method where the regularization is inherently built into the iterative procedure (Park, 2002). However, as a result of repeated calculation, they demand a tremendous amount of computer time, therefore, they are still expensive methods.

Successive approximation methods are iterative in that they attempt to make better approximations to the solution, these methods can work well if an effective mechanism for updating the approximations is readily available (Karr, 2000).

In general, for different types and different applications of inverse problems, the methods used to solve them are quite different. If the inverse problem can be formulated well mathematically, then various numerical methods can be exploited to solve the inverse problems, and then obtain an exact inversion or a pretty good approximation to the exact inversion. Dulikravich (Dulikravich, 1999) pointed out that the inverse problems are solvable if additional information can be obtained and if appropriate numerical algorithms are used.
However, most of inverse problems solved with standard methods exhibit a high numerical instability (Hruz, 1999). They are so called “ill-posed” because they incorporate an inversion which lacks good properties of the original model. Hruz also mentioned two most critical problems. First, there is no solution to the inverse problem. Secondly, the solution is not stable (inverse operator is not continuous). Generally, “a prior” information is used to make the problems solvable, or the problems are regularized. For instance, linearization involves approximating a highly nonlinear problem with linear equations, i.e., substituting a “nearby” problem for the true nonlinear problem. The inverse linear problem that results is usually far easier to solve than its nonlinear counterpart. Of course, the danger with this approach is that the linear solution is not always a good approximation of the true, nonlinear solution. (Karr, 2000)

All the above approaches are analytical methods based on some mathematical modeling. The mathematical modeling of the metal forming process has long been recognized to be a desirable approach to aid in investigating metal forming operating practice, and the design of equipment to improve productivity and quality. However, many factors, such as strain hardening and strain rate hardening, friction condition, wearing of dies, deflection of the metal forming and temperature, as well as their interactions, make the theoretical analysis of the metal forming process very complex and time-consuming. Therefore, sometimes it is very difficult to employ the methods described above to analyze the process, and perform the inverse calculation to obtain the appropriate process settings and material properties to obtain the goal of the
2.2 Literature Search for Minimum sensitivity Design Problems

Since the metal forming process design is based on deterministic process mode, any variation in the design parameters is likely to make the design infeasible and useless. This design may be extremely sensitive to small variations in a parameter which was assumed to be a constant in the problem formulation; these variations are often due to the process noises which are inevitable in the actual metal forming processes. Therefore, the problem of designing metal forming processes under uncertainty is considered. The basic idea is to ensure the quality at the design stage by minimizing sensitivity of the response to uncertain variables by proper selection of design variables settings.

In the application of steel, surface quality is a very important quality control parameter. For example, the surface defects in bar rolling are caused by exogenous entrapment, bad surface condition of input billets, non-uniform thermal profile during rolling, incorrect guide setting, improper reduction schedule and improper roll pass design (Topno, 2002). In forging, cold finishing, and machining, the majority of rejections are due to surface imperfections (Iron and Steel Society, 1996). Many of these are seams that originally appeared as surface breaks during the primary rolling or
blooming mill reduction. The author mentioned that the design parameters are subject to variability in many optimization models. Since an optimal point often lies on the boundary of the feasible domain, any variation in the design parameters is likely to make the design infeasible and useless.

Most of these may be removed if there is an opportunity for conditioning the bloom before rolling the final product, some remnants may appear greatly extended after further rolling (Florchak, 1961). These techniques are only focused to control and reduce the variability of the control parameters. However, the variability can not be eliminated. Therefore, a robust roll pass design, which is insensitive to the presence of variability in the actual working environment, is extremely important. A robust design is needed to accommodate the variance in the rolling process.

Taguchi (1985) pointed out the importance of robustness in the process. Taguchi’s theory is generally realized by conducting planned experiments (Belegundu, 1989). In this approach, the objective is to ensure product quality at the design stage. Other approaches addressing uncertainties at the design phase use probabilistic concepts. These approaches treat the uncertain variables as random variables with a known distribution. Probabilities of failure are determined and minimized. For nonlinear random behavior, probabilities have been estimated using Monte-Carlo simulation and Taylor series approximations. In the design stage, the distribution of noise is not known; therefore, minimum sensitivity analysis offers a straightforward procedure for robust design and can be implemented in a general manner (Belegundu, 1989). It is
shown that reduction in sensitivity leads to an increase in probability of safety by several researchers as described below.

Adali (2001) conducted a minimum sensitivity design of laminated shells under axial load and external pressure. In structural design problems, it is often important that designs be insensitive to variations in parameters that affect the desired response. In order to design structures which are insensitive to manufacturing imperfections, the sensitivity of a structure to variations in design parameters can be taken as the objective of the design optimization problem. In this paper, a laminated cylindrical shell of finite length under combined loads is optimized for minimum sensitivity of buckling load to variations in ply angles to a constraint on buckling load. Belegundu (Belegundu, 1989) obtained a robust mechanical design through minimum sensitivity. Here the problem of designing mechanical systems or components under uncertainty is considered. The basic idea is to ensure quality control at the design stage by minimizing sensitivity of the response to uncertain variables by proper selection of design variables. Rao (Rao, 1992) also performed multiobjective insensitive design of structures. Here, Rao described that the design parameters are subject to variability in many optimization models. Since an optimal point often lies on the boundary of the feasible domain, any variation in the design parameters is likely to make the design infeasible and useless. At last, Rao concluded that the designs obtained from the present methodology yield highly insensitive, robust and reliable designs. The insensitive design procedure is illustrated through the design of two truss examples.
Parkinson (1997, 2002) presented the variability optimization to conduct the robust design problems. First a deterministic method of robust design against design parameter uncertainty is described. Based on known or assumed uncertainties in the parameters of the measure and its known dependency on these parameters, a variability function for the performance measure under consideration is defined. It is assumed that the design parameters are subjected to constraints in their individual values and interactions and that the performance measure is required to have a specified nominal design point value when the design parameters are at their chosen nominal values.

2.3 Approach and methodology of the research

2.3.1 Approach for the inverse problem

All kinds of classical methods have been applied to inverse problems in metal forming. Karafillis and Boyce (Karafillis, 1993) applied a linear inverse technique for designing die shapes for sheet forming using a springback calculation. Zabaras and Badrinarayan (Zabaras, 1993) discussed possible candidate techniques of attacking inverse problems in metal forming. Maniatty and Chen (Maniatty, 1994) developed numerical tools based on inverse methodology for the design of forming processes such as drawing and rolling. Lorenzo and Micari (Lorenzo, 1998) applied an inverse approach for the design of the optimal preform shape in cold forging. Rodic and Gresvonik (Rodic, 1998) used a transformational approach to enforce parameter constraints in inverse and optimization problems in cold forging. Karr (Karr, 2000) has tried to solve inverse
initial-value, boundary-value problems via genetic algorithm (GA).

However, these methods, including classical analytical methods and genetic algorithm, would have the “ill-posed” problems. Moreover, most of the work focuses on a specific situation which can be described with term off-line because the final goal is given statically at the beginning and the solution is computed for the whole process from the start to the end. These approaches are sufficient for many processes; however, on-line problems need the algorithms that can persistently read the process data and set the parameters so that the distributed quantities are maintained in certain or varying bounds.

Inspired by biological systems with a large amount of neurons, artificial neural networks can perform tasks that even the most advanced computers have not been able to match. Researchers are attempting to explore the nervous systems, and trying to capture the power of the biological systems. Artificial neural networks have been applied explosively in various fields, such as linear and nonlinear optimization, speech and image recognition, automatic control, and so on.

Neural technology has been frequently used in the metal forming process. Larkiola et al. (Larkiola, 1996) integrated neural computation and physical models to predict the rolling force in cold rolling. Nilsson (Nilsson, 1998) used a three-layer perceptron network to predict the average temperature of the transfer bar after rolling in the rougher. Korczak et al. (Korczak, 1998) employed a neural network approach to predict mechanical properties after hot plate rolling processes. Chun et al. (Chun, 2001)
also developed a neural computation model to predict the width variation in a plate mill. Up to now, neural networks in metal forming have concentrated on forward process prediction.

Some researchers have applied neural networks in the selection of parameters. Chun (Chun, 1999) used neural networks to predict parameters in the hot working of aluminum alloys. Kim (Kim, 1997) determined the initial billet geometry for a forged product using neural networks. Ko (Ko, 1999) applied artificial neural network and Taguchi method to preform design in metal forming considering workability. However, neural networks in these papers are essentially still the forward predicator.

Since solving the inverse problem is equivalent to approximating an inverse mapping, it is logical to consider using neural networks. Artificial Neural Networks (ANN) can be taught the mapping between inputs and outputs through training patterns, and at the same time, determine the new data patterns based on previous knowledge. What a ANN performs can be called vector mapping, all neural networks are special cases of vector mapping (Gunasekera, 1998). The mapping relationship is encoded in its structure. The weights within ANN defines the relationship between the input and output vectors. Since 1982, when the valuable properties of ANN were discovered again, many researches had been performed to explore the ability of ANN to capture and retain underlying complex, nonlinear patterns (Luxhoj, 1998). Overcoming the limitation of the traditional inverse methods described in the above section, ANN can solve problems which are difficult to solve using the logical, analytical techniques or
traditional approaches, where rules are not known.

ANN can offer the advantages of execution speed once the network has been trained. A Common characteristic is the ability to classify streams of input data without the explicit knowledge of rules, and to use arbitrary patterns of weights to represent the features of the different categories. ANN is self-adapting systems, processes information dynamically in response to external inputs. Therefore, ANN is suitable to solve the inverse problems.

Neural networks have already been applied into various areas for inverse problems. Zhong et al. (Zhong, 1996) applied neural technology for robot inverse compensation, for both local and global problems. They present simulation and experimental results for a Puma robot to show the effectiveness of the NN-based approach. In the paper by Fairbairn et al. (2000), neural networks are used to evaluate the parameters characterizing the statistical distribution for a given response of the structure following an inverse analysis procedure. Jones et al. (Jones, 1999) describes methods of applying a neural network technique to the magnetic inverse problem of determining the anisotropy filed distribution from experimental transverse susceptibility data. Wang et al. (Wang, 1999) describes a two-stage network architecture to enhance network approximation capability and solved the inverse scattering problem with RBF neural networks.
Traditionally the designer solves this inverse problem through “intuition” and “trial and error” methodologies. In this research, the inverse problem will be solved based on artificial intelligence together with optimization techniques, explore the method used in finding the settings for processing and materials, and ensure to obtain the final rolled product with both desired internal and external properties even for a very complicated metal forming process.

For the minimum sensitivity process design problem, first, the selection of the design parameters is based on the prior knowledge about the process, and it could be from the experienced engineers, or from existing knowledge base, such as handbook or internet. Then all the main available design parameters are used for the rolling process. Consider all kinds of noises in the actual rolling process. Then small perturbations are added to each factor on purpose. By analyzing the sensitivity of all the parameters, the reaction of all factors to the perturbations can be mimicked. Only those significant parameters are kept. In the second design stage, variability optimization technique is used to obtain the robust nominal settings, which are insensitive to the process noises. The design of experiment is performed to prepare the input array for the FEM simulations.
2.3.2 Approach for the minimum sensitivity design

Figure 2.3 shows the overall strategy of the approach. First, the selection of the design parameters is based on the prior empirical knowledge of the metal forming process, and it could be from the experienced engineers, or from existing knowledge base, such as handbook or internet. All the main available design parameters are used for the metal forming process. Consider all kinds of noises in the actual metal forming process. Then small perturbations are added to each factor on purpose. Then these uncertainties in the process conditions need to be propagated through the process model to discover the uncertainty in the final product. By analyzing the normalized sensitivity of all the design parameters, the reaction of all factors to the perturbations can be mimicked. Only those significant parameters are kept. In the second design stage, minimum sensitivity design technique is used to obtain the robust nominal settings, which are the least sensitive to the metal forming process noises. The procedures described above are repeated until all the design variables have the minimum sensitivity to the process variances. The design of experiment is performed to prepare the input array for the FEM simulations.
Fig. 2.3 The overall strategy for minimum sensitivity metal forming design.
CHAPTER 3

HOT BAR ROLLING PROCESS DESIGN AND EVALUATION

3.1 Problem statement

During the hot rolling of bars, defects are formed which include flow-related defects such as fins, laps, seams etc. and material related defects such as segregations, inclusions, banding etc. in rolled products. These defects in rolled bars can often lead to failure of the parts in subsequent cold or hot forging applications. Hence it is important to guarantee high tolerance on the shape as well close control of final properties.

Often a major objective in roll pass and mill design is to determine the thermomechanical processing history in the mill for the desired final parameters such as average finishing temperature and the average grain size as they in turn determine the post-cooling final properties of the bar product. This class of problems is basically a backward procedure, therefore they are “inverse problems”. The objective in these
problems is to find a formulation that can efficiently determine the best design parameters, which generate the required product. The roll mill designer solves this inverse problem through “intuition” and “trial and error” methodologies.

With the development of computer systems, numerical analysis has become a leading method for analyzing deformation in rolling processes. 3-D FEM techniques to simulate the shape rolling process were developed by Kiuchi et al. (Kiuchi, 1987) and Kim et al. (Kim, 1991). Pauskar et al. (Pauskar, 1996) modified and improved Kim’s software. Computer aided roll pass design systems have also been developed in the last decade. Shin (Shin, 1995) has reviewed some of the important work relevant to computer aided roll pass design. However, all the numerical techniques solve the “forward problem” for a set of boundary conditions and energy or momentum balance. In addition they are time and computational resource intensive.

The approach used in this research integrates artificial neural networks (ANN), the finite element method (FEM), and design of experiments (DOE) for inverse computation of the input conditions when the required final conditions are given. Two sets of training patterns calculated by FEM are used to train the neural networks. Both the forward and the inverse iterations are carried out by ANNs without the need for FEM simulations. FEM simulations are used for verifying the accuracy of the process design determined by the ANN solvers.
3.2 Introduction to rolling process

As an example, rolling is the process of reducing the thickness or changing the cross section of a long workpiece by compressive forces applied through a set of rolls (Kalpakjian, 1995). Figure 3.1 shows that two rolls revolve in opposite directions to reduce thickness. The primary objectives of the rolling process are to reduce the cross section of the incoming material while improving its mechanical properties and to obtain the desired section at the exit from the rolls. This is the most wildly used metalworking process because it lends itself to high production and close control of the final product. Rolling accounts for about 90 percent of all metals produced by metalworking process (Kalpakjian, 1995). Then the manufactured steel goes as raw material for other processes, such as forging, extrusion, machining, etc. Therefore it is important to get rolled product without defects, or else these defects will be carried down the line and affects the properties of the following end products.
Fig. 3.1 Mechanics of the rolling process (Kalpakjian, 1995)

Rolling process is a complicated process. To achieve optimum final product, it is necessary to know how each rolling process variable affects the production process. For instance, a typical hot strip rolling mill can be illustrated in figure 3.2. It consists of five steps (from Lenard et al., 1999):

1. Reheating: Billet is heated up to hot rolling temperatures (1200~1250°C) to dissolve most alloying elements and remove the cast dendrite structures.

2. Rough rolling: The scale of hot billet is first removed by high-pressure water spray (descaling). Then the billet passes through rough stands that reduce the thickness from approximately 270 mm to 50 mm. Sometimes
for the convenience of the steels to enter the mill, some groves are made to get better bite condition. During rough rolling, edge rolls control the billet width. After rough rolling, the billet is transferred to the finishing mill by the transfer table. The surface speed of the strip after the first several reductions in rough rolling is relative low, maybe from 4 to 10 m/s.

3. Finish rolling: The billet continuously passes through five to seven rolling stands. The temperature and the thickness of the billet at the exit of each pass are measured. An automatic gauge control (AGC) system controls the exit thickness according to the measured thickness and adjusts tension between rolls to compensate for thickness error. Usually the finishing temperature after finishing rolling is between 850 °C and 900 °C. The surface speed of the strip after the final several reductions in finish rolling is relative high, maybe larger than 30m/s.


5. Coiling: Long lengths of sheet issuing from the rolling mill are coiled. Coils weight up to 30 Mg (33 tons). At the exit of the runout table, the coiler coils the strip and the temperature of the strip is measured.
3.3 Process modeling tool ROLPAS

With the development of computer systems, numerical analysis has become a leading tool for analyzing deformation in metal forming processes. 3-D finite element methods to simulate the shape rolling process were developed by Kiuchi et al. (Kiuchi, 1987) and Kim et al. (Kim, 1991). Pauskar et al. (Pauskar, 1996) modified and improved Kim’s software. Computer aided roll pass design systems have also been developed in the last decade. Mauk et al. (Mauk, 1982) developed a computer aided roll design system for relieving the designer of tiresome routine work while leaving critical decisions to the roll pass design expert. Perotti et al. (Perotti, 1990) introduced a new approach for computer aided roll pass design by combining empirical formulae and iterative schemes. Alberti et al. (Alberti, 1991) proposed an integrated approach...
based on knowledge based systems and FEM methods. Shin (Shin, 1995) has reviewed some of the important work relevant to computer aided roll pass design.

In this research, ROLPAS is utilized to analyze rolling process. The Manufacturing Research Group (MRG) at The Ohio State University has developed software to predict the quality of the rolled bar. An integrated system developed for modeling metal flow (ROLPAS) and microstructural evolution (MICON) during shape rolling has been developed. The system includes modules for modeling of phase transformation (AUSTRANS) during table cooling and the prediction of mechanical properties of the rolled product. The central feature of the current integrated hot rolling model is a 3-D finite element program ROLPAS for simulating multi-pass shape rolling (Figure 3.3). This FEM code predicts the distribution of temperature, strain, strain rate, the material flow as well as the roll separating forces and torques. The code is being used by a number of steel companies for metal flow simulations and has yielded good results. Details on the formulation of the FEM model can be found in Pauskar (Pauskar, 1998). Such a system has been shown to be a powerful analysis tool that can be used as an inexpensive alternative to the traditional trial and error approach in roll pass design.
The microstructural evolution module MICON (Figure 3.3) uses the thermomechanical history computed by the FEM program in conjunction with empirical microstructure models to predict the evolution of austenite during hot rolling. The microstructural changes occurring in bar rolling are primarily due to static recrystallization and grain growth that occur in the interstand region. In roll passes where accumulated strain is large, meta-dynamic recrystallization is modeled in the interstand region following Sellars (Sellars, 1979). The ability of the program to model the evolution of austenite during rolling with reasonable accuracy was demonstrated by Pauskar et al. (Pauskar, 1997). ROLPAS uses the microstructural evolution data to model subsequent deformation and to compute the thermomechanical history. This thermomechanical history data is in turn used to model microstructural evolution in the next interstand.

Hence by using the rolling model, it is able to predict the final properties of the billet as well as the loads and torques at individual passes. State variables such as the
geometry of the billet and its microstructure (austenite grain size and different phases) are also predicted in this analysis step. Even though this simulation is relatively quick due to the advancements in computer technology and improvements in the FEM software, it is not instantaneous and takes a few hours depending on the computer used, the number and type of passes.

In ROLPAS, the penalty term approach is used. The equilibrium for a rigid-viscoplastic von Mises material derived from variational principle can be presented as follows (Pauskar, 1998):

\[
\int_\Sigma \frac{2}{\sqrt{3}} \frac{\sigma}{\varepsilon} \delta \varepsilon_{ij} dV + k \int_\Sigma \dot{\varepsilon}_{kk} \delta \varepsilon_{kk} dV - \int_{\Sigma_f} t^* \delta \nu_i dS = 0
\]  

(1)

Where \( k \) is an arbitrarily large penalty constant used to satisfy the incompressibility condition in plastic flow. The integral equation in the matrix-vector form instead of tensor notation in ROLPAS is,

\[
\Psi(\dot{\nu}) = \int_\Sigma \frac{2}{\sqrt{3}} \frac{\sigma}{\varepsilon} B^T DB \dot{\nu} dV + k \int_\Sigma \dot{\varepsilon}_{kk} c c^T B \dot{\nu} dV - \int_{\Sigma_f} N^T t^* dS = 0
\]  

(2)

Here, the first and second integrals represent the energy dissipation by shear and dilatational deformation respectively, and the third integral represents the traction boundary condition. ROLPAS uses the following friction model
\[ f = -mk_y \left\{ \left( \frac{2}{\pi} \right) \tan^{-1} \left( \frac{|v_R|}{a} \right) \right\} \frac{v_R}{|v_R|} \]  

Where,

- \( f \) is the friction force
- \( m \) is the friction factor
- \( k_y \) is the shear yield stress
- \( v_R \) is the magnitude of relative velocity between die and workpiece
- \( a \) is a constant several orders of magnitude less than the die velocity (~ \( 10^{-5} \))

Because of the non-linear nature of the equations, an iterative approach has to be resorted to. Two iteration techniques are used in solving this set of equations:

- The direct iterative method
- Newton-Raphson iterative method

For a given workpiece cross section geometry (2-D mesh in the cross-section of incoming bar), the program ROLPAS automatically generates the 3-D finite element control volume in the roll gap using eight-node hexahedral isoparametric elements.
After the initial control volume is established, traction and velocity boundary conditions are assigned to the nodes after determining the geometrical relationship between workpiece and rolls. The program then solves a set of simultaneous nonlinear equations under the assigned boundary conditions. In order to find the kinematically steady state geometry, ROLPAS updates the geometry of workpiece after every iteration in the solution process based on the velocity field obtained. Iteration is continued until convergence of solution occurs.

The transient heat transfer problem is governed by the following equation:

\[ -\left(\frac{\partial q_x}{\partial x} + \frac{\partial q_y}{\partial y}\right) + \dot{Q} = \rho c \frac{\partial T}{\partial t} \]

Where,

- \( q_x \) and \( q_y \) are the components of the heat flow rate vector per unit area
- \( \dot{Q} \) is the internal heat generation rate per unit volume = \( \bar{\sigma} \dot{e} \)
- \( \rho \) is the material density
- \( c \) is the specific heat of the material
3.4 Introduction to Artificial Neural Network (ANN)

An ANN consists of many artificial neurons that are linked together according to specific network architecture (Hertz et al., 1991). Figure 3.4 shows the architecture of a three-layer ANN. The objective of the ANN is to transform the inputs into the corresponding outputs. At the neural level, the learning happens by changing of the synaptic strengths, i.e., weights, until the computation epochs reach a predetermined value, or the mean square error between the actual output and the target output is smaller than the tolerance. Finally, at the end of the training process, the knowledge is stored in the weights between individual neurons, which are used for generalization. To validate the ANN, it is exposed to the different input and output patterns, which are not shown in the training process.
Generally, various activation functions are employed in the ANN training process. One frequently used activation function employed for both the hidden and output layers is:

\[ g(x) = \frac{1}{1 + e^{-x}} \]  

(5)

Weights are assigned randomly to all the connections before training the neural networks. The network is then trained by employing the errors to update the weights. The errors are obtained by comparing the actual output data and the target output data corresponding to the input data. The error function can measure the square error:
Where $E$ is the total error in the output layer, $T_i$ is the target output, and $O_i$ is the actual output. The back-propagation algorithm is used to move the weight vector $W$ in the direction of reducing errors:

$$W \leftarrow W - \alpha \frac{\partial E}{\partial W}$$

(7)

$\alpha$ is the learning rate. The training process is finished after the errors are lower than the threshold.

In theory, the multi-layered perceptron can learn to approximate any function given sufficient layers and neurons. Generally it has been proven that a single hidden layer is enough to learn the approximation of a nonlinear function, thus forming a mapping from inputs to outputs. Moreover, a neural network with two hidden layers is not better than one with a single hidden layer.
3.5 Inverse agent architecture

As long as the required final properties $Y_d$ are given, the inverse agent should decide the process settings $X$, which will lead to the properties of the final product $Y$ being close to the goal $Y_d$. The rolling process is very complex; with lots of variables affecting the final product at the same time. As a result of the complexity during the process of rolling, the non-linearity of the problem, it is difficult to meet all the requirements at the same time. To fulfill this objective, a forward and an inverse solver were employed. Here, the inverse agent receives the desired final product properties and calculates the corresponding bar rolling process settings using an error feedback corrector.

![Diagram](image)

Fig. 3.5 Development of forward and inverse neural solvers.
To develop the inverse agent, one forward neural solver and one inverse neural solver are needed. \( X \) is considered as the input to the forward neural solver and the output of the inverse solver. At the same time, \( Y \) is the output of the forward neural solver and the input to the inverse neural solver. Figure 3.5 illustrates the development of the forward and inverse neural solvers based on FEM simulations (ROLPAS).

Initially training patterns have to be created to offer guidance and supervision for both the forward and inverse solvers, which are based on neural networks. For this first task, the DOE technique is used to create different combinations of the process settings \( X \). These combinations are then simulated using FEM. Here the outputs are final product properties \( Y \). After all the simulations have been finished, the input-output samples are used to train the forward neural network solver. The inverse neural network solver is trained by feeding the input-output patterns in the reverse order. As long as both the forward and inverse neural networks are trained, the knowledge about the current process is stored in the weights of the neural networks. Also quadratic regression is used to get the relationship between \( X \) and \( Y \), which is then used for the corrector in the inverse agent.

Back propagation learning is one of the most important advances in neural computation, and is used to adjust the weights. However, when the number of training patterns is relatively large, it is difficult to obtain a fast convergence. Therefore, to
accelerate the training process, and get a fast convergence, a batch mode weight update is employed. Instead of updating the weights for each training pattern, the weights are updated once after all the training patterns are presented to the network. Furthermore, instead of using a fixed learning rate and momentum term, error dependent changes are made to get a faster convergence. A program has been developed for this application in the C programming language.

The trained neural networks are now ready to be employed in the inverse agent. Instead of using a direct inverse neural model, an error-feedback corrector is employed which improves the performance of the inverse agent. Figure 3.6 shows the architecture of the inverse agent with the corrector.
After the user inputs the desired final properties, $Y_d$, the inverse neural solver outputs the required process settings, $X$. This is then fed to the forward neural solver for the purpose of verification. If the error between the results $Y$ and the goal $Y_d$ is within tolerance, the estimated process settings $X$ are output to the users. However, if the error is not acceptable, the results from the inverse neural solver are considered as an
initial guess. A corrector based on this error is now used to adjust the process settings, and will be verified by the forward neural solver again, until acceptable process settings are obtained. Finally, to verify the accuracy of the inverse agent, the FEM program is used to test the output X. For most cases, the results are pretty good if the direct inverse neural solver is well-trained. Direct inverse learning can not always ensure optimal processing settings and hence it is necessary to modify the results to minimize the errors of the system. This increases the accuracy of the inverse agent.

3.6 Verification: square-to-round bar rolling

3.6.1 Hot bar rolling process used

The case study chosen to demonstrate the integrated approach is an actual 8-pass square to round sequence used in a steel company. The billet material is AISI 1050. The initial billet temperature is 1150 °C, initial grain size is 300 microns and the angular velocity of the first roll 10 rpm. The initial billet is a 162.5 mm square while the final billet is round with 56.25 mm diameter. The roll diameters varied from 400 – 500 mm and the roll surface temperature was 120 °C. A friction factor of 0.8 was used to represent the surface conditions. Due to the fact that the billet is symmetrical across both axes a quarter model simulation instead of a full model simulation is run. This reduced the time of computation by a great deal. Each non-isothermal FEM simulation
using ROLPAS takes only about 5 minutes to run including pre-processing and post-processing and hence it is decided to go with the full factorial design. Figure 3.7 shows the 3D FEM mesh in the roll bites.

![FEM meshes in the roll bites](image)

Fig. 3.7 FEM meshes in the roll bites.
3.6.2 Implementations details

Using the results from ROLPAS simulations, both the forward and inverse neural networks for the inverse agent are trained using two methods, which use two different sets of training patterns. The first method assumes that once the roll caliber design is fixed, the average finishing temperature and the average austenite grain size in the rolled bar depend on the initial temperature, the initial grain size and the angular velocity of the rolling mill. The second method utilizes only the initial temperature and the angular velocity of the rolling mill as the control variables. For both of the above methods, the initial angular velocity of the continuous mill determines the angular velocity of individual rolls and the interstand time, which in turn determines the thermomechanical history of the rolled bar. Three levels are used for each variable in the first method. In the second method five levels are used for each input variable, with the nominal level representing the approximate value of the existing design. Full factorial designs are used for the DOE and ROLPAS simulations are run.

Neural networks with one hidden layer are selected for both forward and inverse neural networks in this analysis. Figure 3.8 and Figure 3.9 show the structure of the forward and inverse neural networks respectively for the first method. Figure 3.10 and Figure 3.11 show the structure of the forward and inverse neural networks respectively for the second method. For both methods, the forward neural network takes the initial
settings as inputs, and the final properties as the outputs. The inverse neural network is fed the input-output samples in the reverse order.

Fig. 3.8 Forward neural network solver (method one).

Fig. 3.9 Inverse neural network solver (method one).
All the selected neural networks have 15 hidden neurons. In method one, the forward neural network has 3 inputs and 2 outputs and 1 bias neuron in both input and hidden layers. Hence there are 92 weights that need to be adjusted. In method two, the
forward neural network has 2 inputs and 2 outputs and 1 bias neuron in both input and hidden layers. Hence there are 77 weights that need to be adjusted.

Full factorial design yields 27 training patterns in method one, while in method two, 25 training patterns are generated for the training process. The tolerances are 0.001 for the forward neural networks and 0.01 for the inverse neural networks. For model verification several cases were used. A few of them are included in the paper for illustration.

The training process is stopped if the mean square error is smaller than the required tolerance. When the mean square error decreases, the learning rate is increased, or else, decreased. Thus the training process becomes more stable and robust. This modification also speeds up the neuron computation to a large scale.

3.6.3 Results discussion

After the user inputs the goal properties \( (Y_d) \), the inverse agent then calculates the process settings \( (X) \). The inverse agent is tested using different combinations of average finishing grain size and temperature values, which are not included in the previous training patterns. After the test results \( (X) \) are obtained from the inverse agent, they are fed to the FEM software ROLPAS for verification. The simulation results \( (Y) \) are then compared with the original test values \( (Y_d) \).
Table 3.1 shows comparison of the results from the ROLPAS verification and the inverse agent trained by the first method. It can be seen that the neural network trained by method one does not offer a sound result. Moreover, other combinations tested using method one also does not give satisfactory results.

<table>
<thead>
<tr>
<th>Estimated Settings</th>
<th>ROLPAS Verification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Init. Billet Temp (°C)</td>
<td>Init. Mean Ang. Vel. (rpm)</td>
</tr>
<tr>
<td>1062.94</td>
<td>9.64</td>
</tr>
</tbody>
</table>

Table 3.1 Comparison of inverse agent and ROLPAS verification (850°C/35 microns target, method one).

The initial inverse agent is built using all the possible control variables. After analyzing the sensitivity of the final product properties to the control variables, the control variables that make trivial contributions should be removed and the inverse agent should be rebuilt. Zhu et al. (1998) expressed the sensitivity of the $i$th input $s_i$ as:

$$S_i = \frac{f(x_{\text{avg}}^1, x_{\text{avg}}^2, \ldots, x_{\text{avg}}^i, \ldots, x_{\text{avg}}^n) - f(x_{\text{avg}}^1, x_{\text{avg}}^2, \ldots, x_{\text{min}}^i, \ldots, x_{\text{avg}}^n)}{x_{\text{max}}^i - x_{\text{min}}^i}$$  \hspace{1cm} (8)
where $x_{avg}^i$ is the average of each control variable, and $x_{min}^i, x_{max}^i$ are the minimum and maximum of each control variable. $f(x_i)$ is the mapping function from control variables to final properties. Figure 3.12 shows the sensitivity analysis of control variables in method one. It can be seen that initial average grain size is a trivial factor. Therefore, the forward neural network trained by the first method is not good enough to be used in the feedback corrector to get the final results. Table 3.2 shows a comparison of the results from this forward neural solver and FEM simulations (ROLPAS). Here, it is shown that because the forward neural network is not well trained the inverse agent cannot offer a satisfactory solution in Table 3.1.

Fig. 3.12 Sensitivity analysis of control variables in method one.
Table 3.2 Comparison of forward neural solver and ROLPAS results using method one (first design).

<table>
<thead>
<tr>
<th>Test number</th>
<th>Initial billet temperature (°C)</th>
<th>Angular velocity (rpm)</th>
<th>Initial grain size (microns)</th>
<th>Final average billet temp. (°C)</th>
<th>Final average grain size (microns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1175.00</td>
<td>8.75</td>
<td>300.00</td>
<td>917.06</td>
<td>44.80</td>
</tr>
<tr>
<td>2</td>
<td>1060.00</td>
<td>10.00</td>
<td>320.00</td>
<td>858.39</td>
<td>36.85</td>
</tr>
<tr>
<td>3</td>
<td>1230.00</td>
<td>8.75</td>
<td>280.00</td>
<td>945.33</td>
<td>49.39</td>
</tr>
<tr>
<td>4</td>
<td>1060.00</td>
<td>10.00</td>
<td>320.00</td>
<td>858.39</td>
<td>36.85</td>
</tr>
</tbody>
</table>

Table 3.3 Comparison of forward neural solver and ROLPAS results using method one (second design).

<table>
<thead>
<tr>
<th>Test number</th>
<th>Initial billet temperature (°C)</th>
<th>Angular velocity (rpm)</th>
<th>Final average billet temp. (°C)</th>
<th>Final average grain size (microns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1175.00</td>
<td>8.75</td>
<td>1012.78</td>
<td>56.21</td>
</tr>
<tr>
<td>2</td>
<td>1230.00</td>
<td>11.50</td>
<td>1093.03</td>
<td>66.78</td>
</tr>
<tr>
<td>3</td>
<td>1060.00</td>
<td>11.50</td>
<td>976.74</td>
<td>48.31</td>
</tr>
</tbody>
</table>

Based on the above analysis, the initial grain size is removed from the control variables in method two and the parameter levels are increased to five. A comparison of the results from this forward neural solver and FEM simulations (ROLPAS) using the second method is shown in Table 3.3. From the table it can be seen that the forward neural solver is precise in its predictions. This can be explained by the fact
that the training patterns cover the input space thoroughly, and all the trivial variable are removed from the training patterns. Therefore, this forward neural solver can be used instead of FEM simulations in the inverse agent to test the results from the inverse neural network. This helps in increasing the speed of the inverse agent. Table 3.4 and Table 3.5 show the comparison of the results from the direct inverse neural network and results from the inverse agent trained by the second method. From these two tables, it can be seen that the precision of the inverse agent is enhanced greatly by using the second method. Sensitivity analysis is also performed for the control variables in method two. It is shown that the remaining two factors are not trivial.

<table>
<thead>
<tr>
<th></th>
<th>Estimated settings</th>
<th>ROLPAS verification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Init. billet temp. (°C)</td>
<td>Ang. vel. (rpm)</td>
</tr>
<tr>
<td>Direct inverse NN</td>
<td>1165.84</td>
<td>8.68</td>
</tr>
<tr>
<td>Inverse agent</td>
<td>1174.19</td>
<td>8.17</td>
</tr>
</tbody>
</table>

Table 3.4 Comparison of direct inverse NN and inverse agent (1000°C/55 microns target) (method two).
<table>
<thead>
<tr>
<th></th>
<th>Estimated settings</th>
<th>ROLPAS verification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Init. billet temp. (°C)</td>
<td>Ang. vel. (rpm)</td>
</tr>
<tr>
<td>Direct inverse NN</td>
<td>1200.34</td>
<td>11.38</td>
</tr>
<tr>
<td>Inverse agent</td>
<td>1183.72</td>
<td>11.41</td>
</tr>
</tbody>
</table>

Table 3.5 Comparison of direct inverse NN and inverse agent (1060°C/60 microns target) (method two).

Because of the improved precision in the second method, the results from the direct inverse neural network are sometimes good, and they do not need to be adjusted. For example, when the user wants to get a bar with final average temperature 970°C, and final average grain size 48 microns, the results of the direct inverse model are excellent as shown in Table 3.6. However, for some other test cases, the results still need to be adjusted to get closer to desired final properties as seen in Table 3.4 and Table 3.5. The results from the direct inverse neural network need to be fine-tuned to obtain the desired properties. Many other combinations of test patterns are fed to the inverse agent, and the estimated results suggest that the performance of the inverse agent from the second method is sound.
<table>
<thead>
<tr>
<th>Direct inverse NN</th>
<th>ROLPAS verification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Init. billet temp. (°C)</td>
<td>Ang. vel. (rpm)</td>
</tr>
<tr>
<td>1057.57</td>
<td>10.97</td>
</tr>
</tbody>
</table>

*Table 3.6 Direct inverse model results (970°C/48 microns target) (method two).*

Generally, the selection of the correct training patterns is vital for the performance of the neural network. More training patterns are needed for a complicated process with a high number of input and output parameters. Also, the selection of significant factors for the process control is vital to obtain a sound product.
CHAPTER 4

INFEERENCE CONTROL: SOFT SENSOR FOR THE METAL FORMING PROCESS

4.1 Introduction

The outstanding performance of steel as an engineering material is due to the wide range of microstructures and mechanical properties that are possible when it is subjected to controlled processing and heat treatments. A typical hot forging process can be seen in Figure 4.1. Most hot forging processes are multi step operations and typically have the following steps:

1. Cutting and heating billet
2. Forging in multiple steps
3. Cooling to final forged product
The dimensions and physical properties of the forged steel products depend upon the composition of the material, deformation history in the forging press and the heat treatment after forging. In both process settings, initial billet and final product, some variables are measurable. However, in process control systems of the forging process, as a result of the limitation incurred by process technology or measurement techniques, some important process variables and material properties of the initial billet are very difficult or impossible to monitor and also adjust promptly. These variables would affect the properties of the final product in some ways. Therefore it is critical to guarantee them in the proper settings, thus the product reliability can be improved and scrap rates can be reduced greatly.
As can be seen from the flowchart of measurement system using “soft sensing” in figure 4.2, after direct sensors measure the measurable secondary variables, by adopting “soft sensing” technology, the virtual soft sensor are used to created a virtual measurement for unmeasurable primary variables, which would then be used as a reference for the on-line adjustment correspondingly to optimize the forging process, thus improve process reliability and reduce scrap rates. “Soft sensing” technology has been widely used and researched in different areas.

There are two key components of “soft sensing”, the first is the hardware for the online monitoring of the secondary variables, and the second is the software to find the relationship between the primary and secondary variables, thus the virtual measurements could be created. Here in this research, the focus would be the second component, that is, how to relate the primary and secondary variables together. In the past, lots of researches have been conducted to find the models for hot forging process.
These models include those developed from first principles as well as empirical models. The phenomenological models are based on the first principles. Since the non-linear and multidimensional dependencies nature, the close coupling between the thermal, mechanical and material phenomena of the forging problems, the phenomenological models are very difficult to obtain. Moreover, the empirical models are based on traditional trial and error methods, which are time-consuming for the changing forging process. With the development of computer systems, numerical analysis has become a leading method for analyzing deformation in forging processes faster. Here the trial and error exercise is only carried on a computer instead of an actual press. In a competitive market nowadays, there is a strong need for the development of an analysis tool that would assist the “soft sensing” in forging process design and reduce the using of trial and error approach to achieve the goal.

One of the major objectives in forging process design is to monitor the variances in initial billet dimensions and the process settings for the current online forging control process. Unfortunately some control parameters can not be monitored easily and promptly for on-line control purpose, therefore it would be beneficial by using “soft sensing” in the forging process.

This soft sensor would be capable of avoiding the time-consuming analysis, offering an on-line response to the forging process control, and at the same time, facilitating the process engineer to reduce the variation of the forging process. In this research, the secondary variables are selected as the final critical dimensions of the forged part,
which can be easily obtained from the non-contact sensing technology, which is based on CCD technology and electronic signal processing. The primary variables would be the process variables, such as the lubrication schedule and the press settings etc.

4.2 Development of virtual soft sensor for hot forging

To develop the virtual soft sensor for the hot forging process, the measurable secondary variables need to be mapped to the unmeasurable primary variables. To accomplish this, the relationship between the primary and secondary variables should be discovered and integrated into the virtual soft sensor. As can be seen from the figure 4.3, the calculated unmeasurable primary variables obtained from virtual soft sensors should be as close as to the actual unmeasurable primary variables.

![Diagram showing the development criteria of virtual soft sensors.](image)

Fig. 4.3 Development criteria of virtual soft sensors.
The objective of this research is to develop a virtual soft sensor for the hot forging process, which can relate the primary and secondary variables and map the measurable secondary variables to the unmeasurable primary variables. It can be formulated as following:

Objective:

Minimize \[ |S_{Estimated} - S_{Actual}| \]

Where

\[ S_{Estimated} = Function(P_{Actual}) \]

Where \( S_{Estimated} \) is the estimated value from the “soft sensor” for the unmeasurable variables, \( S_{Actual} \) is the actual value for the unmeasurable variables. Our objective is to make our estimation as close as possible to the actual one. \( S_{Estimated} \) is obtained from “soft sensor” and it is a mapping from \( P_{Actual} \), the actual value of the measurable variables, it is obtained from by the direct measurement tools. It is critical to discover the actual relationship between the primary and secondary variables. Therefore, this is an optimization problem also.

In this research, initially training patterns have to be created to offer guidance and supervision for soft sensors. In addition to experimental methods, the data patterns used can also be generated by numerical simulations from FORGE3. To build a data
base with experimental data, many experiments have to be conducted to gather enough information with good distribution in the input space. Lots of measurements need to be taken, and this can be time-consuming and costly. Therefore, the numerical experimentations through finite element simulations seem superior to experiments in flexibility, and are expected to improve in accuracy as well as speed for practical purposes. And then the “soft sensor” is developed and verified based on the combination of the ANN and Simulated Annealing (SA) algorithms.

4.3 Process modeling tool FORGE3

In this paper, FEM software Forge3 has been used to simulate the hot forging process. Forge3 is a three-dimensional code devoted to three-dimensional metal forming applications. This finite element software is based on an implicit approach. It is able to carry out the large deformations of viscoplastic incompressible materials with unilateral contact conditions. It is based on a mixed finite element formulation with tetrahedral elements. (Chenot, 1996)

In this paper, the materials are assumed to be viscoplastic and incompressible, and elasticity is neglected. The isotropic constitutive equation is written as (Chenot, 1996):

\[
\sigma' = c(\varepsilon; \dot{\varepsilon}, T)\dot{\varepsilon} \quad \text{with} \quad tr(\varepsilon) = div(\varepsilon) = 0
\]  
(1)
Where $\sigma'$ is the deviatoric stress tensor, $\dot{\varepsilon}$ is the strain rate tensor, $\ddot{\varepsilon}$ the equivalent strain and $\ddot{\varepsilon}'$ the equivalent strain rate, $c$ is a scalar. A viscoplastic friction law can be expressed by:

$$\tau = -\alpha(\sigma_n, |\Delta v|, T)\Delta v$$  \hspace{1cm} (2)$$

Where $\sigma_n$ is the normal stress, $\Delta v$ is the tangential velocity difference between the part and the tool, and $\alpha$ is a scalar.

The virtual work principle is stated in the rate form, with a mixed formulation:

$$\int_{\Omega} \sigma' : \dot{\varepsilon}' dV - \int_{\partial\Omega_c} \tau \cdot v' dS - \int_{\Omega} pd\text{div}(v^*) dV = 0$$  \hspace{1cm} (3)$$

$$-\int_{\Omega} pd\text{div}(v^*) dV = 0$$  \hspace{1cm} (4)$$

The velocity field is discretized using isoperimetric finite elements, defined on a mesh with nodal coordinates $X_n$, with shape function $N_n$ and modal vectors $V_n$, so that:

$$v = \sum_n V_n N_n \quad \text{with} \quad x = \sum_n X_n N_n$$  \hspace{1cm} (5)$$
And the $B$ operator is defined by:

$$\dot{\epsilon} = \sum_{n} B_n V_n$$  \hspace{1cm} (6)$$

While the pressure field is expressed with compatible shape function $M_m$:

$$p = \sum_{m} P_n M_m$$  \hspace{1cm} (7)$$

With these notations is discretized according to, for any $n$ and $m$:

$$\int_{\Omega} \sigma' : B_n^\ast dV = \int_{\partial \Omega_c} \tau N_n dS - \int_{\Omega} \text{ptr}(B_n) dV = 0$$  \hspace{1cm} (8)$$

$$\int_{\Omega} \sigma' : B_n^\ast dV = \int_{\Omega} \text{ptr}(B_n) dV = \int_{\partial \Omega_c} \tau N_n dS$$  \hspace{1cm} (9)$$

$$\int_{\Omega} \sigma' : B_n^\ast dV = \int_{\Omega} \text{ptr}(B_n) dV = -\alpha \int_{\partial \Omega_c} \Delta v N_n dS$$  \hspace{1cm} (10)$$

The space and time discretization is needed to carry out the calculation involved. The nodal update can be performed with the Euler explicit scheme:

$$x_{n}^{t+\Delta t} = x_{n}^{t} + \Delta t V_{n}^{t}$$  \hspace{1cm} (11)$$
Forge3’s updated Lagrangian formulation is well adapted to the transient character of strains and stresses. No tool deformation has been included at this stage. (Montmitonnet, 2002).

### 4.4 Simulated annealing

To find the global minimum of an objective function subject to conflicting constraints, is an NP-complete problem, since the objective function would tend to have different local minima. This problem needs to be solved with an efficient implementation, at the same time, having a high probability of finding a near-optimal solution. Recently, simulated annealing has been widely used as a viable technique which meets these criteria.
Simulated annealing is a stochastic optimization procedure, and it is based on the analogy with the annealing of solids. A certain material may have multiple stable states, and these states also may have different molecular distributions and thus different energy levels. For each temperature level, the state of the solid is assumed to reach thermal equilibrium. The simulated annealing algorithm takes random walks through the whole problem space, looking for points with low energies. In general, a step will occur if the new state has a lower energy. However, as can be seen from Figure 4.4 (Tarng, 1995), using simulated annealing algorithm, even if the new energy
is higher, the transition can still have a possibility to occur, and its likelihood is proportional to the temperature $T$ and inversely proportional to the energy difference between the new and the old states. The probability of being in a state $s_i$ with energy $E_i$ is given by the Boltzmann distribution

$$w_T(s_i) = \frac{1}{Q(T)} \exp\left(-\frac{E_i}{k_B T}\right)$$  \hspace{1cm} (12)

where $k_B$ denotes the Boltzmann constant and $Q(T)$ is a certain normalizing factor. The acceptance rule for the new state is called the Metropolis criterion. The downhill move ($\Delta E < 0, p=0$) is always permitted. At the same time the Metropolis criterion attempts to permit small uphill moves ($\Delta E > 0$) while rejecting large uphill moves. This is to prevent the algorithm from becoming stuck in a local minimum. For uphill moves, the new state generated is accepted or rejected according to the Metropolis criterion given by:

$$\exp\left(-\frac{\Delta E}{T}\right) > rand$$  \hspace{1cm} (13)

where $\Delta E$ is the change of potential energy (i.e. the objective function) after the perturbation of the current state and $rand$ is a number sampled from a uniform random distribution ranging from 0 to 1.
An initial guess for the state should be supplied. Also the temperature $T$ should be initially set high enough, and a random walk within the state space subjected to all the constraints is taken at that temperature. Then the temperature is lowered according to the defined cooling schedule and another random walk is taken. This slight probability of taking a step that gives higher energy is what allows simulated annealing to frequently get out of local minima. Eventually the temperature is lowered until the material freezes. If the temperature is lowered sufficiently slowly then the annealing process always picks out the global minimum energy state from the almost infinite number of other possible states. (Levin, 1998)

### 4.5 Soft sensing approach

In this approach, the unmeasurable primary variables for the forging process are determined based on the measurable secondary variables with respect to the minimum difference between the primary and secondary variables, subject to a set of practical constraints. The objective function would be the one that considers not only the minimum difference, but also the practical constraints. In this approach, Simulated Annealing (SA) algorithm would be used to find the primary variables, which would use ANNs to evaluate the results for the primary variables. SA is a stochastic optimization procedure, and it can find the global optimum of an objective function, which subject to conflicting constraints. It is superior to genetic algorithms in speed, and better than simple ANN in accuracy.
In essence, SA draws an initial random point as the primary variables to start its search. From this point, the algorithm takes a step within a range predetermined by the user. The evaluation value of this new point's objective function is then compared to the initial point's value in order to determine if the new value is smaller. By occasionally accepting points with higher values of the objective function, the SA algorithm is able to escape local optima. As the algorithm progresses, the length of the steps declines, and the algorithm stops in on the final solution. The Metropolis criteria uses the initial user defined parameters, $T$ (temperature) and $R_T$ (temperature reduction factor) to determine the probability of accepting a value of the objective function that is higher. $T$ is reduced by the function $T_{i+1} = R_T \times T_i$, where $i$ is the $i$th iteration of the function evaluation after every $N_T$ iterations. $N_T$ is the parameter which establishes the number of iterations between temperature reductions. Unlike other algorithm, the performance of the SA algorithm depends on user defined parameters, they are problem specific. Since the performance of the SA is significantly impacted by the choice of these parameters a range of values were used for three variables ($T, R_T, N_T$). For traditional cooling schedule of SA, $N_T$ is a fixed preset number for each temperature. However, in our algorithm, a dynamic changing $N_T$ is employed, considering the fact of thermal equivalence, which makes the algorithms more efficient. The details are discussed later.

Figure 4.5 shows the architecture of the second soft sensor approach based on the simulated annealing optimization method, and they are explained in detail as follows:
1. First, after the secondary variables are obtained from the direct sensors, the rough guess for the initial guess state of the primary variables should be obtained, which should subject to all the constraints. Then the initial temperature, $T_0$, should be initialized to enough high. There is no intuitive way of deciding what the value of $T_0$ should be (Levin, 1998). In this approach, it is set to an appropriate temperature according to experience.
2. From the initial guess state determined before hand, the algorithm takes a step
determined by the neighborhood function, which is problem specific. The step
should be within the applicable range, i.e., meet all the constraints. If any
violation occurs, a new step should be performed again until creating a feasible
new state for the primary variables.

3. In order to determine whether the new state is superior to the old state or not,
the algorithm would evaluate the objective function of the new states, then it is
compared with the objective function of the initial state. The following two
rules are then considered to determine whether the new state would be
accepted or not:

   a. If there is an improvement in the objective function of the new states
      compared to the initial state, then the new state would be accepted and
      the new point from which the algorithm will continue.

   b. If there is no improvement, and the objective function of the new state
      is worse than the initial state. It also might be accepted based on
      Metropolis criteria, which have been described above.

4. Check whether the equilibrium has been reached or not at the current
temperature. If so, then the algorithm would then proceed with a lower
temperature, which is determined by the predetermined cooling schedule.
Otherwise, the algorithm would repeat step 2 described above.
5. The algorithm would proceed until the stopping criteria are met. Finally, it will output the value of primary variables corresponding to the secondary variables from the direct sensors.

There are some issues in this second approach, the processing time of the virtual soft sensor is critical, especially when the soft sensor is going to be used for on-line purpose. To reduce the running time of the program, various techniques can be adopted. To ensure a SA algorithm work efficiently, a cooling schedule and neighborhood function needs to be designed for the particular case, since they are case-dependent. Hence, the initial state to start, neighborhood function and cooling schedule are discussed in the following to improve the overall capability of the algorithm.

- **Starting point / Initial State**

Starting with a good initial state would reduce the processing time greatly. To obtain a good starting point, several researchers have made attempts in achieving good initial state. Hosokawa (Hosokawa, 2002) combined the Genetic Algorithm (GA) with the powerful neighborhood search of Simulated Annealing (SA). GA is used for global search in the initial stage, and the search space is narrowed to the optimal neighborhood. Then the local search is performed by SA so that bad searches are
reduced, and the optimal global solutions are approached rapidly. However, the process time of GA is still long, especially when the algorithm is used on-line. Zolfaghari (Zolfaghari, 1998) employed an improved Hopfield network method to generate a good seed solution and shorten the convergence time. Therefore, in this approach, an inverse ANN is used to create a start state for the SA algorithm to obtain a short processing time. The inverse ANN has been discussed in detail in the paper by Ji etc. (Ji, 2003). Instead of using the inverse agent described in that paper, here, the direct inverse ANNs are trained and generalized to obtain the rough guess for the initial state. The initialization procedures of initial temperature and initial state can be found in Figure 4.6.

Fig. 4.6 The Initialization Procedures.
• **Neighborhood function**

For simulated annealing a new state is generated from the old state by a problem-dependent neighborhood function that returns a random new state in the neighborhood of the old state. Levin (Levin, 1998) has summarized several kinds of neighborhood function suggested in the past literature.

Saravanan (Saravanan, 2003) used Gaussian distribution neighborhood function in his paper. Line adjustment function converges faster than Gaussian distribution neighborhood function. However, at the end of the optimal state searching process, Gaussian distribution neighborhood function would be more preferable because of better accuracy. Therefore, in this paper, to obtain the advantages of both neighborhood functions, the combination of line adjustment and Gaussian distribution neighborhood function are employed. It is a new variation of the SA algorithm.

• **Cooling schedule**

Cooling schedule is the rule to determine when the current temperature should be lowered, by how much the temperature should be lowered, and when the annealing should be terminated. A standard cooling schedule for SA algorithm would let the Metropolis algorithm run for a fixed number of times before it is lowered by a factor $\rho$, $0 < \rho < 1$. Here, to make the algorithms more efficient, the concept of “thermal
equilibrium” is included. The termination criterions for the SA algorithm at the current would also depend on the improvement of the current states compared to the prior states. If there is consistent improvement over the currents, then the algorithm should keep running at the current temperature. On the contrary, if there is no improvement for some period, that means, the “thermal equilibrium” is reached in the current temperature, then it should be lowered according to the cooling schedule. By this way, the SA algorithm is dynamic and adaptive. The efficiency would be increased in a large scale.

A flag is used in the approach to determine the state of “thermal equilibrium”, the pseudo-code is as following, when flag equals to 1, thermal equilibrium happens, the temperature should be lowered.

\[
\begin{align*}
\text{Flag}=0; \\
\text{If no improvement,} \\
\text{increase counter by 1} \\
\text{else if counter==10} \\
\text{“thermal equilibrium” happens} \\
\text{counter is reset} \\
\text{flag=1;}
\end{align*}
\]

4.6 Application: wheel hub forging

The case study chosen to demonstrate the integrated approach is an actual wheel hub forging in a forging company. The wheel hub of the front axle is being hot forged on the 3000 Ton Kurimoto Press. The wheel hub manufacturing process is described as
The billet is heated to around 2300 F in an induction heater and then the part is forged. It is fed into the Kurimoto Press where it is forged, pierced and trimmed. The forging
process is a 3 step process:

- Upsetting in buster in 1st Station
- Blocking in 2nd Station
- Finishing in 3rd Station

Figure 4.7 shows the shape and effective strain in the billet after each of the operations.

The aim of the implementation was to find the primary variables such as friction factor, press stroke and other unmeasurable parameters at the different stages of the forging process based on the measurable secondary variables. Traditionally, the product is cooled before the dimensions can be measured. As shown in Figure 4.8, there are totally fourteen attributes of the part that are checked by various gauges for quality control purposes. OG Technologies, Inc. (OGT) has invented HotEye™, a breakthrough technology in non-contact sensing. HotEye™ is a proprietary imager, designed for high temperature applications. HotEye™ can capture the image of an object that is as hot as 1,450°C (tested, equivalent to 2,640°F) with the same image quality as if the object were at room temperature. This innovation is based on OGT’s expertise in optics, CCD technology, and electronic signal processing. HotEye™ can be used in imaging systems for dimensional measurement and surface defect detection at up to 1,450°C. Therefore, it would be possible that the measured hot dimensions by HotEye can serve as the secondary variables to obtain primary variables, which would be better for the soft sensor in performance compared to the cold dimensions.
4.6.1 Process modeling

The hot forging process has been modeled using computer simulations by FORGE3 software so as to generate the data used to train the ANN and also the SA computation. Since the part has a three dimensional shape, three dimensional forging process simulations were run using the software package FORGE3 v6.2 (FORGE3 was used on a 1.5GHz, 512K cache Intel Xeon dual processor PC with 1 GB SDRAM). Solid Edge v12 was used for solid modeling (creating STL files) of the billet and dies for
geometry input into FORGE3. Initially a full model was simulated, but finally the 30
degree simulation model was chosen taking advantage of the symmetry of the wheel
hub.

The simulation data used for all the simulations were as follows:

- initial billet temperature - 1260 °C,
- die temperature - 260 °C,
- rigid dies and rigid viscoplastic workpiece,
- billet material - 36Mn4/1.0561 (German Standards),
- interface heat transfer coefficient with dies - 2000 W/m/°K,
- interface heat transfer coefficient with air - 10 W/m/°K,
- Tresca friction model with m = 0.3
- And a mechanical press with 60 spm and stroke of 360 mm.

Some of the parameters considered as unmeasurable input parameters are

- Actual stroke of the press
- Transfer time from induction heater to forging press
- Amount and type of lubrication

The above parameters are needed to be determined from the soft sensors.
To develop data patterns for the training the algorithm, the simulations of the wheel hub were run based on the designed DOE. Table 4.1 shows the 7 process parameters chosen along with the nominal, low and high values. These values were based on nominal values used at the plant. Using DOE methods, 57 design runs were chosen based on the Box Behnken design. A full factorial design would have 2187 runs and hence we save a lot of time and effort by running the Box Behnken design.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Nominal (0)</th>
<th>Low (-1)</th>
<th>High (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Billet Length (mm) Cold</td>
<td>162</td>
<td>160</td>
<td>164</td>
</tr>
<tr>
<td>Billet Diameter (mm) Cold</td>
<td>71.04</td>
<td>70.04</td>
<td>72.04</td>
</tr>
<tr>
<td>Billet Temp (°C)</td>
<td>1246.1</td>
<td>1218.3</td>
<td>1273.9</td>
</tr>
<tr>
<td>Billet Transfer Time (s)</td>
<td>15</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>Friction Factor</td>
<td>0.15</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Press Stroke (mm)</td>
<td>Depends on station</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>Die Temp (°C)</td>
<td>260</td>
<td>148.9</td>
<td>371.1</td>
</tr>
</tbody>
</table>

Table 4.1 Process parameters and their levels for the Kurimoto DOE.

Some of the parameters considered as measurable input parameters are

- Billet dimensions
- Billet temperature
- Die temperature
They are also included in the DOE, so they may offer as a reference for the optimization results.

Based on the design matrix values upsetting simulations were run for each of the 57 different runs. The initial billet dimensions were varied from the cold to their hot values based on initial billet temperature and coefficient of thermal expansion. Also compensation was made for volume loss due to FEM. After the simulations the output attributes of the forged part were calculated.

As shown in Figure 4.8, there are totally 14 quality control attributes, which can be measured, some of them are not important, some of them are correlated with each other, if a condensed version of quality control attributes can be formed, then the algorithm would achieve better accuracy and processing efficiency. Therefore, the number of attributes is reduced without compromising its ability. To illustrate the approach, and verify the algorithm, 4 critical dimensions have been chosen from 14 attributes, they can be seen in Figure 4.9.
Figure 4.9 Output attributes $D_4$, $D_5$, $D_6$, and $D_7$.

Figure 4.10 Correlation of output attributes $D_4$, $D_5$, $D_6$, and $D_7$. 
4.6.2 Procedures for seeking the relationship for soft sensors

To reduce the number of the quality attributes such that the performance of the algorithms can be improved. The correlation between these dimensions will be investigated and utilized to reduce the size of training patterns. Figure 4.10 shows the trend of correlation of dimensions D4, D5, D6, and D7. A correlation coefficient is a number between -1 and 1 which measures the degree to which two variables are linearly related. If there is perfect linear relationship with positive slope between the two variables, we have a correlation coefficient of 1; if there is positive correlation, whenever one variable has a high (low) value, so does the other. If there is a perfect linear relationship with negative slope between the two variables, we have a correlation coefficient of -1; if there is negative correlation, whenever one variable has a high (low) value, and the other has a low (high) value. The equation for the correlation coefficient is:

\[
\rho_{x,y} = \frac{\text{Cov}(X,Y)}{\sigma_x \sigma_y}
\]  

(14)

Where \( \rho_{x,y} \) is the correlation coefficient, and \(-1 \leq \rho_{x,y} \leq 1\).

\[
\text{Cov}(X,Y) = \frac{1}{n} \sum_{j=1}^{n} (x_j - \mu_x)(y_j - \mu_y)
\]  

(15)
By using the above equation to calculate the correlation coefficient of $D_4$, $D_5$, $D_6$, and $D_7$, the results are shown in Table 4.2. As can be seen from the table, $D_5$, $D_6$, and $D_7$ are almost linearly correlated with each other. Therefore, we may find the relationship between them as follows:

$$D_6 = 0.4869* D_5$$

$$D_7 = 0.5184* D_5$$

Now the critical dimensions can be reduced to only 2, they are $D_4$ and $D_5$.

<table>
<thead>
<tr>
<th>Correlation Coefficient</th>
<th>D4</th>
<th>D5</th>
<th>D6</th>
<th>D7</th>
</tr>
</thead>
<tbody>
<tr>
<td>D4</td>
<td>1</td>
<td>-0.78388</td>
<td>-0.78407</td>
<td>-0.78356</td>
</tr>
<tr>
<td>D5</td>
<td>-0.78388</td>
<td>1</td>
<td>0.999998</td>
<td>0.999929</td>
</tr>
<tr>
<td>D6</td>
<td>-0.78407</td>
<td>0.999998</td>
<td>1</td>
<td>0.999929</td>
</tr>
<tr>
<td>D7</td>
<td>-0.78356</td>
<td>0.999929</td>
<td>0.999929</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 4.2 The correlation coefficient of $D_4$, $D_5$, $D_6$, and $D_7$.**

Now using the training patterns obtained from FEM simulations based on DOE, the architecture of both the forward and backward ANN are shown in Figure 4.11 and Figure 4.12. 57 data patterns from the simulation are split to train and generalize Both of ANNs. And the inverse ANN is used for the initialization purpose for the SA algorithms, the forward ANN is used to replace the FEM simulations to evaluate the objective function.
Figure 4.11 The architecture of forward ANN.

Figure 4.12 The architecture of backward ANN.
4.6.3 Determining accuracy of soft sensors

Out of 57 data patterns from the FEM simulations, 54 data patterns are randomly chosen to train both the forward and backward ANNs. Both of them have 15 hidden layers. Figure 4.13 and figure 4.14 show the generalization result of the test patterns for $D_4$ and $D_5$, they show that the forward ANN is accurate enough to replace the actual FEM simulation in the algorithms for the objective function evaluation.

Figure 4.13 The generalization result for $D_4$. 
Figure 4.14 The generalization result for $D_5$.

Figure 4.15 The training process of inverse ANN.
Fig. 4.15 shows the training process of the inverse ANN, it can be seen, the final error is still significantly large. However, it would offer a good initial start state for the SA algorithm. After the requirement of final target wheel hub is given, the SA algorithm would begin with an initial guess given by the inverse ANN, and then give the process design and the selection of the initial workpiece. The algorithm is tested using several different combination of $D_4$ and $D_5$, the result is shown in Table 4.3, and the corresponding detected process settings is shown in Table 4.4. Suppose the dimensions from the HotEye camera are 77.4998 and 32.1797. The soft sensor gives the possible process settings, from which 76.18932 and 31.51252 can be obtained.

<table>
<thead>
<tr>
<th></th>
<th>$D_4$</th>
<th>$D_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target</td>
<td>77.4998</td>
<td>32.1797</td>
</tr>
<tr>
<td>Actual</td>
<td>76.18932</td>
<td>31.51252</td>
</tr>
</tbody>
</table>

Table 4.3 The result for target state $D_4$ and $D_5$ are (77.4998, 32.1797).

<table>
<thead>
<tr>
<th>Best States</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Billet length real</td>
<td>160.8263</td>
</tr>
<tr>
<td>Billet Dia real</td>
<td>70.82638</td>
</tr>
<tr>
<td>Billet temp real</td>
<td>1243.553</td>
</tr>
<tr>
<td>Transfer time real</td>
<td>10.17255</td>
</tr>
<tr>
<td>Friction factor real</td>
<td>0.129708</td>
</tr>
<tr>
<td>Press stroke</td>
<td>-0.99679</td>
</tr>
<tr>
<td>Die temp real</td>
<td>275.8033</td>
</tr>
</tbody>
</table>

Table 4.4 The best process design for target state $D_4$ and $D_5$ are (77.4998, 32.1797).
Among all the inferred process settings, some of them are measurable, such as the billet dimensions and temperatures, and then they can be used as the reference point to verify the unmeasurable results, such as the friction, the press stroke, and the transfer time.

Many other combinations of test patterns are fed to the algorithm, and the estimated results suggest that the performance of the current approach is better than the traditional SA algorithm in the following aspects:

- Faster convergence as a result of the initialization by inverse ANN and the adaptive cooling process.
- Better accuracy by using different neighborhood function

### 4.7 Discussion

In this chapter, the soft sensor framework has been developed, and it is applied in a hot forging process. To better represent the actual physical system, more simulations are needed. It can be foreseen that the performance of the approach would be improved greatly by adding more training patterns. Furthermore, the soft sensor needs to be verified and calibrated by information from the actual forging process.
CHAPTER 5

MINIMUM SENSITIVITY ROLL PASS DESIGN

5.1 Need for a roll pass design with a minimum sensitivity

It is wildly known that in the deformation of steel workpiece, surface quality is a very important quality control parameter. For example, in forging, cold finishing, and machining, the majority of rejections are due to surface imperfections (“SBPG”, 1996). Many of these are surface defects that originally appear as surface breaks or seams during the primary rolling or blooming mill reduction. For example, the rolling seam defect often leads to “End Cracks” in the long shafts that were cold extruded (Figure 5.1). The traditional roll pass design assumes the process is deterministic by ignoring the process variations that are common in hot rolling, such as material properties, initial billet dimension and surface condition, lubrication condition, and bar guide settings, etc. However, in many instances of real life situation, the surface defects may appear due to process variances, which are a result of unavoidable uncertainties.
In a statistical analysis of seams in a hot rolling mill, Jin et al. (2004) discussed the random nature of the seams occurrence. The frequency of the defects in this case was found to vary depending on the material grades and heats. The defects per billet vary from zero to five from the results. The seams are detected online by a specially designed CCD camera. The process variables considered include the heat number, strand number, and billet-location. Table 5.1 shows an abbreviated portion of the sensing information table. He tried to identify the impacting factors of surface defects in the hot rolling processes. The surface finish for the rolled bar is varied for different
heat number, strand number, and billet-locations. “SBPG” (1996) also confirms the random nature of the seams in the hot rolled bar product.

<table>
<thead>
<tr>
<th>Billet ID</th>
<th>Heat</th>
<th>Strand</th>
<th>Billet Location</th>
<th>Billet Speed</th>
<th>Billet Grade</th>
<th>Defects Per Billet</th>
</tr>
</thead>
<tbody>
<tr>
<td>1217328000</td>
<td>123000</td>
<td>1</td>
<td>2</td>
<td>18.43</td>
<td>4140</td>
<td>1</td>
</tr>
<tr>
<td>123737000</td>
<td>123602</td>
<td>2</td>
<td>3</td>
<td>18.418</td>
<td>4140</td>
<td>5</td>
</tr>
<tr>
<td>127763100</td>
<td>123003</td>
<td>3</td>
<td>10</td>
<td>18.406</td>
<td>4140</td>
<td>1</td>
</tr>
<tr>
<td>129735900</td>
<td>123004</td>
<td>4</td>
<td>7</td>
<td>18.411</td>
<td>4140</td>
<td>3</td>
</tr>
</tbody>
</table>

**Table 5.1 Data from hot rolling process** NN (Jin et al. (2004))

The surface defects, including seams, in bar rolling are caused by exogenous entrapment, bad surface condition of input billets, non-uniform thermal profile during rolling, incorrect guide setting, improper reduction schedule and improper roll pass design (Topno, 2002). The above factors contribute to the random nature of the seam formation from pass to pass, heat to heat and etc. To effectively cope with surface defects, one practice in the industry is to strip or grind the surface of the steel bars off. This approach typically results in the loss of material, and increasing the costs of steel.

The deep surface defects, deeper than the peel off depth, cannot be addressed by grinding. Current design practice tends to account for these uncertainties by specification of closer tolerance or use of a factor of safety. This is expensive. To minimize the effect of the variance by the rolls deflection in the real production
process, backup rolls are incorporated into mill housing to reduce elastic deflection of the work rolls, as shown in figure 5.2. However, the variance effects can not be eliminated. Some unexpected factors may still influence the surface quality. The above techniques are only focused on controlling and reducing the variability of the control parameters. However, the variability can not be eliminated. Therefore, a robust roll pass design, which is the least sensitive to the presence of variability in the actual working environment, is extremely important. A design with minimum sensitivity is needed to accommodate the variance in the rolling process.

Several papers have discussed the techniques to improve the rolling quality. Taguchi (Taguchi, 1985) pointed out the importance of the robustness in the process. Taguchi’s
theory is generally realized by conducting planned experiments (Belegundu, 1989). In this paper, the objective is to ensure product quality at the design stage. Other approaches addressing uncertainties at the design stage use probabilistic concepts. These approaches treat the uncertain variables as random variables with a known distribution. Probabilities of failure are determined and minimized. For nonlinear random behavior, probabilities are often estimated using Monte-Carlo simulation and Taylor series approximations. Unfortunately in the design stage, generally the distribution of noise is not known; therefore, minimum sensitivity analysis offers a straightforward procedure for robust design and can be implemented in a general manner (Belegundu, 1989). It is shown that reduction in sensitivity leads to increase in probability of safety by several researchers. For example, Adali (Adali, 2001) conducted a minimum sensitivity design of laminated shells under axial load and external pressure, Rao (Rao, 1992) performed multiobjective insensitive design of structures, Belegundu (Belegundu, 1989) obtained a robust mechanical design through minimum sensitivity, and Parkinson (Parkinson, 1997, 2002) discussed the variability optimization to conduct the robust design problems.

In this research, a minimum sensitivity approach is proposed, which explores the robust parameters design by perturbing the reductions in flat passes, they are less constrained and easy to manipulate. A typical roll pass sequence consists of flat/box passes followed by round or oval passes. Major reduction is taken in the flat and box passes while the shape and dimension are controlled in round and oval passes. First, a brief description of the finite element code ROLPAS for modeling the rolling process
is provided. And then small perturbations to the original nominal design are analyzed and those variables significant to process variances are selected. Finally, the minimum sensitivity analysis is conducted to determine the robust settings for the rolling sequence. A case study using this approach is presented, that demonstrates the efficacy of this approach in analyzing the potential seams formation, and the designing of a safe roll pass.

5.2 Minimum roll pass design strategy

5.2.1 Seam formation mechanism and seam recognition criteria

The premise of the minimum sensitivity roll pass design for seam reduction hinges on predicting the formation of seams. It is assumed that the seams are longitudinal discontinuities in the steel bar that have been closed but not welded. After an underfill occurs in a specific pass of a sequence, the cross section of the billet is deformed in a direction perpendicular to the previous pass. This causes the underfill to fold over creating a seam. The above assumption is made to avoid irregularities in FEM description due to “folding” of elements. A schematic of these assumptions can be seen in figure 5.3. This figure also contains the cross-section of seams from Topno (2002).
In this research, a binominal function is used to determine the formation of potential seams based on the comparison between the actual underfills and the critical underfill values ($d_c$).

- Potential seam exists if underfill $d \geq d_c$.
- No potential seam exist if underfill $d < d_c$.

Where the underfill ($d$) values are defined as the differences between maximum and minimum radii for hot rolled bar. Based on the duality principle, the overfill can be
regarded as a special case of underfill. In this paper, the potential surface defects, seams, are considered as the results of underfills in the rolled bars.

5.2.2 Problem formulation

In many instances, seams may appear due to uncertainties in process variables. Some of them are design variables, while others are uncertainties. Generally, it can be expressed as the following:

\[
Underfill = Underfill(R, x)
\]

(1)

Where:

- \( R \): the nominal design variables in less constrained passes. \( R(r_1, r_2, \ldots, r_i \ldots) \).

- \( x \): The uncertain variables (noises). These uncertainties are due to changes in billets condition, temperature, friction and other things which may affect the roll mill structure. \( x(x_1, x_2, \ldots, x_i \ldots) \).

The uncertain variables \( x \) is assigned to a fixed value in the deterministic design stage. However, in the actual working process, considering the process variability,
uncertainties would take random values, after these variations are propagated to the final stage, they would lead to variances in the final product.

Let $x^a$, $x^a(x^a, x^a, \ldots, x^a, \ldots)$ be the actual value of $x$. Therefore, the problem is formulated as the following:

**Objective:**

Find $R^*$

Such that

$$\left| \frac{d\text{Underfill}(R^*, x^a)}{dx} \right|$$

is a minimum

Subject to Constraints:

$$\text{Underfill}(d) < \varepsilon$$

$$\Delta\text{Avg. Grain Size} < \varepsilon_i$$

Where $\Delta\text{Avg. Grain Size}$ is the changes in the average size from the original nominal design, and $\varepsilon$ are $\varepsilon_i$ very small numbers.

Therefore, the objective would be the change in design variables $\Delta x$ will lead to the minimal change $\Delta\text{Underfill}$ in underfill value of the final product.

$$\Delta\text{Underfill} = \sum_i \frac{d\text{Underfill}(C^*, x^a)}{dx_i} \Delta x_i$$  \hspace{1cm} (2)

Thus, the design $R^*$ with minimum sensitivity will keep the change $\Delta\text{Underfill}$ to a minimum value, thus improve the performance of the process under
variances. Any uncertainty $\Delta x$ will result in a minimum departure of underfill form its minimum value.

For any poorer design $R^p$, the change in underfill values would be larger than the one with minimum sensitivity. The minimum sensitivity approach generally leads to a design that is more robust and hence of better quality, larger tolerance resulting in a less expensive product.

$$\text{Underfill} = \text{Underfill}(R^p, x^a)$$  \hspace{1cm} (3)

$$\sum_i \frac{d\text{Underfill}(R^p, x^a)}{dx_i} \Delta x_i > \sum_i \frac{d\text{Underfill}(R^*, x^a)}{dx_i} \Delta x_i$$  \hspace{1cm} (4)

5.2.3 Approach implementation

In this paper, the variances in the final rolled bar are minimized considering the propagation of the variances in the actual reduction in each pass. The roll pass are designed considering the original nominal designs in reduction and the variances due to roll deflections. Figure 5.4(a) shows two cylindrical work rolls revolving at the same peripheral speed in opposite directions to reduce the flat workpiece to a thinner
gage. During the rolling process, the rolls are supported in housings, and the roll gap can be adjusted by mechanical or hydraulic means. Some variability would occur during the rolling process, which may affect the surface quality. For example, as can be seen from figure 5.4(b), the gap between two rolls may change randomly due to the variance in the initial billet and processing conditions. The roll deflection may lead to the variance in the dimensions and profiles of the part, so underfill may appear and thus the possibility of surfaces defects, such as seams and laps, will be increased later on. It is extremely important to make sure the roll pass design is robust enough to decrease the scrape rate.

Some unforeseen variances may influence the surface quality. Therefore, a robust roll pass design would be needed, and it should be the least sensitive to the variances. Then it will have lower risk of seams formation. Here all the significant roll pass design settings are determined in the design stage, they are preset to the robust nominal values, the deviation of the rolling process would be the smallest and some variability in these factors won’t affect the resulting surface quality.
Fig. 5.4 (a) Two rolls revolving in opposite directions to reduce thickness, (b) Rolls and parts deflection caused by the variation of roll separation force

Considering the relationship between the design variable $R : (R_1, R_2, \cdots, R_8)$ and the noise of roll deflection: $\Delta R : (\Delta R_1, \Delta R_2, \cdots, \Delta R_8)$:

$$R(r_1, r_2, \cdots, r_i \cdots) = R^n(r_1, r_2, \cdots, r_i \cdots) + \Delta R : (\Delta R_1, \Delta R_2, \cdots, \Delta R_8)$$  \hspace{1cm} (5)

Where $R^n(r_1, r_2, \cdots, r_i \cdots)$ is the nominal setting for the design reductions. The actual reductions would be the combined effects of nominal one plus the variances in roll
deflection. Generally the deterministic design assumes zero or a fixed value for the variances in roll deflection, here in this paper, a random value would be assumed for the minimum sensitivity design.

Fig. 5.5 The overall strategy for the robust roll pass design process.
Due to the linear correlation described above, in the analysis below, only the actual value of \( R : (R_1, R_2, \cdots, R_n) \) is considered, since it has already considered both nominal design settings and the random variances.

Figure 5.5 shows the overall strategy of the approach. The roll pass design is fixed and already is a good design, and it is not changed during numerical experiments. In the paper, only the reductions in each pass are considered, since they are influenced greatly by the roll deflections. First, we start from the nominal roll pass design. The minimum sensitivity analysis procedure is the following:

1) Simulate the roll pass sequence at nominal reduction settings \( R_n \).

2) Keeping the roll pass sequence fixed, presents the reductions with small variation due to noise \( \pm \Delta R(\Delta x_i) \), and measure the effect in the underfill, \[
\frac{\Delta d}{\Delta x_i}.
\]

3) Passes with small sensitivity \( \frac{\Delta d}{\Delta x_i} \), are already robust, they are kept at their nominal values.

4) Pass with high sensitivity and less constraint (flat and box passes) are selected for design of experiments (DOE) and FEM simulations.

5) From the design of experiments, a response surface is plotted for critical passes.
6) A least sensitive region in the response hyperspace is determined for least sensitive design ($R_d$) with largest working window.

7) The least sensitive design (new nominal reductions) is verified by propagating uncertainties.

8) The procedures described above are repeated until all the passes have the minimum sensitivity to the process variances.

5.3 Approach applied to an actual hot bar rolling process

The same 8-pass square to round sequence is used here as the one in chapter 2. Figure 5.6 shows the roll pass design and corresponding 3D FEM mesh in the roll bites respectively. In this roll pass sequence, pass 1, 3, 5 and 6 are flat passes, pass 2 and 3 are box passes, pass 7 is an oval pass and pass 8 is a round pass (final pass).
5.3.1 Select noise-sensitive parameters

As discussed above, various reasons are involved in the formation of seams. Among all of them, roll pass design is an important parameter to be considered. If the roll pass design doesn’t fall in the range which is the least sensitive to the variances, there is a higher risk that the final rolled bar may have surface defects. Various roll pass design can achieve seam free final rolled bar, however, some of them are sensitive to
variances in the production process, our aim is to look for a roll pass design which is the least sensitive to the process settings, which is called the minimum sensitivity roll pass design.

To achieve the roll pass design with the minimum sensitivity, the first thing to do is to choose the significant roll pass design parameters, which are very sensitive to perturbations incurred by process noises. Then they are preset to a robust value, such that the minimum variability in the final surface defects can be assured. Also the deviation from the ideal is the minimum at a low cost. This is the stage for obtaining the minimum propagated variances from design variables to the underfills.

Various roll pass design parameters can be selected. Here, only those parameters, which are sensitive to the perturbations, are selected. This is realized by propagating these uncertainties in the design parameters through the model to discover the uncertainties in the predicted consequences. Firstly, all possible roll pass design parameters are selected based on the experiences, then a normalized sensitivity analysis for their reaction to the perturbations is conducted to remove those parameters with robust settings. After analyzing the sensitivity of the final product properties to the different variables, the variables that are already robust should be removed and the remaining design parameters need to be optimized to robust settings. Since the last pass, pass 8, aims to form the final part and it is also a fully constrained pass for metal flow. Considering the above factors, the reductions in all first 7 pass are chosen as the roll pass design parameters at first. The following equation is used to
perform normalized sensitivity analysis for the reaction of roll pass design parameters to perturbations:

\[
S_i = \frac{\text{Underfill}^N(R_{\text{avg}}^1, R_{\text{avg}}^2, \ldots, R_{\text{avg}}^i, \ldots, R_{\text{avg}}^7) - \text{Underfill}^N(R_{\text{avg}}^1, R_{\text{avg}}^2, \ldots, R_{\text{avg}}^i, \ldots, R_{\text{avg}}^7)}{R_{\text{max}}^{Ni} - R_{\text{min}}^{Ni}}, (i = 1, 2, \ldots, 7)
\]  

(5)

where

- \( S_i \) is the normalized sensitivity of underfills to reductions at \( i_{th} \) pass, i.e., their responses to the perturbations.

- \( R_{\text{avg}}^i \) is the nominal settings for reductions at different pass \((1, 2, \ldots, 7)\)

- and \( R_{\text{min}}^{Ni}, R_{\text{max}}^{Ni} \) are the normalized reduction values at \( i_{th} \) pass where minimum and maximum underfills occurs, when the actual calculation, they are coded to \([0,1]\) for comparison only.

- \( \text{Underfill}^N(x_i) \) is the normalized mapping function from control variables to final properties, here, i.e., the function to obtain normalized underfill from the actual reductions in designed passes.

<table>
<thead>
<tr>
<th>Reductions</th>
<th>Pass 1</th>
<th>Pass 2</th>
<th>Pass 3</th>
<th>Pass 4</th>
<th>Pass 5</th>
<th>Pass 6</th>
<th>Pass 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Larger (inch)</td>
<td>0.01</td>
<td>0.0061</td>
<td>0.0065</td>
<td>0.0059</td>
<td>0.0308</td>
<td>0.0072</td>
<td>0.0065</td>
</tr>
<tr>
<td>Nominal (inch)</td>
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<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
</tr>
<tr>
<td>Smaller (inch)</td>
<td>0.0063</td>
<td>0.0043</td>
<td>0.0056</td>
<td>0.0068</td>
<td>0.0069</td>
<td>0.0312</td>
<td>0.0315</td>
</tr>
</tbody>
</table>

Table 5.2 Underfill values for pass 1 to 7 with nominal and perturbations
The reductions are based on the nominal values. As can be seen in figure 5.4, for both the box pass and flat pass, the reduction are described in the figure. Then based on the nominal reductions values in each pass, to mimic the process variances, some perturbations are added on purpose as described in the previous section, and the corresponding underfills are recorded for normalized sensitivity analysis based on the result of underfills from ROLPAS simulations.

To conduct the ROLPAS simulations, due to the fact that the billet is symmetrical across both axes, a quarter model simulation instead of a full model simulation is run. This reduced the time of computation greatly. Table 5.1 shows the underfills at pass 1 to 7 for the perturbation analysis. Table 5.2 shows the normalized sensitivity of underfills to reductions perturbations at pass 1 to 7. Figure 6 shows the plot of the normalized sensitivity analysis for reduction perturbations at all first 7 passes. From figure 5.7, reductions in pass 1, 2, 3 and 4 are more robust to the perturbations, and they are more tolerant to the process noise compared to the reductions in pass 5, 6 and 7.
7. So they are removed. Now keeping pass 7 unchanged would be the best situation, since it is only one pass away from the final product, any change should be avoided if possible. Therefore, only pass 5 and 6 are kept for further for minimum sensitivity roll pass design to obtain a more noise-tolerant roll pass design, after that, all the pass will be checked again.

![Normalized Sensitivity vs Pass](image)

Fig. 5.7 Sensitivity analysis for reduction perturbations at all 6 passes.

### 5.3.2 Knowledge preparation for the minimal sensitivity roll pass design

From the above discussion, pass 5 and 6 are kept for the minimum sensitivity roll pass design. The specific rolling process information would be needed during the roll pass design stage. Design of experiment based on billet reductions at pass 5 and 6 are
conducted. Since each non-isothermal FEM simulation using ROLPAS takes only about 5 minutes to run including pre-processing and post processing and hence it is decided to go with the full factorial design. The 3-D deformation in this process is complex and hence three levels are used for each input variable, with the nominal level representing the approximate value of the existing design. Since there are two design variables, each at three levels a full factorial design consists of 9 simulations. Design array for FEM simulations is shown in the table 5.3. Here, the design array is formed based on the settings for pass 5 and 6, with a variation from -0.09 to +0.09 inch.

<table>
<thead>
<tr>
<th>Noises</th>
<th>Pass 5</th>
<th>Pass 6</th>
<th>Underfil</th>
<th>Seam?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.09</td>
<td>-0.09</td>
<td>0.0249</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>-0.09</td>
<td>0</td>
<td>0.0045</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>-0.09</td>
<td>0.09</td>
<td>0.0339</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>-0.09</td>
<td>0.0367</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0.0061</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0.09</td>
<td>0.0063</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>0.09</td>
<td>-0.09</td>
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<td>1</td>
</tr>
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<td>8</td>
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<td>0</td>
<td>0.0105</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>0.09</td>
<td>0.09</td>
<td>0.0248</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 5.4 Design array for FEM simulations and results of seams recognition.

According to the steel bar product guidelines by the iron & steel society, the traditional amount of surface removal used to minimize occasional surface imperfections and decarburization: for the standard use, 0.001 inch per 1/16 in
diameter, for cold working, 0.00063 inch per 1/16 in diameter. Here in our case, the final diameter is 2.21 inch. The underfills from the above two criteria are 0.03 inch and 0.02 inch. Since in real production, lots of unexpected factors may happen, so here in the FEM simulation, some safety factor is given in determining the potential seams. Considering the underfill results from ROLPAS simulations, as shown in figure 5.8, considering the profiles of the final profiles, an underfill of 0.01 inch is taken as the threshold to determine the potential seams as following:

- Potential seam exists if underfill is larger than 0.01 inch.
- No potential seam exist if underfill is smaller than 0.01 inch.

For each simulation run, underfill is evaluated by the difference of the maximal/minimal radius and the nominal radius as shown in figure 5.8(b). And then the threshold value is selected to differentiate the existence of the potential seams. Figure 5.9 shows the simulation results for all the runs in the design array.

Table 5.3 also presents the results obtained by applying the threshold for seams recognition. For each simulation, the underfill is given along with the reductions respectively. The criteria for seams determination is discussed below.
As shown in figure 5.8(a), a seam-free design can be assumed from the profiles of the rolled bar after the final pass, while figure 5.8(b) shows the potential seams exist as a result of underfill. As described above, underfills in the final part would lead to potential seams later on.

Fig. 5.9 Simulation results for underfills.
5.3.3 Seek the roll pass design with minimum sensitivity

The minimum sensitivity design can be achieved by exploiting the nonlinearity of the hot bar rolling process. As discussed in the previous section, to obtain a wide working window $S_2$ as shown in figure 5.10, the gradient needs to be minimized subjecting to some constraints:

![Diagram showing selection of minimum sensitivity design](image)

Fig. 5.10 Illustration of selection of minimum sensitivity design.

However, the strict analytical expressions are not easy to obtain for this close coupling, complicated rolling problems. To solve this searching problem, marching the contours for the whole feasible domain is adopted. A design should have an underfill less than
the critical value. At the same time, a working window as large as possible is also desired for a design with minimum sensitivity. Since the number of the design variables is two, a 2D geometric approach is adopted to identify the working window for minimum sensitivity design.

From an engineering viewpoint, it is often desirable to approach the optimum from inside the feasible region (Vanderplaats, 1984). By analyzing the 2D contours shown in figure 5.11, it can be seen that the minimum sensitivity roll pass design would be the one with the longest distance to the circumambient boundaries of the inner contour, where the underfills is less than the critical value. This is with roll pass settings varied from the nominal one with (0.01 inch and 0.04 inch) in pass 5 and 6 respectively. The gradients discussed above here are relatively smallest in all 2 directions comprehensively. Therefore, this roll pass design with minimum sensitivity is considered as the safe roll pass design with the largest permissible working window.
5.3.4 Verification

After obtaining the roll pass settings with minimum sensitivity, the verification is conducted for further improvement if necessary. Figure 5.12 shows profiles of recrystallized grain size of the nominal design and the minimum sensitivity safe design in the final pass. It can be noticed that the final profiles don’t show the existence of the potential seams formation. Also, the grain size is not worse than the nominal design.
Fig. 5.12 Profiles of recrystalized grain size of the nominal and minimum sensitivity design.

Figure 5.13 shows the profiles of the bar after the 8th pass with some perturbation to the new robust roll pass design at pass 5 and pass 6. It can be seen that even after the perturbations, all the final profiles are still safe, without signs of potential seams.

Fig. 5.13 Profiles of the roll pass design with perturbation to the minimum sensitivity design.
Now the new roll pass design with the minimal sensitivity is perturbed to some extent in all first six passes. The same perturbation analysis procedures are used as to the nominal design, table 5.4 shows the results of underfills for safe design (pass 1 to pass 7) with perturbations of 0.01 inch.

<table>
<thead>
<tr>
<th>Pass Perturbation</th>
<th>Pass 1</th>
<th>Pass 2</th>
<th>Pass 3</th>
<th>Pass 4</th>
<th>pass 5</th>
<th>pass 6</th>
<th>pass 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Larger (0.01 inch)</td>
<td>0.0071</td>
<td>0.0097</td>
<td>0.0105</td>
<td>0.0099</td>
<td>0.0053</td>
<td>0.006</td>
<td>0.0069</td>
</tr>
<tr>
<td>Nominal (No)</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
<td>0.0061</td>
</tr>
<tr>
<td>Smaller (0.01 inch)</td>
<td>0.0099</td>
<td>0.0099</td>
<td>0.0096</td>
<td>0.0067</td>
<td>0.0065</td>
<td>0.0061</td>
<td>0.0056</td>
</tr>
</tbody>
</table>

**Table 5.5 Underfill values for pass 1 to 7 with safe design and perturbations.**

Figure 5.14 shows the comparison of the sensitivity to perturbations for both initial nominal design and new robust design with minimum sensitivity. It can be seen from the figure, the new design is much more robust to the perturbations in each pass, which is due to the inevitable noises during the hot bar rolling process. Therefore, the new design is more robust, no further step is taken after checking the normalized sensitivities of all passes.
Fig. 5.14 Comparison of the normalized sensitivity to perturbations for both initial nominal design and safe insensitivity design.

Finally the new design should be subjected to all constraints. Figure 5.15 shows the effect of different roll pass design on final average grain size. It can be observed that the minimum sensitivity roll pass design can be conducted to obtain seam-free final product without deteriorating the final microstructural distribution.
Fig. 5.15 Effect of different roll pass design on final average grain size.
CHAPTER 6

SUMMARY OF CONCLUSIONS AND FUTURE WORK

6.1 Conclusion

With the development of the computer science, the utilization of computers in manufacturing process provides a powerful tool for process design and which control. Timely response to the customer’s needs is extremely important at the same time the internal and external of the product need to be ensured. A good process design and control technique would lower the production cost, at the same time, reduce the scrap rate. However, the non-linear nature of the manufacturing problem, the close coupling between the thermal, mechanical and material phenomena, and the multi-step nature of optimization makes the problem difficult to formulate and solve. Advances in the numerical analysis tools have made it possible to model the metal flow in non-isothermal manufacturing processes. However, the calculations often become time and computer resource intensive. Process optimizations become very difficult and unstable limiting the numerical tools to a trial and error approach.
In order to improve the process capability of the metal process, the work completed can be summarized as follows:

1. A hybrid computer model has been developed which utilizes the numerical efficiency and accuracy of the finite element method, and the fast processing and decision making ability of ANN techniques. It uses an inverse approach as the problem is often posed as follows: “Optimize the rolling process for the given final geometric tolerance and material properties of the rolled rod.” A 3-D finite element model was used to analyze deformation and microstructural evolution based on Design of Experiment (DOE). Then a preliminary ANN based inverse agent was developed and calibrated on previously reported results and numerical simulations. This inverse agent resulted in sound estimations of roller settings and material selections for an 8-pass square to round sequence. The model will help to optimize the rolling sequence to obtain a part with required toughness and ductility.

2. A virtual soft sensor has been developed for the hot forging process, which can relate the primary and secondary variables and map the measurable secondary variables to the unmeasurable primary variables. This soft sensor is capable of avoiding the time-consuming analysis, offering an on-line response to the forging process control, at the same time, facilitating the process engineer to reduce the variation of the forging process. In this research, the secondary variables are selected as the final critical dimensions.
of the forged part, which can be easily obtained from the non-contact sensing technology, which is based on CCD technology and electronic signal processing. The primary variables are the controllable process variables, such as the lubrication schedule, furnace temperature, and the press settings etc.

3. A minimum sensitivity roll pass design is proposed. The rolled seams are reduced by looking at the flat passes in a multi-pass square-to-round sequence. The flat pass designs are less constrained and easy to manipulate. Small perturbations to the original nominal design are given and those variables that significantly affect the objectives are selected for design. The minimum sensitivity analysis is conducted to determine the robust settings for the rolling sequence. A case study using this approach is presented, which demonstrates the efficacy of this approach in analyzing the potential for the formation of rolling surface defect called seam.

6.2 Future work

Source of the future advance could be improving the approach efficiency by finding technologies to extract more information from limited data to build the knowledge base and train the neural networks. Moreover, since the actual working condition vary from time to time, technologies are needed to accommodate this new information in the system. In order to do that, the online-updating system needs to be developed that
system may be adaptive. It would be very powerful and drive the generation of process models more accurate.

Currently the soft sensor model has not been implemented in the actual plant. It needs to be verified and calibrated by the actual data later on. In the future, the approach needs to be validated by taking measurements and comparing them to the soft sensor estimations for a wide selection of process parameters.

The statistical model should be developed to relate the process design to the final quality of the product through stochastic techniques. For example, due to the process variances, Bayesians neural networks can be used for the probability analysis of the failure.


Iron and Steel Society, Steel Bar Product Guidelines, September, 1996


