University of Alberta

Optimization of Industrial Shop Scheduling Using Simulation and Fuzzy Logic

by

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A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of

Master of Science

in

Construction Engineering and Management

Department of Civil and Environmental Engineering

Spring 2010
Edmonton, Alberta

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Abstract

The percentage of shop fabrication, including pipe spool fabrication, has been increasing on industrial construction projects during the past years. Industrial fabrication has a great impact on construction projects due to the fact that the productivity is higher in a controlled environment than in the field, and therefore time and cost of construction projects are reduced by making use of industrial fabrication. Effective planning and scheduling of the industrial fabrication processes is important for the success of construction projects.

This thesis focuses on developing a new framework for optimizing shop scheduling, particularly pipe spool fabrication shop scheduling. The proposed framework makes it possible to capture uncertainty of the pipe spool fabrication shop while accounting for linguistic vagueness of the decision makers' preferences using simulation modeling and fuzzy set theory. The implementation of the proposed framework is discussed using a real case study of a pipe spool fabrication shop.

In this thesis, first, a simulation based scheduling framework is presented based on the integration of relational database management system, product modeling, process modeling, and heuristic approaches. Next, a framework for optimization of the industrial shop scheduling with respect to multiple criteria is proposed. Fuzzy set theory is used to linguistically assess different levels of satisfaction for the selected criteria. Additionally, an executable scheduling toolkit is introduced as a decision support system for pipe spool fabrication shop.

Acknowledgment

I would like to express my gratitude to my supervisor, Dr. Robinson Fayek, to whom I am deeply indebted for her support and guidance during my research. I would also like to thank my thesis examination committee members, Dr. Yasser Mohamed and Dr. John Doucette.

I would like to genuinely thank Ledcor Industrial for providing me with data and facilitating my work by sharing their knowledge in a friendly manner.

Especially, I need to thank my husband Yasser who supported me by all means. I am also grateful to my parents, my sisters, and my brother for their love and encouragements.

Last but not least, I would like to thank my friends and fellow graduate students for their supports and friendship.

To my husband

Yasser

And to my parents

For their love, and supports

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CHAPTER 1 - Background and Problem Statement

1.1 Overview

Satisfying customers' ever growing expectations has become a significant challenge for survival in today's extremely competitive marketplace. The response of researchers and practitioners in academia and industry to this challenge contributes to the development of new concepts, strategies, and even research disciplines (Ebrahimy 2006).

One of the research areas developed in response to such a challenge is operations research (OR). Over the years, firms and corporations have been trying to improve their performance, productivity, and profitability by using and adopting the studies developed on topics such as factory layout, inventory control, process control, scheduling, and resource utilization. Amongst all topics in the operations research area, one of the most popular research topics is sequencing and scheduling, which plays an important role in the success of organizations: for instance, effective scheduling enables corporations to increase throughput, reduce cycle time, reduce work in progress inventory and thus reduce cost. Therefore, scheduling has attracted significant research for the last five decades.

Scheduling as a form of decision making deals with the allocation of resources to activities over given time periods, and its target is optimizing one or more objective functions. It plays an important role in production systems, manufacturing, and also transportation (Pinedo 2008). The resources and activities may take different forms. For example, resources can be machines in a workshop, runways at an airport, crews at a construction site, and so on. The activities can be operations in a production process, take-offs and landings at an airport, stages in a construction process, and so on. There are also various forms of objectives. One objective may be the minimization of the completion time of the last activity (i.e. Make Span), and another may be the minimization of average flow time or the minimization of number of activities completed after their particular due dates. A comprehensive introduction to scheduling can be found in French (1982), Brucker (2007), Pinedo (2008), and Baker and Trietsch (2009).

The construction industry has employed and adopted some concepts and tools of scheduling. There are many studies that have used project scheduling techniques such as critical path method (CPM) and Program Evaluation and Review Technique (PERT) in construction for controlling and managing construction projects, risk analysis, resource leveling, and resource forecasting. However, the quantity of research conducted in developing a feasible schedule for shop environments in the area of industrial construction is very limited. Although many research projects have been carried out to analyze the productivity of several shop floors in industrial construction, there have been few studies on developing feasible and optimized schedules for the shop floors. Notably, CPM and PERT are tools for presenting schedules, but not for developing optimum or good schedules.

Most scheduling problems are known to be NP-hard, meaning that the problems do not have a polynomial time algorithm. The time required for solving the problem grows exponentially with an increasing number of machines or jobs.

Accordingly, a great deal of work has been dedicated to development and analysis of approximate algorithms.

Although most scheduling problems are solved based on a single criterion (i.e. objective), there are some studies on multi-criteria scheduling problems due to the fact that in practice these problems often have multiple criteria. In multi-criteria scheduling, several objectives are considered in the problem. Optimizing all objectives in such problems is impossible, given that in most cases the objectives conflict with each other. Therefore, such scheduling problems do not have a single optimum solution. There exist a set of different solutions, which produce trade-offs (i.e. conflicting scenarios) among different criteria, which means that a solution that is extreme with respect to one criterion requires a compromise in other criteria (Kalyanmoy 2001). Consequently, in multi-criteria scheduling, the problem is modeled by taking into account the preferences and experience of decision makers. Depending on the preferences of the decision maker, some objectives are considered more important than others, or a degree of satisfaction is measured for each objective based on the expectation of the decision maker. This approach makes it possible to construct a set of satisfactory solutions according to the preferences of the decision maker. It is important for the decision maker to have a set of possible solutions to be able to select the most suitable solution based on the state of the existing decision at a given time. Particularly, the preferences of the decision makers are usually described in natural language. Therefore, the application of the fuzzy set theory is an appropriately good fit in order to account for imprecise linguistic aspirations of the decision maker.

The research presented in this thesis is intended to develop a new framework for optimizing industrial shop scheduling, specifically, pipe spool fabrication shop scheduling, with respect to multiple criteria. The methodology provides the opportunity to capture the uncertainty of the industrial shop, while accounting for the linguistic vagueness of the decision makers' preferences by using simulation modeling and fuzzy set theory. Furthermore, a scheduling toolkit is developed as a decision support system for a pipe spool fabrication shop. This toolkit provides decision makers with the opportunity to select an appropriate scheduling solution based on their objectives.

1.2 Research Objective and Expected Contributions

The main objective of this study is to develop an application using concepts and methods of job shop scheduling problems for a pipe spool fabrication shop in order to reach a reasonable, and near optimum schedule subject to decision makers' implicit objectives. To realize these objectives, three steps are identified:

1. Understanding theory, algorithms, and systems of scheduling

2. Developing a simulation model based on Product Model (PM) to model scheduling problems in spool fabrication shop

3. Developing a model to solve scheduling problems for spool fabrication shop by heuristics, and using fuzzy set theory to solve multi-objective scheduling problems

The research contributions of this study include:

1. Using and adopting concepts and theories such as production scheduling in industrial construction management.

2. Modeling a new scheduling problem in construction management as well as production research.

3. Developing a novel simulation model, based on product modeling connected to the database of the industrial shop. This simulation model can be used as a baseline for future studies on the spool fabrication shop.

4. Developing a new method of solving multi-criteria (objective) scheduling using fuzzy set theory.

The research also contributes to the industry by developing a toolkit, which can be used as a decision support system by coordinators and superintendants of spool fabrication shops for the sequencing and scheduling of jobs in the fabrication shop. Using the proposed toolkit, they can improve productivity, throughput, and the shop's works in progress, as well as ensure that jobs are completed on time. The toolkit has been developed using VB.NET and Simphony.Net as an underlying simulation environment.

1.3 Research Methodology

This research was conducted using the following methodology: first, spool fabrication shop processes and stages each spool should go through during the fabrication of spools were identified. The fabrication processes were mapped out by questioning and interviewing the fabrication shop staff. Moreover, the procedures were studied by observing and visiting the shop floor. The constraints and limitations of resources were also verified in order to properly model the fabrication shop. Additionally, the configuration and constraints of the shop, including space constraints, safety constraints, and constructability constraints, were identified.

A product model was then developed for spools using both a spool fabrication shop database, as well as drawings of spools from the drafting department's database, in order to identify jobs and model the spool fabrication. In reality, the way the components or assemblies connect to each other (for example, whether two pipes make parallel or perpendicular connections) may change the time and even the type of the process that should be performed on that assembly or spool. Therefore, the product model was designed to incorporate the 3-D relational geometric attributes of the product, i.e. spools, the type and shape of the product components, the relationship between the product components, shop process information, and constraints of the shop. The product model was developed in MS-Access, which was the central database to connect to the simulation model.

Subsequently, a Special Purpose Simulation (SPS) template for pipe spool fabrication was developed in Simphony.Net© (Hajjar and Abourisk 2002), which is an object oriented environment for building SPS templates using VB.net programming language. The SPS template is connected to the central database to use the developed product model. Using the developed SPS template, a simulation model was developed for a real case study.

In the next step, common criteria on which the schedules should be evaluated, i.e. objective functions, were identified. Then, suitable dispatching rules and heuristics were identified, and new combinatorial dispatching rules were established by combining and weighting multiple parameters. The performance of each rule with respect to different criteria was measured for different scenarios using the simulation model. Then, the performance values estimated by the simulation model were exported to Excel sheets. Fuzzy membership functions were used to evaluate the satisfaction degree of each. Conflicting criteria and the linguistic trade-offs between them were identified using the concept of fuzzy set theory. The data set obtained from the simulation results was analyzed using the concept of Pareto-optimality and Fuzzy C-Means clustering (FCM). In addition, Fuzzy C-Means clustering (FCM) was used to categorize the performance values obtained from the simulation model for different scenarios. The probability and possibility analyses were performed on the results to identify the most efficient and robust rules for each linguistic trade-off between conflicting criteria.

1.4 Thesis Organization

Chapter 2 of this thesis presents an enhanced simulation-based framework for industrial fabrication scheduling. In this chapter the concepts and ideas of scheduling of shop environments, heuristic rules, and simulation modeling is provided. The existing simulation modeling frameworks (Song et al. 2006; Sadeghi and Fayek 2008) are extended and used to develop a toolkit for automated scheduling of the industrial fabrication shop.

Chapter 3 of the thesis focuses on developing a framework for solving multi-criteria scheduling with respect to the linguistic preferences of the decision maker using Fuzzy C-Means clustering and fuzzy set theory. In this chapter the concepts and ideas of fuzzy set theory and its application to the multi-objective scheduling problem are briefly introduced. Moreover, the previous studies on these concepts are summarized.

Chapter 4 of this thesis discusses the implementation of the simulation-based framework for industrial fabrication scheduling, and the multi-criteria scheduling framework on a real case study to experiment with the effectiveness of the scheduling model. The results are validated to identify the accuracy of the proposed methodology for multi-criteria scheduling.

Chapter 5 of this thesis describes the conclusions, contributions, and recommendations for future research.

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CHAPTER 2 - A Simulation-Based Framework for Industrial Shop Scheduling

2.1 Introduction

In this chapter, an enhanced framework for developing simulation-based scheduling for industrial construction is proposed. The proposed framework enhances the existing simulation models, and can be used as a toolkit for automated scheduling. The proposed framework is developed based on the integration of database management systems, product modeling, simulation modeling, and heuristic approaches to streamline the scheduling process of industrial fabrication shops. The proposed framework is illustrated and discussed using pipe spool fabrication processes.

The background of simulation modeling and industrial shop scheduling is presented in section 2.2. The previous models are also reviewed in this section to justify the need for extending the functionality of existing simulation models. The processes of spool fabrication are explained in Section 2.3. Section 2.4 provides the formulation of the industrial shop scheduling problem. Section 2.5 presents the proposed simulation-based scheduling framework. The potential improvement for the future development of the framework is reviewed in section 2.6. Section 2.7 summarizes the contributions of this chapter.

2.2 Background

2.2.1 Discrete Event Simulation in Construction

Discrete event simulation is a common technique for modeling manufacturing and construction systems. Overviews on simulation and its application in industries, such as electronics manufacturing, shipbuilding, and bridge fabrication are available in several publications (Banks 1998; Law and Kelton 2000; Jahangirian et al. 2009).

Discrete event simulation has been widely used in construction industry since Halpin (1977) developed the first construction simulation system, CYClic Operation NEtwork (CYCLONE). It is defined as a chronological sequence of events and transitions between those events. MicroCYCLONE was developed by Lluch and Halpin (1982) to increase the functionality of CYCLONE. Many discrete event simulation frameworks have been developed to address construction operation simulation problems after that, such as RESQUE (Chang 1986), CIPROS (Odeh 1992), HSM (Sawhney 1994), STROBOSCOPE (Martinez 1996) and Simphony© (Hajjar and AbouRizk 1999).

Simphony© is based on Special Purpose Simulation (SPS) (Kim 2007), which provides a user-friendly interface and allows the developer to build the model intuitively. It also provides graphical and hierarchical modeling. Simphony© is capable of modeling complex and large construction projects by using modular and hierarchical structures (Davila Borrego 2004).

2.2.2 Industrial Shop Scheduling

There are two main types of scheduling problems in the construction industry. The first type is project scheduling, which is activity-oriented and concerns project resource usage, total project cost, and total project duration. In project scheduling, the sequences of activities are determined to optimize one or a set of objective functions while meeting the precedence constraints. The target in this type of scheduling problem usually involves addressing a trade-off between project resources, project cost, and project duration. Examples of this type of scheduling are construction scheduling of infrastructure, tunnels, and building construction projects. Several studies have been done on such scheduling problems based on critical path method (CPM), including studies carried out by Schmidt and Horning (1990), which aims to modify resource allocation in CPM; Fan et al. (2003), in which an object oriented scheduling method is introduced; Karim and Adeli (1997), to schedule highway constructions; Chan et al. (1996), which models resource allocation in project scheduling; Karim and Adeli (1999), which models construction scheduling and change management; Leu and Yang (1999), which models construction project scheduling using genetic algorithm; and Adeli and Karim (2001) and Zhang (2006), which optimize projects' resource utilization using search algorithms.

The second type of scheduling problem is production scheduling, which includes scheduling of jobs through multiple work centers to complete the jobs. An example of production scheduling is the scheduling of industrial fabrication, such as steel and spool fabrication shops. The jobs in spool fabrication scheduling are the spools that are being fabricated by going through cutting, fitting, and welding stations or work centers. The usual target in the second type of scheduling problems is to find the best sequence of production or fabrication jobs, which optimizes an objective function or a set of objective functions such as the total flow time, incidents of lateness, or average resource usage. Industrial fabrication scheduling as a major branch of production scheduling problems is job-based.

The term “industrial construction” is used for construction of facilities for basic industries such as petrochemical plants, nuclear power plants, and oil/gas production facilities (Barrie and Paulson 1992). Some parts of industrial construction projects can be pre-fabricated in the controlled environment of fabrication shops. Industrial shop fabrication has had a great impact on reducing on-site fabrication and installation and therefore reducing the cost of construction projects due to reduced uncertainty in a controlled shop environment. Consequently, the percentage of shop fabrication in construction, including steel fabrications and pipe spool fabrication, has been increasing during the last decade. This means that the success of a project depends on effective short-term job-based planning and scheduling, which requires higher levels of modeling accuracy. As existing project management systems such as Microsoft Project and Primavera Project Planner are activity-oriented, they cannot be applied effectively to industrial fabrication scheduling problems (Karumanasseri and AbouRizk 2002). Production engineers usually schedule an industrial fabrication project by creating a practical master production schedule for the project. On the shop floor, experienced superintendents try to complete the jobs by the delivery date estimated in the master production schedule (Song et al. 2006). In this approach, scheduling is based on personal experience, information from component drawings, and knowledge of shop status. Today's complex shop environments, complex products, and many potential influencing factors make it difficult for the human mind to process the information required for an accurate analysis of such a production system. Therefore, developing a scheduling technique to analyze and capture all these complexities would contribute to the better planning and scheduling of fabrication shops.

Traditionally, simulation models are used to mimic the real-world systems and processes in order to analyze and improve the productivity of the systems. In the last decade, simulation has been used as an effective technique for generating and developing production schedules in manufacturing systems (Mazzioti and Home 1997; Marito and Lee 1997; Siva Kumar 1999; Gupta and Sivakumar 2002).

2.3 Spool Fabrication Processes

Spool fabrication is an industrial shop that produces pipe spools to be used in pipe spool modules, which are then utilized in developing modular construction units in refineries and oil processing plants (Mohamed et al. 2007). Spool fabrication processes in a typical fabrication shop involve cutting, fitting, tacking, and welding (Wang 2006). Each spool is a portion of a piping system composed of a number of pipes and fittings, such as elbows and tees, valves, reducers, and supports, assembled together according to fabrication drawings. Figure 2.1 shows an example of a spool which is composed of five pipes, three elbows, one valve, and one reducer.

In the pipe spool fabrication shop, three methods of welding are usually employed: (1) roll welding, in which the welder uses a pipe turner to weld faster; (2) SAW welding, which is the fastest method of welding using the Submerged Arc Welding (SAW) machine; and (3) position welding, which takes much longer than the other methods as the welder cannot use any machine to turn the pipes. SAW is done by the SAW machine, and its duration is less than roll or position welding. In roll welding, the welder does not move the rod; instead, the pipe is turned by a roll welding machine (pipe turner or chuck positioner), while in position welding, the welder must move the welding rod around the pipe to weld the pipe. Position welding is used when the pipe has long branches and cannot be rolled by a pipe turner. In order to properly simulate the fabrication shop, these three types of welding should be modeled separately for each spool.

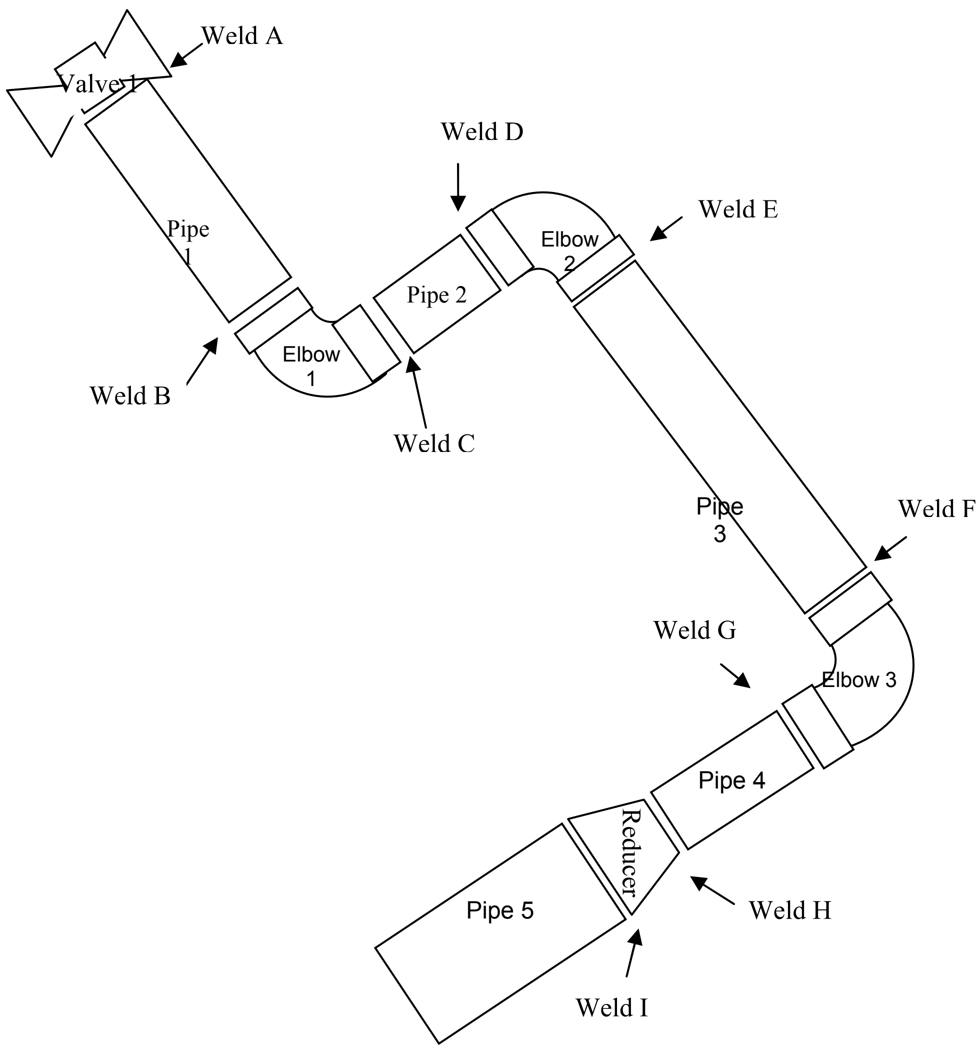


Figure 2.1 Components of pipe spool (adopted from Sadeghi and Fayek (2008))

In the spool fabrication shop, the fitter usually breaks down the spool into smaller assemblies (Figure 2.2) that are easier for fabrication (Sadeghi and Fayek 2008). Each assembly contains several piping components (such as pipes, elbows, tees, valves, etc.) as the most basic elements in the fabrication process. During the fabrication of spool some processes, such as cutting, are performed on piping components. Piping components then are assembled together to produce assemblies. This procedure is continued until the final product or spool is produced. As previously mentioned, welding operations can be performed by three different methods, including position welding method, roll welding method, and SAW method. For roll welding and SAW operation there are physical constraints. For example, roll welding cannot be performed on assemblies with long branches as shown in Figure 2.3. On the other hand, SAW and roll welding are more efficient due to the fact that in these two welding methods not only is the welding process faster, but also the quality of weld is better than position welding. To comply with such constraints, each spool is decomposed into assemblies to use roll welding and SAW as much as possible. Therefore, a spool is broken down to assemblies in such a way that the position welding is minimized with respect to technological constraints.

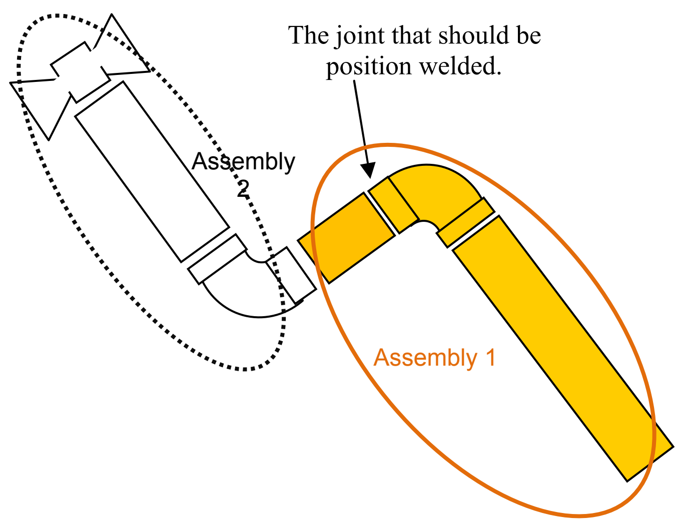
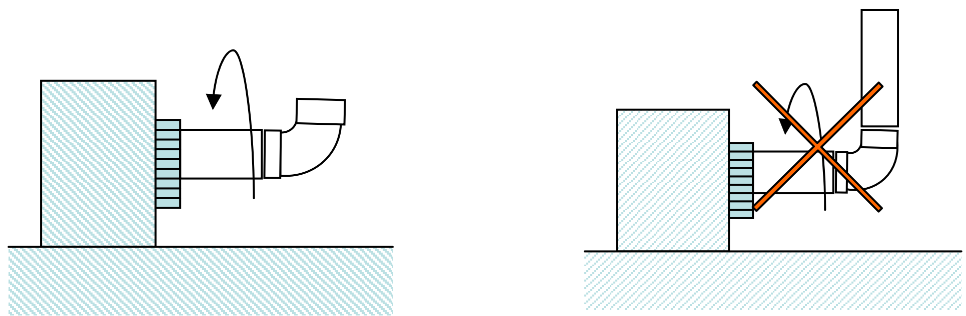


Figure 2.2 Assembly parts of a spool



(a) (b)

Figure 2.3 Example of roll welding constraint: (a) Roll welding is feasible; (b) Roll welding is not feasible (adopted from Sadeghi and Fayek (2008))

According to the flowchart of processes shown in Figure 2.4, the first process of pipe spool fabrication shop is cutting the pipes to their required size. The duration of pipe cutting depends on pipe diameter and wall thickness. Different pipes of one spool can be cut in any sequence or simultaneously. A fabrication shop may have different types of cutting machines for different types of pipes according to the pipe's diameter and wall thickness. After the cutting process is finished for all pipes and components of a spool, they are sent to the roll fitting station. In the roll fitting station, pipes or other components, e.g. elbow, valve, and reducer, are tacked together for welding. The tacked pipes then go to a roll welding or SAW welding station, depending on their diameter and wall thickness, to be welded. The fitter may fit two or more components at a time before sending it to welding station. The number of time a product goes back and forth between fitting and the roll welding station depends on the structure of product and the number of joints that should be welded (Sadeghi and Fayek 2008). In roll fitting, roll welding, and

SAW processes, the assemblies of spool are completed to be sent to a position fitting station.

In the next step, assemblies of spool are fit and tacked together by the fitter. Then, the spool is produced into the final product by performing the position welding process. The final fitting and position welding usually are performed in the same station (Sadeghi and Fayek 2008), which means that there is no material handling between these two processes. After the final fitting and welding, the quality check process is carried out to ensure the quality of welds. The quality check can be performed at any stage of processes, but it is usually implemented after position welding. During the spool fabrication process, components, assemblies, and spools are handled and moved by bridge cranes.

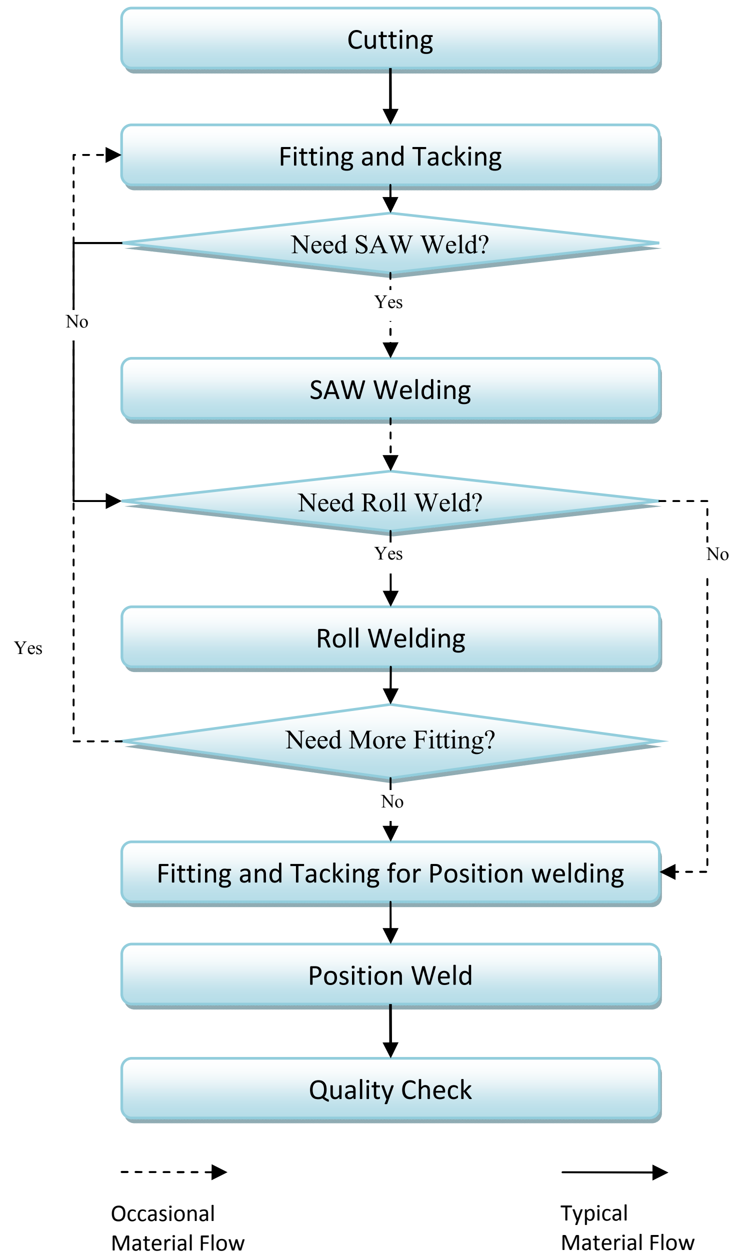


Figure 2.4 Flowchart of pipe spool fabrication process

2.4 Scheduling Problem

At the operational level of a fabrication facility, the scheduling problem consists of a set of products, which are usually referred to as jobs in manufacturing terminology, $J = \{J_1, J_2, \ldots, J_n.\}$, that must be processed through a set of stages, I = {1, 2, …, i, …, C}, in series; each stage includes m parallel resources, e.g. welding machines. The processing time of product j ($j \in J$) in the stage i ($I \in I$), shown by t_{ji}, is unique and depends on the attributes of the corresponding job or product.

A representation of the problem is given in Figure 2.5. Products have to pass through stages in such a sequence that some objective function(s) is (are) optimized. This problem is a generalization of the classical job shop problem and is among the hardest combinatorial optimization problems.

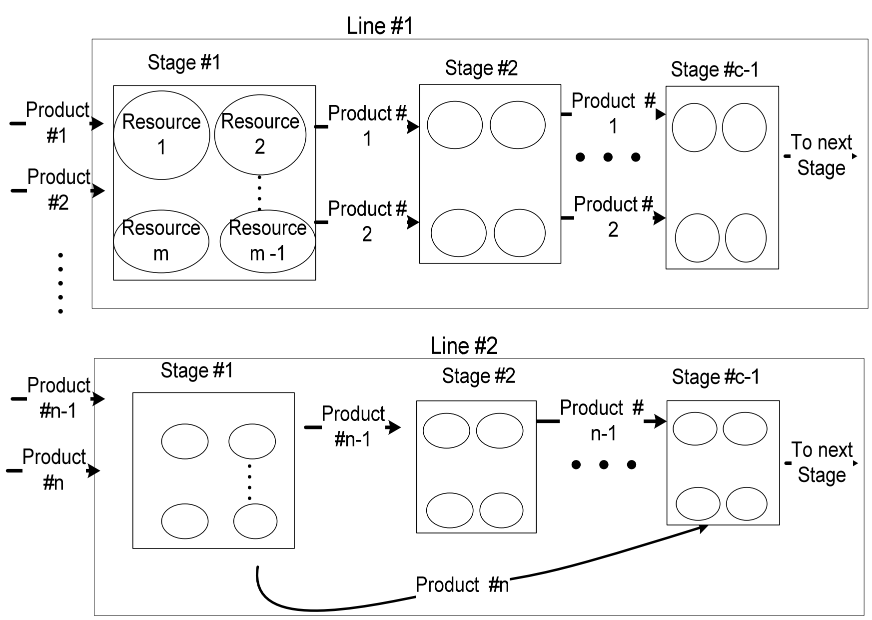


Figure 2.5 Overview of scheduling problem

The production-scheduling techniques in the literature can be divided into three major categories: exact algorithms, meta-heuristic techniques, and constructive heuristics. Exact algorithms or mathematical algorithms, e.g. branch and bound, guarantee to find an optimal solution but are case-based and include many simplifying assumptions. Meta-heuristic techniques, such as genetic algorithms (GA), sacrifice the guarantee of finding optimal solutions in order to get near-optimum solutions in reasonable and practical computational times. According to Osman and Laporte (1996), a meta-heuristic is an intelligent searching and learning method for exploring the feasible space. Constructive heuristics such as dispatching rules (or priority rules) are the fastest scheduling algorithms and need less computational time (Zobolas et al. 2008). Scheduling optimization problems are known to be NP-hard (non-deterministic polynomial-time hard), meaning that there is no polynomial time algorithm to solve such problems (Baker and Trietsch 2009). The time required for solving these scheduling problems grows exponentially with an increasing number of machines or jobs. Therefore, mathematical algorithms are not appropriate for the scheduling of industrial fabrication facilities. While meta-heuristics can produce a good sequence of jobs to get a near-optimum solution, they make the controlling problem of shop floor more complicated and they should also re-run as the jobs' composition in the shop changes. These problems make it difficult to use meta-heuristics in practice and provide a satisfactory solution.

Constructive heuristic techniques generate solutions from scratch by gradually adding parts of the solution to the initially empty partial solution. Constructive heuristics are the fastest approximate algorithms. Their advantage in computational time requirements is counterbalanced by generally inferior quality solutions when compared to meta-heuristic techniques. However, they are often preferred to meta-heuristic techniques due to fact that they are easier and faster to implement, and provide a satisfactory solution.

2.5 A Simulation-based Framework for Industrial Fabrication Scheduling

Although simulation-based scheduling techniques has been widely applied in manufacturing systems (Gupta and Sivakumar 2002), their application in industrial fabrication is limited (Mohamed et al. 2007; Taghaddos et al. 2009). Some researchers have developed frameworks for industrial fabrication virtual planning (Song et al. 2006; Sadeghi and Fayek 2008). These frameworks are useful for long term planning purposes, yet there are still some challenges in using them for scheduling purposes. The industrial fabrication planning and scheduling frameworks are generally comprised of two main components. The first component is a product model, which helps define the jobs to be fabricated or that pass through the production line. The second component is a production or process model, which calculates the time of each process for each job or each major part of a job. Processes usually include cutting, fitting and welding, as discussed in Section 3.2. The challenges hindering the use of the proposed frameworks also relate to these components.

Firstly, the product models proposed for industrial fabrication, although theoretically correct, do not recognize the importance of geometrical properties of the spools at different levels of the product model and the fact that different processes in industrial fabrication should be performed at different levels of the work breakdown structure (product model). In industrial construction, products are decomposed into smaller pieces, known as assemblies, at the operational level in order to meet the constraints and limitations of the shop as explained earlier. Thus, each product usually travels in the system not as one entity but as raw materials or different components (Sadeghi and Fayek 2008). For that reason, Sadeghi and Fayek (2008) have extended the product model suggested by Song et al. (2006) to model the flow of raw materials and components of a product as individual entities in a simulation model. However, the product model developed by Sadeghi and Fayek (2008) does not consider the geometrical properties at each level of the product model. In reality, the way the components or assemblies connect to each other, e.g. whether two pipes make perpendicular or parallel connections, may change the time and even the type of process that should be performed on that assembly or spool. By ignoring the geometrical properties of the components of an assembly, any assembly with a certain quantity of components, e.g. any assembly with a certain linear meters of pipe and certain number of welds, is modeled exactly the same. Any configuration of the product model that ignores the geometrical properties at different levels of the product model hinders the development of an accurate scheduling framework.

Secondly, the process models used to calculate the time of each process for a job or parts of a job are not accurate enough for short-term planning. The proposed process models are based on simple statistical modeling or neural networks. In the proposed process models, the processing time of each activity is represented by a probabilistic distribution, which is calculated using productivity values estimated by experts and the amount of work units for each spool. The variance of such a probabilistic distribution is usually high due to the variety of products. For example, using this information suggests that welds with identical diameter inches have the same duration regardless of different thicknesses or types, which is not accurate. If the durations of different processes for the jobs cannot be calculated accurately enough, the scheduling results will not be accurate.

In addition to the above challenges, these frameworks only discuss the need to use a scheduling algorithm or schema, without referring to the type of scheduling method to be used or proposing any practical solution for incorporating the scheduling engine into the framework. The choice of the scheduling algorithm is very important. For instance, while meta-heuristics such as adaptive memory programming, ants systems, evolutionary methods, genetic algorithms, and greedy search procedures can produce a good sequence of the jobs to get a near optimum solution, the fact that they should be run on a daily basis as the composition of the jobs in the shop changes makes them quite unattractive for practical purposes.

In this section an enhanced framework for the industrial fabrication scheduling problem is introduced. This framework has been developed to address the limitations identified in the previous frameworks, as discussed. This research enhances and extends the framework suggested by Song et al. (2006) in order to consider optimality of the schedule with respect to the user's criteria, 3-D geometric attributes of the product, and the site's constraints and factors affecting the product and process model.

2.5.1 Proposed Framework

To overcome the aforementioned challenges, the following aspects are considered in the proposed framework:

- 3-D geometric attributes of the product;
- type and shape of the product components;
- relationship between the product components;
- shop process information;
- constraints of the shop, i.e. space constraints, safety constraints, and constructability constraints, which are not included in the current modeling frameworks.

The framework for industrial fabrication scheduling proposed in this chapter has three major components:

1. The product hierarchy modeling component, which consists of the product model and the process model;
2. The simulation environment, which models the production and is linked to the product and process models;
3. The scheduling engine.

The overall architecture of the proposed framework is illustrated in Figure 2.6. The product hierarchy modeling (PHM) provides a mechanism to define the industrial fabrication products by capturing the complexity and uniqueness of the products by defining entity hierarchy (EH). The PHM is implemented in a central database system, which is a relational database management system (RDBMS). The central database interfaces with shop drawings and gets the product's information from CAD drawings and the material information database. It uses the product's information and shop constraints to build the product hierarchy (PH). The process model defines the processes that should be performed on each product. The EH is then constructed by integration of product and process data. The EH is used to produce entities for the simulation model.

The scheduling engine includes a library of heuristic rules, i.e. dispatching rules, that can be used in the simulation model for sequencing the products. The heuristic rule is to prioritize the jobs waiting in the queue of a machine: the job with the highest priority is selected to be processed in the corresponding machine. Each time a new job enters the queue of a machine, the jobs in the queue are prioritized based on the selected dispatching rule. The heuristic rules can be tested in the simulation model. The performance of each rule is measured by various statistics that are collected during simulation runs, including tardiness statistics of completed jobs, mean flow time, machine utilisation, and queuing statistics, e.g. average waiting time. The production schedule generated by each scheduling rule is maintained in the central database. Based on the performance measure of each heuristic rule, the decision maker can select the appropriate production schedule.

The simulation environment enables the user to reproduce the industrial fabrication facility as a computer model. The simulation environment models different components of an industrial shop including production lines (or bays), working stations, shop configurations (such as shop layout, number of working station, and storage capacity), movement paths, handling, equipment, and labour. A pipe spool fabrication template is developed to model the components of the pipe spool fabrication shop.

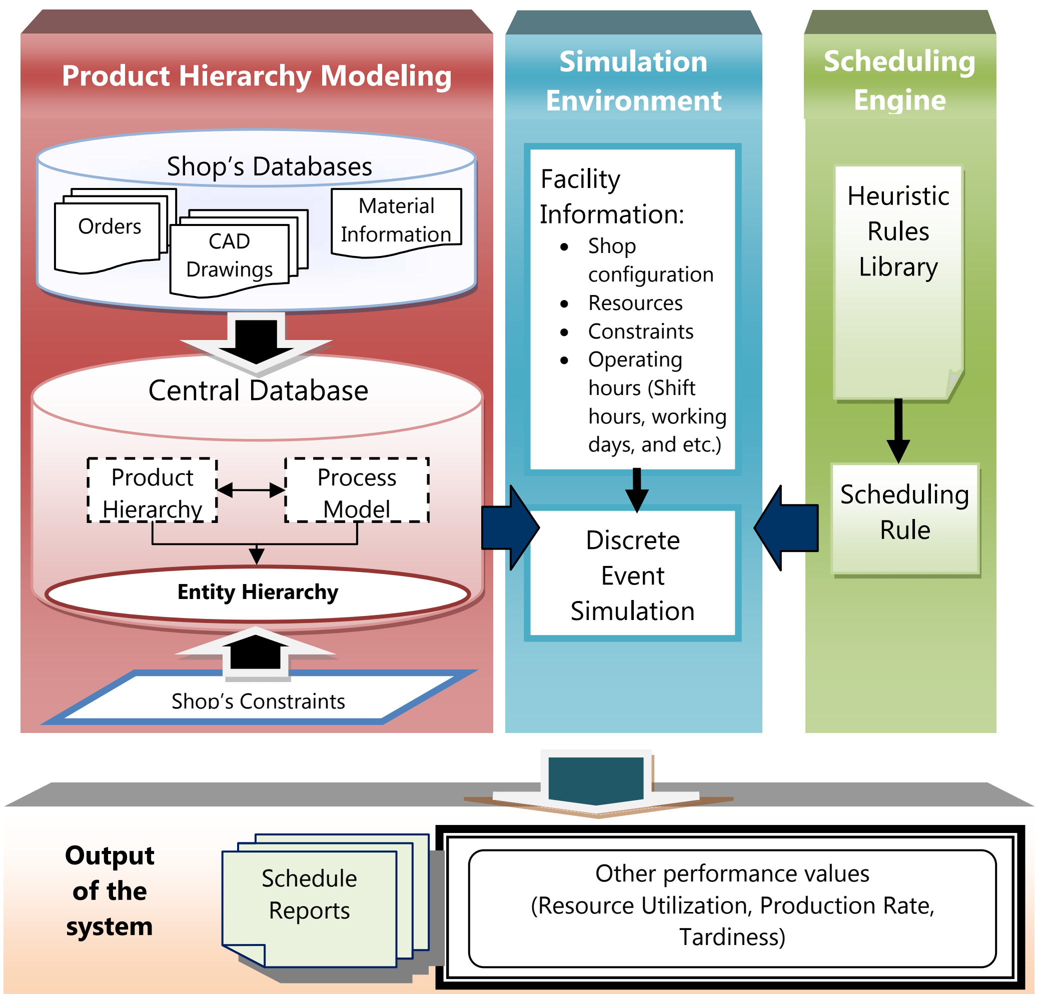


Figure 2.6 Architecture of proposed framework for industrial fabrication scheduling

2.5.2 Product Hierarchy Modeling

The product hierarchy modeling system is used for defining the product and identifying its most basic components, i.e. product atomic components (Xu et al. 2003), as well as recognizing the product's processes and operations. The system is developed using CAD drawings and RDBMS.

2.5.2.1 **Product Hierarchy**

Every level of the product model (PM) represents a level of the product's work breakdown structure (WBS) and corresponding processes. A typical WBS for a project in pipe spool fabrication shop is shown in Figure 2.7. In the pipe spool fabrication shop, each spool corresponds to a project. Each spool is detailed on a fabrication drawing, which is prepared by the drafting department based on the project's ISO drawings and requirements from the client. Several spools are usually grouped into batches by the project coordinator before they are issued to the work stations. As mentioned earlier, in the operational level of industrial fabrication shops, the product is usually broken down into smaller assemblies that are easier for fabrication. All welding processes of an assembly are done by roll welding and SAW welding. Each assembly contains several components (such as pipes, elbows, tees, valves, etc.) as the most basic elements in the fabrication process.

Collecting product data for industrial fabrication is challenging and time consuming because of large amount of unique products. Generally, CAD systems of pipe spool fabrication allow exporting all components' data of a product into an external standard file structure. Examples of components' data include physical and material feature of pipes, valves, and fittings, as well as 3-D coordinates of each component obtained from the spool's drawing. Form and quantity of welds are other examples of information that can be exported to an external file. Therefore, the automation of generating product components is an easy task. However, the main challenge is developing the product hierarchy using this information. The product hierarchy is developed using logical groupings from product components based on the shop's limitations and standards.

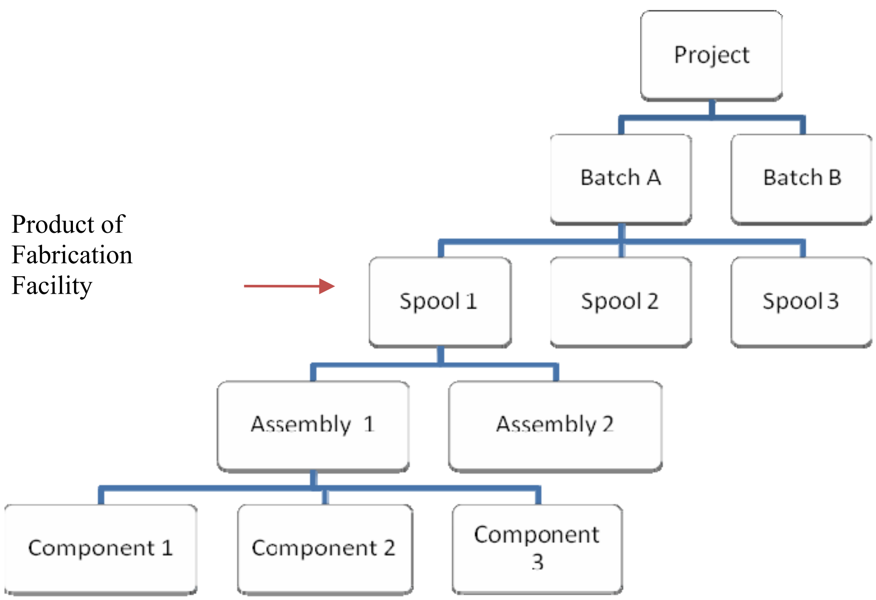


Figure 2.7 Typical work breakdown structure for spool fabrication

In order to develop the product hierarchy model of spools, assemblies and the quantity of each type of weld (position, roll, and SAW) should be known. In the previous practices of fabrication shop simulation (Sadeghi and Fayek 2008), probabilistic distributions are generally used for these quantities. Probabilistic distributions are generally known as the best representation of uncertainty in the simulation models. Probabilistic distributions are used when required information for estimating a deterministic number does not exist, or when there is random uncertainty. The variance of the probabilistic distributions can be reduced by considering factors that affect the variables (AbouRizk and Sawhney 1993).

In this case, having the 3-D geometry of spools from the CAD drawings, it is possible to identify the assemblies of the spool and determine their attributes to develop the product hierarchy model. This problem can be solved as a combinatorial optimization problem in which the sequence of welding should be optimized considering minimization of position welding as an objective function. Considering the spool shown in Figure 2.8 as a simple example, the optimum sequence of welding for the spool is E-D-B-A-C, which minimizes the amount of position welding and results in two assemblies and one position weld (weld C); therefore, Assembly 1 includes pipe3, pipe2, and elbow1 connected together by weld A and weld B, while assembly 2 includes all other components such as pipe1, elbow2 and valve1. At the same time, choosing E-D-C-A-B as the sequence of welding operations results in three assemblies and two position welds (Welds B and C). Other sequences of the welds result in either an equal or more number of position welds.

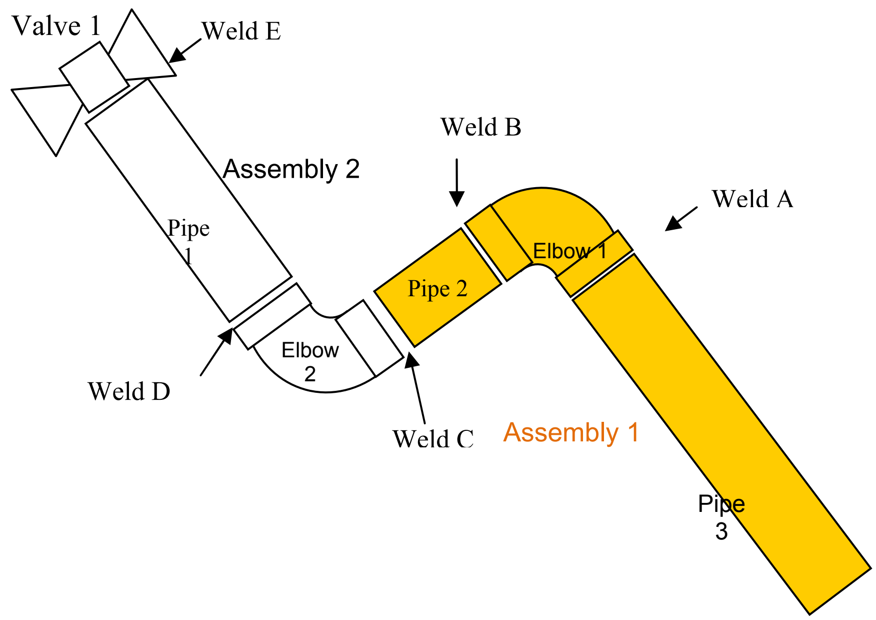


Figure 2.8 Components and assemblies of a spool

Although this problem can be solved by any meta-heuristic or exact algorithm optimization techniques, these techniques are not feasible approaches due to the large number of spools, some of which have up to 25 welds. As a result, a hybrid heuristic algorithm is developed to complete the product hierarchy model automatically, using exported data from CAD drawings and material information databases. The algorithm is shown in Figure 2.9.

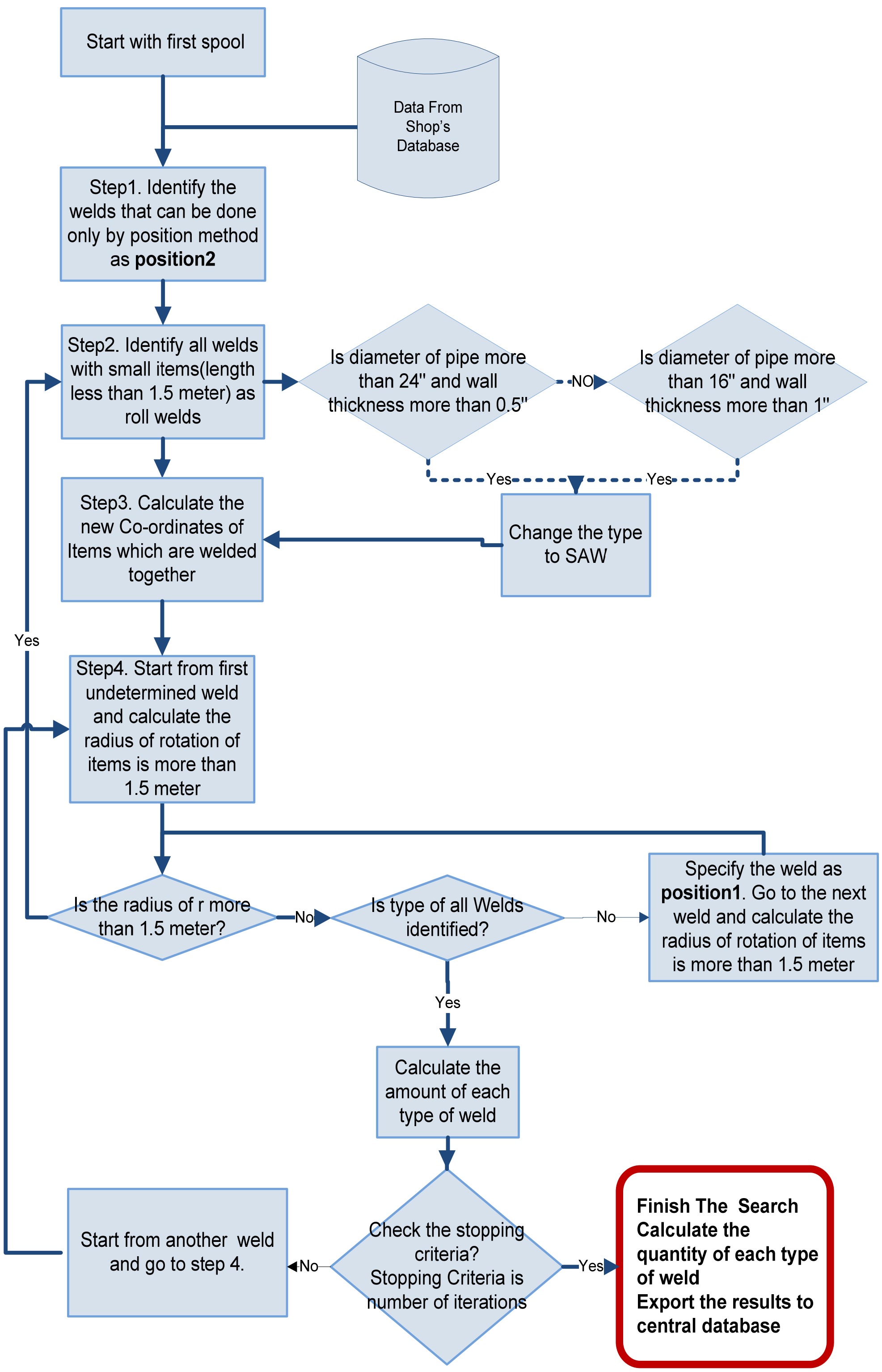


Figure 2.9 Heuristic search algorithm used for determining types of welds

In the proposed algorithm (Figure 2.9), based on an initial candidate sequence of welds, the components of the spool are sequentially connected together to form a new piece with new dimensions and coordinates for each weld. At each stage of connecting the pieces, if both roll welding and SAW welding are not feasible based on physical and technological constraints, the weld is determined as a position weld and the spool is broken down to assemblies at the corresponding weld. The process is repeated for several sequences and the best sequence that results in minimum position welds is selected. Therefore, the assemblies resulting from the best sequence are identified as the assemblies of the spool in the PH. The main challenge in the search algorithm is the large number of solutions in the search space; for example, for a spool with four welds the number of possible sequences is '4!' or '24'. Therefore, the proposed algorithm employs heuristic rules to identify types of certain welds, based on the form of welds and joints in order to reduce the search space.

As shown in Figure 2.9, two types of position welding are considered in the algorithm. In the spool fabrication shop there are different forms of welds, which can be obtained from the spool's drawing. An example of these forms of welds is the butt weld, which involves welding a joint by fastening its ends together without overlapping, and socket weld, in which a pipe is inserted into a recessed area of a valve, fitting, or another pipe. Different forms of welds are depicted in Appendix I.

As illustrated in Figure 2.10, some forms of welds can only be done using position welding. The term "position2" refers to these forms of welds. "Position1" is the term used to refer to forms of welds that can be done by any method of welding, i.e. roll, SAW, and position, but are recognized as position welding by the proposed algorithm due to the long branches of the spool pieces, i.e. assemblies, and physical restrictions of the shop. The position2 welds are identified at the first step, "step1," of the algorithm, as shown in Figure 2.9. In the second step, small branches that do not influence the results are identified as roll or SAW welds, based on the diameter and wall thickness of the components. In the third step, the new coordinates for the pieces that were built in step1 and step2 are identified. Step1, step2, and step3 of the proposed algorithm reduce the search space. The rest of the algorithm is an iterative search process to sequence the unidentified welds and find the best solution. Constraints used in this algorithm, including the radius of rotation constraint for roll and SAW welds, as well as the diameter and wall thickness constraints for SAW welds, are determined by the shop manager and can be changed through the interface developed for the case study developed for a pipe spool fabrication.

The proposed hybrid heuristic algorithm was tested for ninety-eight spools collected from various projects at a pipe spool fabrication shop in Alberta. The accuracy of the results was calculated by Equation 2.1.

$$accuracy\% = \frac{N_c}{N} \qquad \text{(Equation 2.1)}$$

Where, N_c is the number of spools in the assemblies and type of welds that are predicted correctly by the model, and N is the total number of spools. The accuracy of the results was 87%, based on the tested spools. In other words, the results for 87% of the spools were the same as what foremen identified in the drawings, and happened in the shop floor. The results for other spools were slightly different from foremen and estimators' inputs, mostly by one weld.

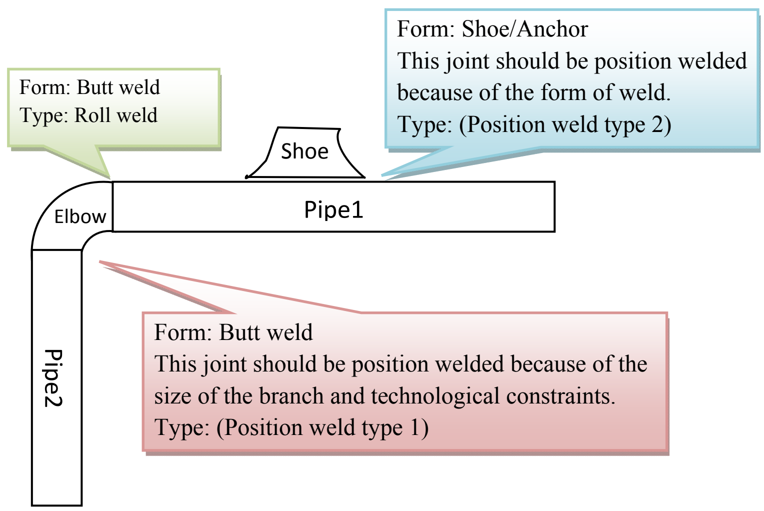


Figure 2.10 Examples of different types of position welds

As a result of performing the proposed hybrid heuristic algorithm, the product hierarchy (PH) is constructed as shown in Figure 2.11. The developed PH involves three levels: the final product, which in case of pipe spool fabrication shop is the spool, is in the first level; the assemblies of the product are in the second level; and the components of each assembly, which are in fact the product's raw materials, are in the third level. The PH carries physical features of the product, assemblies, and components, as shown in Figure 2.11. Examples of physical features include the type of material, weight, and length, as well as the 3-

D coordinates. Each level of PH is connected to the upper and lower level by an ID number in the central database.

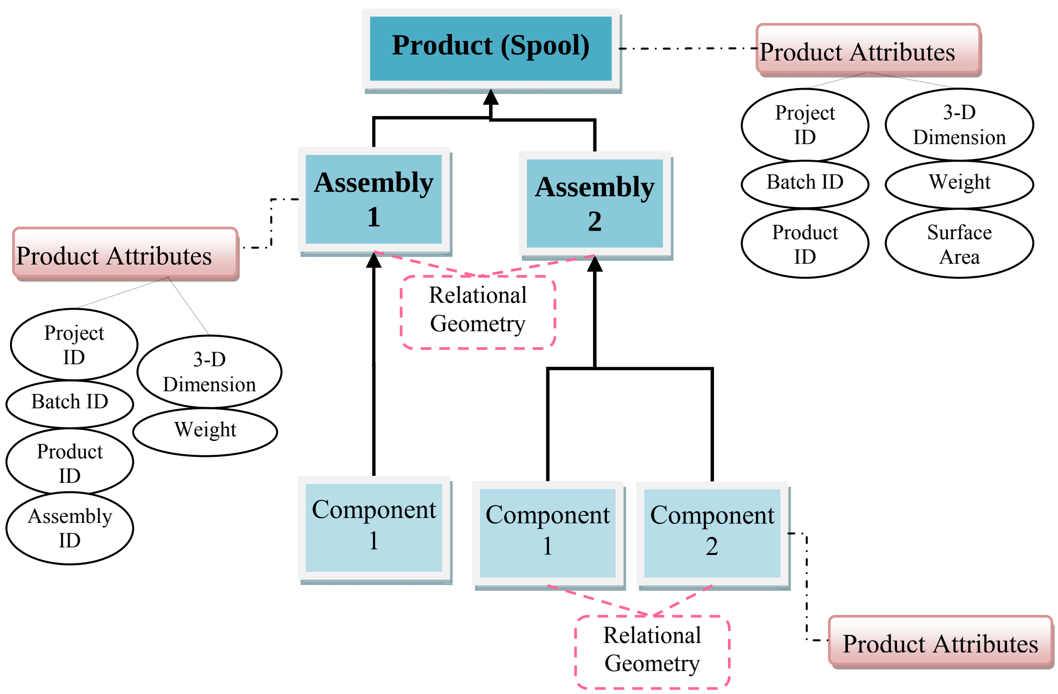


Figure 2.11 Product hierarchy (PH) for spool

2.5.2.2 **Process Model**

Depending on a product's unique attributes, different processes may be performed on the product. Common processes performed on almost all products are cutting, fitting, welding, and testing. Different processes are performed on different levels of a product's PH. For example, the cutting process is performed on the component level, which is the lowest level of PH. Then the components are attached together to produce assemblies, which are at a higher level of PH.

Finally, assemblies are put together to produce the final product. Therefore, the elements of every level of PH are assigned within a process model. The process model specifies the operations and their respective sequence. The process model also contains the appropriate stations and resources for each operation. Consequently, the ability to more accurately differentiate between different assemblies or spools is very critical to the accuracy of the process model and therefore to the successful implementation of the scheduling framework. Table 3.1 shows a sample process plan for spool fabrication shop. It is assumed that the assemblies of a spool can be handled in parallel. Also each assembly may go through the fitting and welding stations several times which is modeled using probabilistic distribution based on the number of parts (i.e. components) of the assembly.

Table 2.1 Sample process plan for pipe spool fabrication shop

Operation	Level Of PH	Station	Resource	Sequence
Cutting	Level 3	Cutting Station	Cutter	1
SAW Fitting	Level 2	WorkStation - SAW	Fitter	2
SAW Welding	Level 2	WorkStation - SAW	Welder	3
Roll Fitting	Level 2	WorkStation – Roll Fitting	Fitter	4
Roll Welding	Level 2	WorkStation – Roll Welding	Welder	5
Position Fitting	Level 1	WorkStation – Position	Fitter	6
Position Welding	Level 1	WorkStation – Position	Welder	7
Quality Check	Level 1	Checking Station	QC Crew	8

Having the product model information the processing time of each operation is estimated using the Equation 2.2:

$$t_{ij} = \frac{\Pr_j \times (wu_i)}{nw_j} \qquad \text{(Equation 2.2)}$$

Where, t_{ij} the processing time of job i for the process j, $\Pr_j$ is man-hours required per unit of the work for process j (Equation 2.3), wu_i is the amount of work unit of job i, and nw_j is the number of workers that are working on the product in process j.

$$\Pr = \frac{man-hours}{Amount\ of\ Work\ units} \qquad \text{(Equation 2.3)}$$

The productivity value for each process depends on the on the product's physical attribute and weld's specification such as form of weld, type of material, and wall thickness and is provided in tables in central database.

In the context of simulation model, products or components routed through processes are represented by entity flow (Song et al. 2006). Figure 2.12 is an extension of the product hierarchy model shown in Figure 2.11. In Figure 2.12, the process model is illustrated in relation to the overall product model of the spool. As illustrated in this figure, processes and their attributes can be defined at different levels of product hierarchy model to construct entity hierarchy (EH), which is used to produce entities for the simulation model. The EH defines different assemblies and components of each spool as an exclusive entity. Therefore, different components and assemblies of spool can flow as unique entities in the simulation model. Moreover, the process information for each entity is identified as shown in Figure 2.12. The developed EH is maintained in this central database, which is connected to the simulation model.

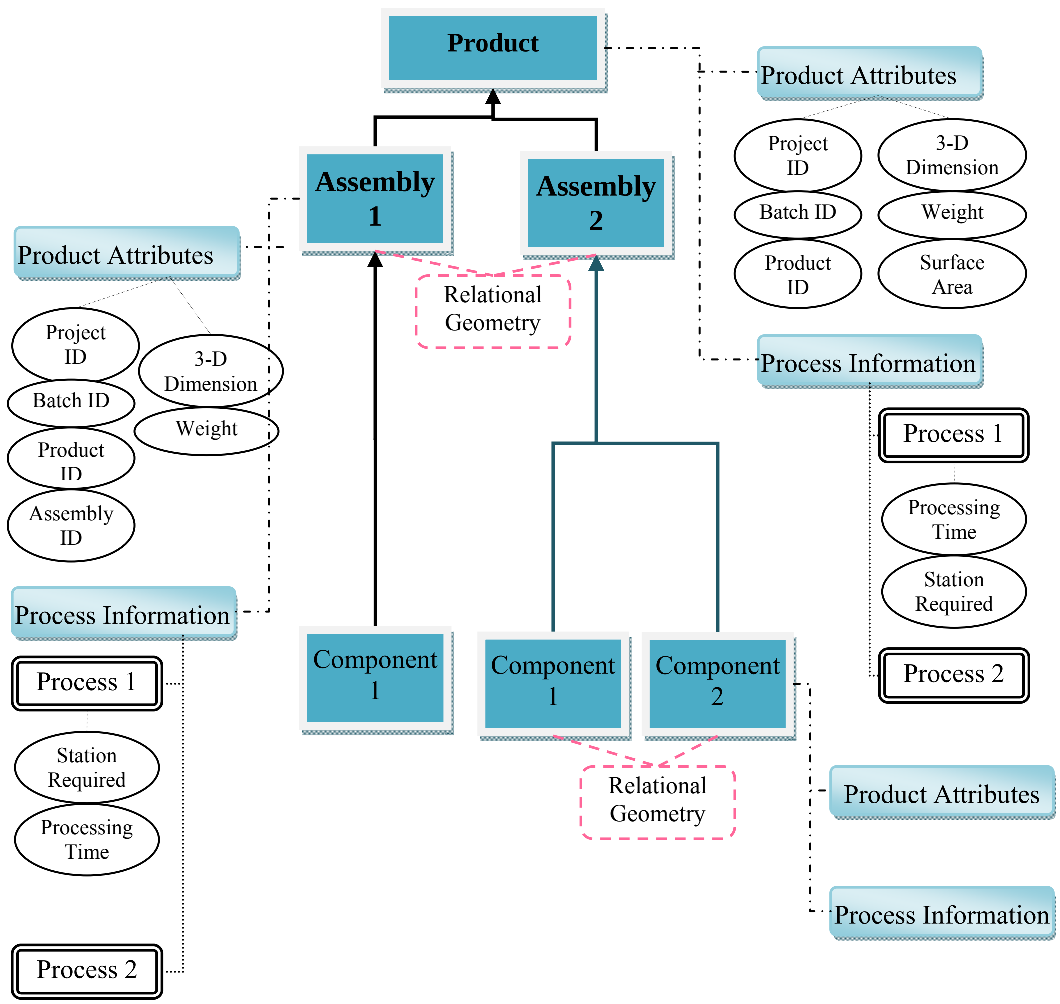


Figure 2.12 Process model for spool in relation to spool's product model

2.5.3 Scheduling Engine

The scheduling engine contains a library of heuristic rules, i.e. dispatching rules, including shortest remaining processing time (SRPT), shortest imminent processing time (SI), longest remaining processing time (LRPT), longest imminent processing time (LI), first come first served (FCFS), minimum remaining processing time per imminent processing time (RPT/I), fewest remaining operation (FRO), minimum remaining processing time per remaining operation (RPT/O), earliest due date (EDD), minimum slack (SLACK), minimum slack per operation, and least critical ratio (CR). The user can select the appropriate heuristic rule, and the model produces a schedule based on the selected heuristic. Heuristic rules are formulated in Table 2.2.

The following is the definition of symbols used in the Table 2.2:

- z is the priority index, where the product with the smaller value of priority index has the higher priority;
- t_{ji} is the processing time of product j in the stage i;
- p is the present date;
- d_i is the due date of product i;
- S_i is the set of remaining stations or processes through which the product i should pass to be completed;
- I_{ij} is an indicator variable, which is 1 if the product i should be processed in stage j and is 0 if otherwise;
- r_i is the release time of product i in the system. Usually the product is released when all corresponding materials and drawings are ready.

Table 2.2 Scheduling Heuristic Rules

NO.	Rule	Rule Description	Formulation
1	SRPT	Shortest Remaining Processing Time	$z = \sum_{j \in S} t_{ij}$
2	SI	Shortest Imminent Processing Time	$z = t_{ij}$
3	LRPT	Operation with longest remaining job processing times	$z = -\sum_{j \in S} t_{ij}$
4	LI	Longest Imminent Processing Time	$z = -t_{ij}$
5	FCFS	The first operation in the queue of jobs waiting for the same machine	$z = r_{ij}$
6	RPT/I	Shortest Remaining Processing Time per Imminent Processing Time	$z = \sum_{j \in S} t_{ij} \Big/ t_{ij}$
7	FRO	Fewest Remaining Operations	$z = \sum_{j \in S} I_{ij}$
8	EDD	Earliest Due Date	$z = d_i$
9	Slack	Minimum Slack time	$z = d_i - p - \sum_{j \in S} t_{ij}$
10	Slack/OPN	Least Slack per Number of Remaining Operation	$z = d_i - p - \sum_{j \in S} t_{ij} \Big/ \sum_{j \in S} I_{ij}$
11	Slack/totalP	Minimum slack per total processing time	$z = d_i - p - \sum_{j \in S} t_{ij} \Big/ \sum_{j \in S} t_{ij}$
12	CR	least Critical Ratio (Time to due date per total remaining production time)	$z = d_i - p \Big/ \sum_{j \in S} t_{ij}$

2.5.3.1 **Shortest Remaining Processing Time (SRPT)**

Remaining processing time is defined as the time required for processing all remaining operations for product. According to this rule, products with the least remaining processing time will be scheduled. This rule is used for reducing average flow time.

2.5.3.2 **Shortest Imminent Processing Time (SI)**

Imminent processing time is defined as the time required for processing the upcoming operation for a product. According to this rule, products with the least imminent processing time will be scheduled first.

2.5.3.3 **Longest Remaining Processing Time (LRPT)**

According to this rule, products with the highest remaining processing time will be scheduled before orders with a higher value. This rule is used to reduce the mean lateness of products.

2.5.3.4 **Longest Imminent Processing Time (LI)**

Based on this rule, products with the highest remaining processing time will be scheduled before orders with a higher value. This rule is used to reduce the mean lateness of products.

2.5.3.5 **First Come First Served (FCFS)**

According to this rule, the product with the earliest release date will be scheduled first.

2.5.3.6 **Fewest Remaining Operation (FRO)**

Remaining operation is the total number of operations that should still be performed on a product in the system. This rule selects a product with lowest number of remaining operations to increase the system production rate.

2.5.3.7 **Minimum Remaining Processing Time per Remaining Operation (RPT/O)**

Based on this rule, at every station the product with the least value of remaining processing time per remaining operation is scheduled first.

2.5.3.8 **Earliest Due Date (EDD)**

For each product a due date is assigned in the database, which determines when this product is required to be at site. According to this rule, products with earlier due dates will be given higher priority.

2.5.3.9 **Minimum Slack (SLACK)**

The difference between the base date and the due date minus the cycle time for the product is defined as slack, which is the amount of time available before work must start to ensure the project is finished on time. According to this rule, products with the least slack will be scheduled first.

2.5.3.10 **Minimum Slack per Operation**

Based on the minimum slack per operation rule, product with the least slack per number of remaining operations is scheduled first.

2.5.3.11 **Least Critical Ratio (CR)**

Critical ratio is defined as the ratio of remaining time to due date of a product and the processing time of the product. The model calculates the critical ratio for each product by calculating the actual time left between ‘‘current date’’ and the due date of the product. The product with the lowest critical ratio is scheduled first.

The performance of the system under each heuristic is recorded. After comparing the heuristics, the one with the best performance is selected by the user. The selected rule then is used to build the schedule by use of the simulation environment. The interface is illustrated in Chapter4.

2.5.4 Simulation Environment

The simulation environment enables the user to model the fabrication shop including shop components, resources, and working stations. The simulation model identifies the performance of the system by determining the production rate of the system, resource utilization, flow time, and tardiness of products. Furthermore, the simulation model integrated with a scheduling engine produces a production schedule for the system. A customized discrete event simulation tool is developed for modeling any industrial fabrication facility. The simulation is connected to a central database to import products defined by the product hierarchy in the central database.

2.5.4.1 **Special Purpose Simulation Model for Industrial Fabrication**

This section introduces the Special Purpose Simulation (SPS) template that was developed by the author to model the processes of industrial fabrications. Although the SPS template is originally designed for pipe spool fabrication shops, it can be used for any other industrial fabrication facility, such as steel fabrication shop. The SPS template was developed in *Simphony.net*© (Hajjar and Abourizk 2002), which is an object-oriented environment for building SPS templates using VB.net programming language. The SPS templates allow users to model a project within the domain for which SPS templates are designed, using visual modeling elements. The SPS template developed for pipe spool fabrication includes 12 modeling elements: industrial shop, product, dispatch controller, cutting station, bay, product hierarchy adjusting, worker, material handling, crane, waiting, working station, and output reports. Table 2.3 presents a brief description of these elements.

Table 2.3 SPS Modeling Elements for Pipe Spool Fabrication Shop

Element	Description
Worker	This element represents the labourers such as fitters and welders as resources.
Waiting	This element models the buffer areas where the product can wait for resources, station, and handling.
Crane	The crane element models the material handling resources, such as bridge cranes, and tower crane.
Working Station	This element models a station which is performing a specific fabricating process such as cutting, fitting, or welding. In this element the priority of the products are determined based on the selected heuristic rule
Material Handling	The material handling element, along with the crane element, models the process of handling material between stations.
Industrial Shop	This element contains all elements of the fabrication shop. It also contains all scheduling heuristic rules.
Product	The product element connects the simulation model to the central database. It imports products defined by the product hierarchy model in the central database to the simulation environment. It then releases products according to their release time specified in the database (based on their expected material release date).
Cutting Station	This element represents a cutting station.
Bay	All stations and resources are the sub-elements of this element. Bay is a production line of industrial fabrication. There might be several bays (or production lines) in the industrial fabrication.
Dispatch Controller	Allocates spools to each bay based on the average waiting time for processing in that bay or queue length. It also considers facility constraints for some bays such as weight, diameter, and material group.
Product Hierarchy Adjusting	Before every station is a product hierarchy adjusting element. It adjusts the product to the appropriate level of its hierarchy.
Output Reports	This element exports data collected for the fabrication plant, products, stations, resources, and the material handling system to the central database for reporting and analysis by users. The reports include production rate, resource utilization, waiting times, and start time and finish time of every operation for each product.

The most important element is the product element, which connects the simulation model to the central database to import products into the simulation model. This element then sends the products into a dispatch controller element. In this element, the job is dispatched to the appropriate production line (bay) according to the average waiting time, queue length, and buffer capacity, i.e. storage capacity, of the bay. The physical and technological constraints of equipment pieces in the bay are also modeled in the dispatch controller. In summary, this element models the decision making process performed by foremen and superintendents of the industrial fabrication shop, and sends out the product to the appropriate bay. The bay element sends out the product to the appropriate station according to the process plan of the product. Before every operation there is a product hierarchy adjusting element to adjust the product to the appropriate level of product hierarchy. If the operation corresponds to a higher hierarchy of the product's hierarchy model, the element assembles the components to a higher level. If the operation corresponds to a lower level of product hierarchy model, the product hierarchy adjusting element decomposes the product to the lower level of product hierarchy.

In the station element, there is a process controller which controls the product's process plan and directs the product to the appropriate operation. Furthermore, the station is capable of calculating the priority index of the jobs that are waiting to be processed based on the selected scheduling heuristic rules. The library of scheduling heuristic rules is available in the industrial shop element. The user can select the appropriate heuristic rule from the available alternative in the industrial shop element. For each bay there is a common buffer that is modeled by waiting element. The storage capacity is controlled by a dispatch element, and the product waits in the dispatch element until there is enough space in the related buffer. Every product waits in the buffer until the resources and stations are available. The SPS template also includes an output reports element, named "Output Reports", for exporting the results of the simulation experiment to the central database. This element exports data collected for the fabrication facility, products, stations, resources, and the material handling system to the central database for reporting and analysis by users. The reports include production rate, resource utilization, waiting times, as well as the start date and finish date of every operation for each product for reporting and analysis by users. The schedule report is generated based on the integration of the start and finish time of every operation for each spool, the working calendar, e.g. shift hours and working days; and the starting date of the simulation. Figure 2.13 depicts the described elements and process. The implementation of the model is described in Chapter 4 of this thesis.

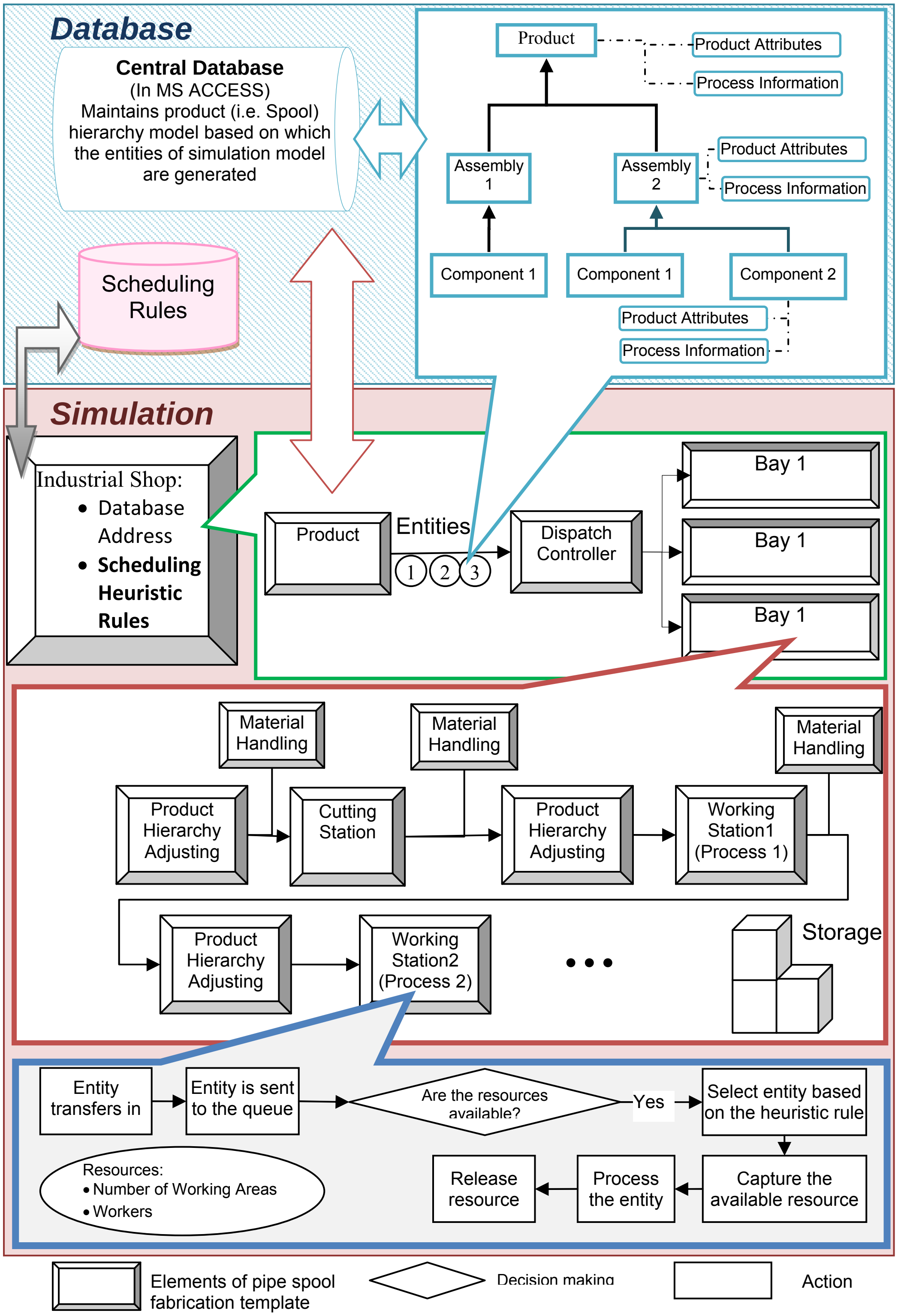


Figure 2.13 The processes and elements of pipe spool fabrication template

2.6 Potential Improvements for Further Development

The following are some potential improvements to the simulation model that may increase its accuracy and capabilities:

2.6.1 Additional Data Collection Needed to Enhance the Model

Simulation is an analysis tool used to analyze the system by producing data. The data produced by the simulation is directly affected by the input data. If the data that populates the model is incorrect or incomplete, the simulation model is not usable. Because simulation is not yet an accepted part of the business practices of most companies, these practices are not structured with simulation in mind. The data collected within the company may be appropriate for tasks undertaken by managers or assembly workers, but not always useful in simulation. The simulation analyst then struggles to make use of the data collected for other purposes (Portnaya 2004).

For example, in the current project, the durations of activities should be calculated from their productivity (man-hours/ diameter inches) using Equation 2.4:

$$t_{ij} = \frac{\Pr_{ij} \times (DI)_i}{n_j} \qquad \text{(Equation 2.4)}$$

Where, t_{ij} the processing time of job i for the process j, $\Pr_{ij}$ is man-hours required per unit of the work (Productivity), DI is the amount of work unit of job i, which is measured in terms of diameter inches of the product, and n_j is the number of workers working in the work station j.

However, the productivity value for each product (i.e. spool) is not the same. In addition, the available productivity values are not separated for different activities such as roll welding SAW welding, and position welding. Therefore, some assumptions must be considered based on expert opinion to separate the values for different activities. The main problem in calculating productivity is that the available productivity value is given by diameter inches, while different factors such as wall thickness, material, and different weld type (butt weld, socket weld, dummy leg, etc.) are not considered in calculating diameter inches. In addition, the shape and geometry of a spool influences the productivity value for each spool. Therefore, in order to have an accurate simulation model, it is important to estimate the productivity of each process for every spool. A fuzzy expert system is one of the best methods for calculating productivity, since it is capable of considering both qualitative (i.e. subjective) and quantitative (i.e. objective) factors in estimating productivity.

2.6.2 Developing a Fuzzy Expert System to Estimate the Productivity

Productivity is usually measured by cost per unit of work or man-hour per unit of work. Because the spool fabrication shop is labour-intensive, productivity is measured by man-hour per unit of the work. There are several productivity models in the literature. Lu (2000) developed a model based on ANN (Artificial Neural Networks) to estimate the productivity of spool fabrication shops. Song (2004) developed a productivity model for steel fabrication shops based on ANN and incorporated it with simulation modelling. In another study (Oduba 2002), a fuzzy expert system was developed to estimate the productivity of industrial construction. Shaheen (2005) developed a fuzzy expert system to estimate the productivity of excavation for use in simulation models.

In order to obtain more accurate results for duration of each activity for each spool, the productivity should be measured based on the characteristics and complexity of products and resources. A fuzzy expert system is an appropriate method for calculating productivity, since it is capable of considering both qualitative (i.e. subjective) and quantitative (i.e. objective) factors in estimating productivity. A general overview of the structure of fuzzy expert system is shown in Figure 2.14. As shown in Figure 2.14 the fuzzy expert system consists of input interface, fuzzy inference, and output interface. The input interface accepts the inputs and converts them into propositions that fuzzy inference can use to activate fuzzy rules (Pedrycz and Gomide 2007). The rule base consists of a set of "if-then" rules that describes the relationship between inputs and output. The database stores the membership function of fuzzy sets and the value of the parameters of rule based model. Fuzzy inference performs the inference operations on the fuzzy rules. The output interface transforms the results of fuzzy inference into an appropriate format, such as a fuzzy set or crisp value (Pedrycz and Gomide 2007). As illustrated in Figure 2.14 the inputs of the fuzzy expert system are the characteristics of resource, such as skill of workers, and the characteristics of the products, which can be obtained from the product model. The output of the fuzzy expert system is the productivity value, which can be used in Equation 2.4 to calculate the duration of each activity for every product.

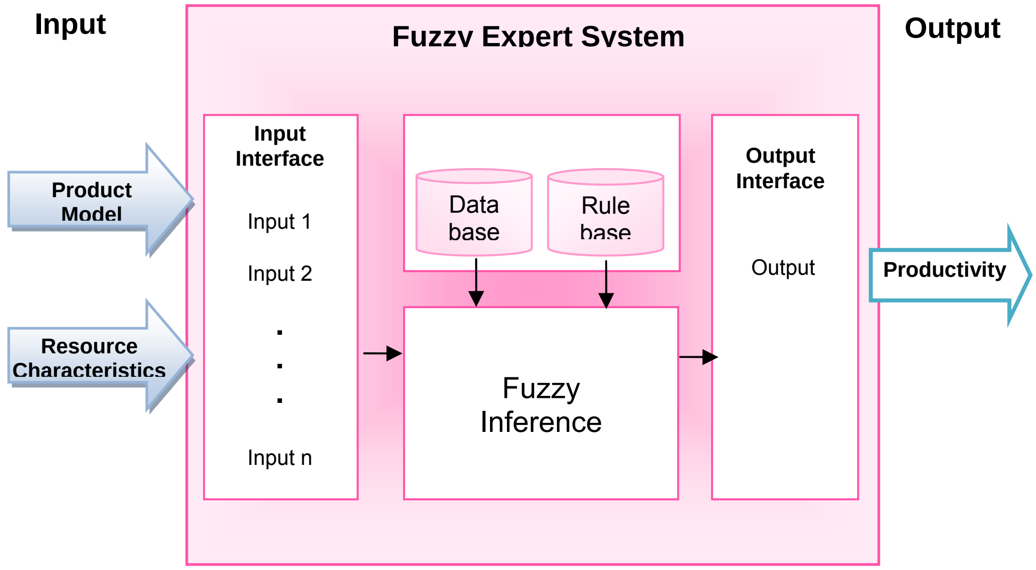


Figure 2.14 The structure of fuzzy expert system

Some important factors that should be considered in developing the fuzzy expert system for welding, cutting, and fitting activities are illustrated in Table 2.4, Table 2.5, and Table 2.6. These factors are identified by shop foremen and estimators, and can be used as the inputs of the fuzzy expert system shown in Figure 2.14. The quantitative factors in the above mentioned tables are the characteristics of the jobs, and the qualitative factors are the characteristics of the resources.

Table 2.4 Factors Influencing Fitting Productivity

Factors for fitting		
Category	**Factor**	**Description**
Quantitative factors	Spool weight	Total weight of spool
	Number of pipes	Each spool consists of a number of pipes that should be joined together by a fitting
	Average length of pipes	Average length of pipes
	Average pipe diameter	Indicates the average diameter of spool
	Average wall thickness of pipes	Average wall thickness of pipe
	Number of tees	Tees are 90° joints between pipes.
	Number of Elbows	An elbow is used to fit two pipes together. Because two pipes are angled to each other, the geometry of spool is complex when there are many elbows in the spool.
	Fittings per linear foot of spool	Number of fittings (tee, elbow, reducer, etc.) per linear foot of spool
	Number of valves	Number of valves in the spool
Qualitative factors	Skill of fitter	Skill level and experience of tradesperson

Table 2.5 Factors Influencing Cutting Productivity

Factors for cutting		
Category	**Factor**	**Description**
Quantitative factors	Spool weight	Total weight of spool
	Number of pipes	Each spool consists of a number of pipes that should be joined together by a fitting
	Average length of pipes	Average length of pipes
	Average pipe diameter	Indicates the average diameter of spool
	Average wall thickness of pipes	Average wall thickness of pipe
Qualitative factors	Skill of cutter	Skill level and experience of tradesperson

Table 2.6 Factors Influencing Welding Productivity

Factors for welding		
Category	**Factor**	**Description**
Quantitative factors	Spool weight	Total weight of spool
	Average pipe diameter	Indicates the average diameter of spool
	Average wall thickness of pipes	The average wall thickness of pipe
	Fittings per linear foot of spool	Number of fittings (tee, elbow, reducer, etc.) per linear foot of spool
	Weld density	Number of welds per linear foot of spool
	Form of weld	Butt-weld, socket weld, nozzle, etc.
	Type of weld	Whether it is roll weld, position weld, or SAW weld
Qualitative factors	Skill of welder	Skill level and experience of tradesperson

2.6.3 Incorporate Uncertainty in Form of Fuzzy Numbers

The output of the fuzzy expert system is usually converted to a crisp value or fuzzy set (Pedrycz and Gommide). Therefore, if the estimation model is developed to identify the productivity for each activity, as explained in Section 2.6.2, the output of the model will be in the form of deterministic values or fuzzy numbers. Shaheen (2005) has integrated the fuzzy expert system and the simulation model by converting the output of the fuzzy expert system to a crisp value. However, the crisp (i.e. deterministic) value obtained from the output of the expert system cannot represents the uncertainty exists in the inputs. The uncertainty regarding the duration can be modeled using fuzzy sets. Consequently, fuzzy discrete event simulation can be applied to use the fuzzy output of the fuzzy expert system.

2.7 Conclusions

In this chapter, a framework is developed for modeling industrial fabrications at the process level. The proposed framework was developed based on pipe spool fabrication shop. This framework addresses the shortcomings of previous systems by considering: (*i*) 3-D geometric attributes of the product, (*ii*) the type and shape of the product components, (*iii*) relationships between the product components, (*iv*) shop process information, and (*v*) constraints of the shop. Moreover, the framework includes a scheduling engine to help the decision maker produce feasible schedules by using an appropriate scheduling heuristic.

The entities of the simulation model are generated using the actual products of the pipe spool fabrication shop, the information of which is available in database of the company. A heuristic search algorithm was developed to create product model based on the CAD drawings and database of the company. The heuristic search algorithm considers geometric attributes of the product, the type and shape of the product, the type and shape of the product components, shop process information, and constraints of the shop.

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CHAPTER 3 - An Optimization Framework for Multi-Criteria Industrial Shop Scheduling

3.1 Introduction

Optimizing production scheduling has received great attention in the recent academic literature due to its critical role in industry. It has become one of the most important steps for improving productivity and customer satisfaction in modern manufacturing. This chapter proposes a framework for optimization of industrial shop scheduling with respect to multiple criteria. Fuzzy set theory is used to linguistically assess different levels of satisfaction for the selected criteria. Moreover, a survey of the literature related to multi-criteria scheduling is presented in this chapter to justify the need for a new approach to multi-criteria scheduling. This chapter also introduces fuzzy set theory and its application in construction.

3.2 Background

3.2.1 Scheduling Optimization Methods

Production scheduling approaches to solve scheduling problems are classified into three categories: (1) mathematical approaches, e.i. exact algorithms, such as branch and bound, (2) meta-heuristic approaches, and (3) heuristic approaches. The mathematical methods are only applicable to problems of smaller size because of the NP-hard nature of the scheduling problem. An NP-hard problem is a problem for which it is impossible to mathematically find a general solution.

This usually happens because of the phenomenon known as the exponential expansion of the feasible area, which is the region containing all possible solutions to an optimization problem. The machine scheduling problem and all its different branches, such as shop scheduling problems, have been shown to be NP-hard problems (Brucker 2007; Pinedo 2008; and Baker and Trietsch 2009). A simple example of machine scheduling problems can easily illustrate the exponential expansion of the feasible region. Given 'n' jobs that can be assigned to two different machines to be processed, the possible number of different combinations of jobs that can be assigned to each machine is 2^n. Furthermore, considering the number of possible sequences for those combinations, the size of the feasible region, that is the number of possible solutions, will be of the order of $n!*2^n$. This means, for a real size problem with a multiple number of stations and resources, the number of possible solutions grows exponentially with the number of jobs that should be scheduled, and therefore mathematical approaches cannot be used to solve such problems (Baker and Trietsch 2009).

Meta-heuristic approaches have been developed to overcome the mathematical complexities of scheduling problems and to solve a wider range of scheduling problems. In meta-heuristic methods, a modified search algorithm is employed by utilizing an iterative generation process for developing and exploring the feasible space in order to find a near-optimum solution (Osman and Laporte 1996). The advantage of meta-heuristic methods is the fact that they commonly produce a good solution that is an acceptable sequence of the jobs. However, these methods are time-consuming for production engineers, and they should be repeated any time that a change is introduced to the system. Therefore for real-size problems heuristic methods are usually preferred. The low computational time, their simplicity, and the fact that they can be used along with simulation models have made heuristic methods the preferred method among practitioners and researchers in academia and industry.

Dispatching rules, i.e. priority rules, are a class of heuristic methods, which are commonly used in the industry because of their simplicity and practicality. The fact that they are online scheduling methods makes them suitable for the dynamic environment of the shop in the sense that they can react to changes in the system setup, such as new shop arrivals and unpredicted interruptions, without consuming too much time to reschedule. Dispatching rules are used for prioritizing jobs and selecting the next job, which is waiting in the queue, to be processed (Bitran and Dada 1983). Dispatching rules can be used together with simulation models to generate a near optimum schedule. The main challenge of using dispatching rules is that no specific rule is known to be the best consistently for all problems, even though they are proven to produce the optimal solution for certain small size problems. Therefore, many studies have been conducted to identify the performance of dispatching rules for different situations (Blackstone et al. 1982; Sabuncuoglu and Homertzheim 1992; Jones et al. 1995; Babiceanu et al. 2005). The studies have shown that some rules perform consistently better than others in optimizing certain objective functions (Blackstone et al. 1982). For example, shortest processing time (SPT) optimizes the average flow time of jobs in the shop for most situations. Nevertheless, it is still difficult to conclude the general usefulness of a rule for a system without testing it. Dispatching problems has not received enough attention in the literature (Kuo et al. 2008). Examples of research conducted on dispatching problems in the literature are the work of Barrett and Barman (1986), which studied the minimization of tardiness in two-stage flow shops considering five possible dispatching rules, and the work of Sarper and Heny (1996), which proposed a simulation approach to solve scheduling problems for a two–stage flow shop considering six possible dispatching rules.

The industrial shop scheduling problem studied in this research, which is explained in Chapter 2, is a hybrid flow shop scheduling (HFS), in which a set of *n* jobs are to be processed in a series of *m* stages with several parallel machine optimizing a given objective function. The HFS problem is, in most cases, NP-hard. For example, HFS restricted to two processing stages, even when one stage includes two machines and the other one a single machine, is NP-hard (Gupta 1988). Also, the flow shop scheduling, which is the special case of HFS including a single machine per stage, and the parallel machine scheduling, which includes a single stage with several machines, are also NP-hard (Garey and Johnson 1979; Ruiz and Vazquez-Rodriguez 2009). Nevertheless, the problem might be solved polynomially for some instances with special properties and precedence relationships (Djellab and K. Djellab 2002; and Ruiz and Vazquez-Rodriguez 2009). According to the survey carried out by Ruiz and Vazquez-Rodriguez (2009), the largest HFS instances solved by mathematical approaches is a two-stage regular HFS (unconstrained number of machines in stages 1 and 2) with make-span criterion. This problem is solved effectively using branch and bound (B&B), which is the preferred technique for solving HFS (Ruiz and Vazquez-Rodriguez 2009). However, the proposed algorithm could not solve many medium instances (20–50 jobs) (Ruiz and Vazquez-Rodriguez 2009). Moreover, a two-stage problem with multiple identical parallel machines at each stage has been studied by Choi and Lee (2009). They have proposed a B&B method for the minimization of tardy jobs. Ruiz and Vazquez-Rodriguez (2009) concluded that the exact algorithms are still incapable of solving medium and large instances and are too complex for real world problems, despite their relative success. Therefore, it is necessary to study non-exact but efficient heuristics. More detailed reviews of B&B algorithms can be found in Kis and Pesch (2005).

3.2.2 Multi-Criteria Scheduling

Although most studies conducted by researchers have focused on single objective scheduling problems, real life scheduling problems usually consist of multiple conflicting objectives. Therefore, there has been an increasing interest in multi-criteria scheduling during the last decade (Lei 2009). According to a survey performed by Lei (2009), most multi-criteria scheduling problems are small size problems, which are solved by meta-heuristic algorithms such as genetic algorithms (GA) and ant colony optimization (ACO). Examples of multi-criteria scheduling by meta-heuristic algorithms are frameworks introduced by Ishibuchi and Murata (1998), Leung and Wang (2000), Kacem et al. (2002), and Petrovic et al. (2007). In these frameworks, multiple criteria are combined into one fitness function to conduct the iteration processes. The aforementioned algorithms are not practically used for real size problems in the industry because of the computational time of algorithms, complexity of the shop environment, and uniqueness of jobs.

A real industrial shop involves dynamic changes of the job set, material shortage, and uncertain environment. On the other hand, industrial shops require fast response time and high flexibility to the changes of the production condition and interruptions in the shop condition such as material shortage, changes in the drawings, and arrival of rush orders. The main drawback of the meta-heuristic optimization approaches is that the procedure of optimizing a schedule for every job set is time consuming and impractical for real life problems (Fanti et al. 1998). It is argued that such approaches, although they improve the performance of the shop floor, make the control problem of the shop floor more complicated (Yang et al. 2007). In addition, the implementation of the proposed approaches in industrial engineering literature needs a sophisticated shop floor control system that can perform the algorithms and control the system (Yang et al. 2007), which is not applicable in industrial construction projects. Therefore, developing a scheduling solution that identifies a robust combinatorial dispatching rule is very important for a dynamic shop environment. A robust combinatorial dispatching rule that produces good performance in situations could decrease the complexity of operational decision making and control, and provide a valuable practical tool for real applications.

For this purpose, a new framework is proposed in this chapter to find a robust combinatorial dispatching rule for industrial shops, specifically pipe spool fabrication shops. The framework is developed using the Pareto-optimality concept combined with fuzzy set theory for multi-criteria optimization. A simulation model is developed using the framework described in Chapter 2 to evaluate the performance of each combinatorial rule. The performance values measured by the simulation model are then transformed to membership degrees in term of the degree of closeness to the ideal solution (or the degree of satisfaction), in which '1' means the ideal solution and '0' means the worst solution based on the corresponding criteria.

3.2.3 Fuzzy Set Theory and Techniques in Construction

The concept of fuzzy set theory was introduced by Lotfi Zadeh (1965) as an extension of the classical set theory. Fuzzy sets are sets with partial membership function. In classical set theory, an element either belongs or does not belong to a set (Zimmermann 1985). It is not allowed to be included in a set and its complementary set at the same time. Fuzzy set theory allows the gradual membership of elements to a set. This is described by the term "membership degree," which has a value in real interval of [0, 1]. The membership degree indicates the degree that the elements are compatible with the properties of the fuzzy set (Klir and Yuan 1995). Therefore, a fuzzy set provides shades of gray rather than black and white, which is in better agreement to the human way of thinking (Chan et al. 2009). A good example is the situation of using imprecise and vague propositions like "the utilization of the resource is high." In Figures 3.1 and 3.2 below, a non-fuzzy set (crisp set) and a fuzzy set are illustrated for resource utilization. To identify whether the resource utilization is high or low based on the percentage of the time the resource is busy (i.e. utilization percent), a threshold is considered in traditional sets (Pedrycz and Gomide 2007). For example, 80% is considered high utilization, while 79% is considered low utilization (Figure 3.1). Fuzzy sets theory allows us to express this concept by assigning a degree of being high or low based on the utilization percent of different resources (Figure 3.2), allowing for a gradual transition between high and low.

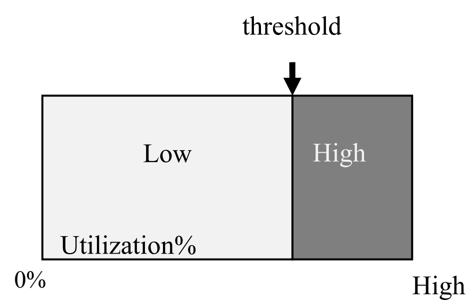

Figure 3.1 The concept of low and high utilization in traditional sets (adopted from Pedrycz and Gomide (2007))

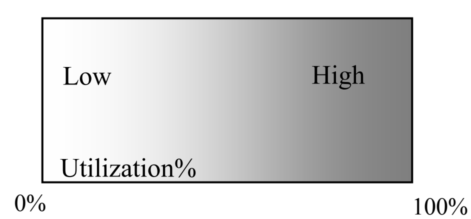

Figure 3.2 The concept of low and high utilization in fuzzy sets (adopted from Pedrycz and Gomide (2007))

A fuzzy set A on the universal set X is defined by its membership function $\mu(x)$ and represents the degree that x belongs to the fuzzy set. $\mu(x)$ is a mapping from X to the real unit interval [0, 1]. For example, Figure 3.3 indicates the membership function of being highly utilized: a resource with utilization percentage equal to equal to 70% is considered to be highly utilized with the degree of 0.5 according to this membership function.

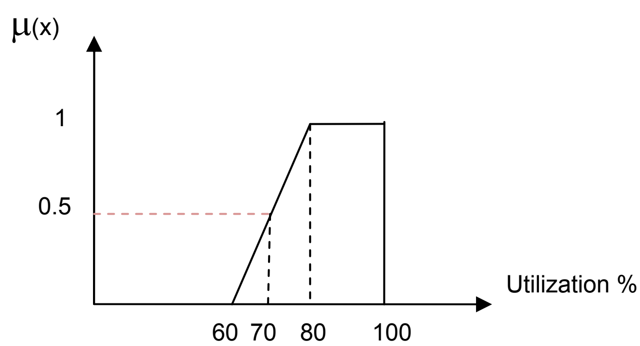

Figure 3.3 Membership function for being highly utilized

Fuzzy logic is the extension of Boolean-conventional logic to handle the truth value between completely true and completely false (Chan et al. 2009; Zadeh 1965; Lah et al. 2005). Chan et al. (2009) has described fuzzy logic as a data analysis methodology to generalize any specific theory from “crisp” to “continuous.” Fuzzy modeling makes it possible to translate any statement in natural language into a fuzzy system using mathematical tools (Chan et al. 2009).

Fuzzy sets and fuzzy techniques are widely used in construction-related studies due to the fact that linguistic terms are common in the construction industry. Also, subjective nature of some variables (e.g. skill of workers), lack of data, and uncertainty due to vagueness rather than randomness can be addressed by applying fuzzy techniques. Some of the studies which implemented fuzzy techniques are: predicting industrial construction labour productivity (Fayek and Oduba 2005), integration of fuzzy set theory with continuous simulation to modeling uncertain production environments (Dohnal 1983; Fishwick 1991; Negi and Lee 1992; Southall and Wyatt 1988). Lam et al. (2001) developed a decision-making model using a combination of the fuzzy optimization and the fuzzy reasoning technique which can be applied to construction project management problems by suggesting an optimal path of cash flow that results in minimum resource usage. The proposed model combines quantitative and qualitative variables, and is used for analyzing the best time to invest in a new project (Lam et al. 2001). Furthermore, fuzzy goal programming has been used to analyze uncertainty in optimization models (Deporter and Ellis 1990; Gungor 2001; Suer et al. 2008).

3.2.4 Fuzzy Logic in Construction Scheduling

Fuzzy logic and fuzzy mathematical models have been used successfully in project scheduling. For example, fuzzy set concepts were used in project scheduling (Ayyub and Haldar 1984) to consider uncertainties in different project settings, which provides possible completion times for each activity in a network. Furthermore, Lorterapong and Moselhi (1996) developed a new network scheduling method based on fuzzy sets theory for estimating of the durations of construction activities. Using this method, the imprecise activity durations can be modeled (Lorterapong and Moselhi 1996). Bonnal et al. (2004) proposed a framework based on fuzzy sets to address the resource-constrained fuzzy project-scheduling problem. Orodñez-Oliveros and Fayek (2005) formulated a new tool to create an updated schedule and to evaluate the consequences of delays on the project.

Fuzzy mathematical models have been used in multi-criteria project scheduling. For instance, fuzzy goal programming and critical path methods (CPM) were used to minimize total cost, total completion time, and total crashing cost in project scheduling (Wang and Liang 2004). Moreover, fuzzy genetics algorithm was used to optimize the multi-skilled labour allocation in the construction projects (Tong and Tam 2003). Castro et al. (2009) used fuzzy mathematical models integrated with critical path method (CPM) to optimize a construction project's schedule with respect to project completion time and crashing costs.

The application of fuzzy set theory and fuzzy techniques in the area of industrial construction is limited. However, there are some fuzzy-based methods developed for manufacturing and industrial systems that can be used in the area of industrial construction. For example, Petroni and Rizzi (2002) developed a fuzzy logic-based methodology to rank shop floor dispatching rules. The drawbacks of this approach are, firstly, that the methodology relies solely on expert judgment to identify the performance of a dispatching rule, and secondly, that only a few simple dispatching rules are considered in this method.

3.3 Proposed Framework for Identifying Optimum Combinatorial Dispatching Rule

The overall architecture of the proposed framework is illustrated in Figure 3.4. As illustrated in Figure 3.4, the proposed framework consists of 4 phases through which a robust composite dispatching rule is identified. In the first phase, the primary criteria on which the performance of the shop should be optimized is identified. Then a membership function for each criterion is developed to measure the distance between the performance of each combinatorial dispatching rule identified by the simulation model and the ideal value of corresponding criterion. The second phase of the proposed framework focuses on designing new combinatorial rules. In this phase, appropriate dispatching rules are identified, and new combinatorial dispatching rules are developed in addition to common combinatorial rules in the literature. In the third phase, first a random set of jobs is selected and the performance of each predefined dispatching rule is measured using the simulation model. Then the candidate dispatching rules are chosen using the concept of Pareto-optimality. Each rule in the Pareto frontier is selected as a candidate rule. This process is repeated several times using different sets of random jobs to obtain all possible candidate rules for further analysis. In phase four, all candidate rules are clustered based on their performance value for each primary criterion. The data are clustered using fuzzy C-means clustering (FCM). The clustering process identifies different classes of trade-off, or zones of compromise, between primary criteria in terms of linguistic variables such as poor, fairly poor, acceptable, fairly good, and good. As a result, the decision maker can choose one of the zones based on his or her preferences. Finally, the statistics of each rule are collected in the fifth phase in order to select a robust solution based on the preferences of the decision maker. The remainder of this chapter is dedicated to further discussion of each phase of the proposed approach.

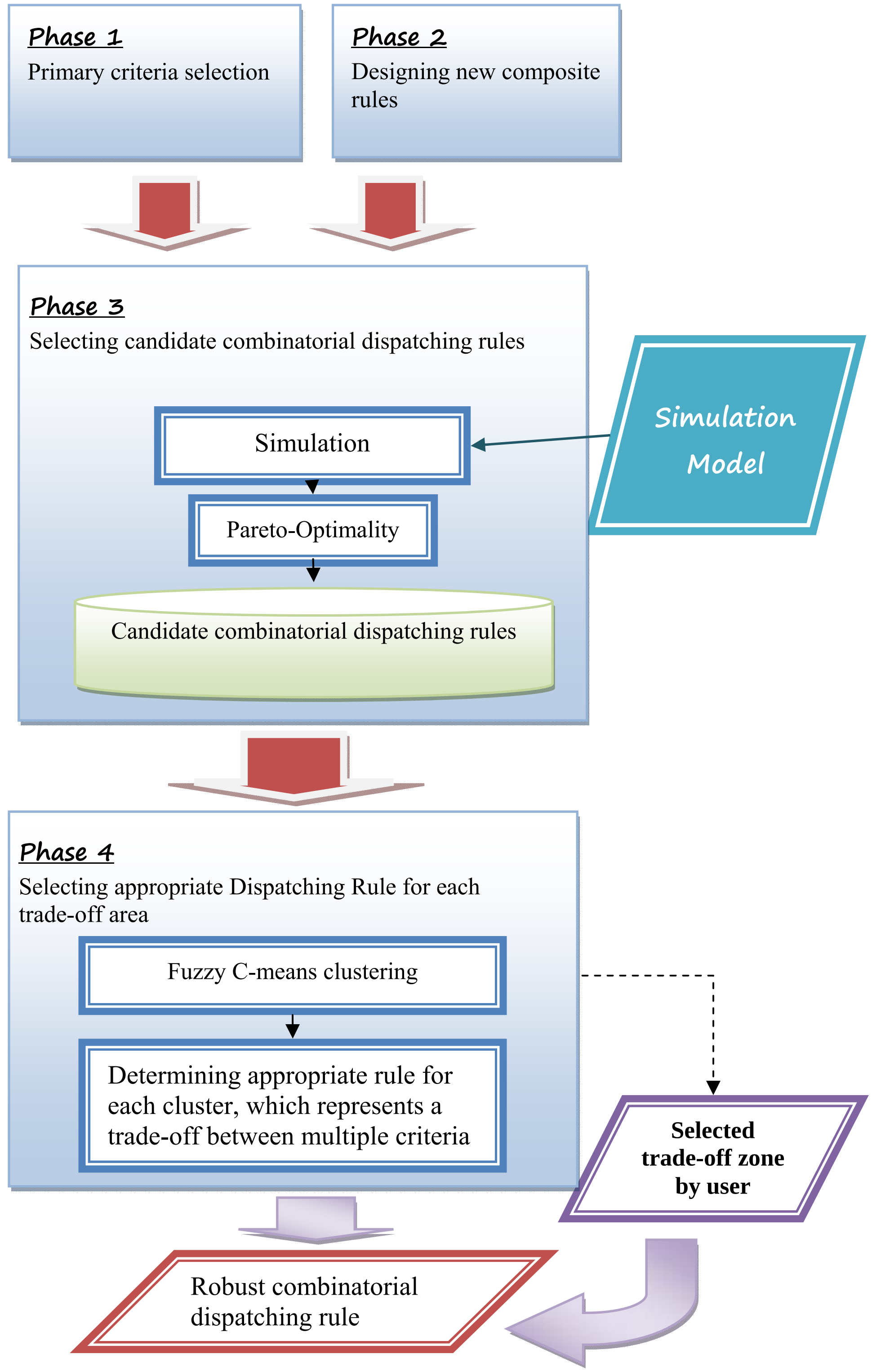

Figure 3.4 The proposed framework for multi-criteria industrial shop scheduling

3.4 Phase 1: Identifying Primary Criteria for Scheduling

The performance of an applied dispatching rule is evaluated by the degree to which it optimizes a given scheduling criterion such as production throughput, make-span, utilization, tardiness, and lateness (Chan et al. 2002). The lateness of the job (i.e. product) j in a given schedule σ, $L_j(\sigma)$,is defined as the difference between the completion time of job j, $C_j(\sigma)$, and due date of job j, d_j, as shown in Equation 3.1.

$$L_j(\sigma) = C_j(\sigma) - d_j \qquad \text{(Equation 3.1)}$$

The value of lateness is '0' when the job is on time, negative when the job is early, or positive when the job is late. The tardiness of job j in schedule σ, $T_j(\sigma)$, is defined as the maximum of lateness and '0', which is obtained from Equation 3.2.

$$T_j(\sigma) = \max\{C_j(\sigma) - d_j, 0\} = \max\{L_j(\sigma), 0\} \qquad \text{(Equation 3.2)}$$

The difference between lateness and tardiness lies in the fact that the value of tardiness is never negative (Pinedo 2008). The opposite of tardiness for job J_j is earliness, $E_j(\sigma)$, which is defined as:

$$E_j(\sigma) = \max\{d_j - C_j(\sigma), 0\}. \qquad \text{(Equation 3.3)}$$

According to surveys (Smith et al. 1986; Gupta et al. 1990; and Chan et al. 2002), the most important scheduling criteria in the manufacturing systems, which are also used in industrial construction projects, are:

- Minimizing (weighted) average lateness ($\overline{L}^w$)

$$\overline{L}^w(\sigma) = \frac{\sum_{j=1}^{n} w_j L_j(\sigma)}{\sum_{j=1}^{n} w_j} \qquad \text{(Equation 3.4)}$$

- Minimizing (weighted) average tardiness ($\overline{T}^w$)

$$\overline{T}^w(\sigma) = \frac{\sum_{j=1}^{n} w_j T_j(\sigma)}{\sum_{j=1}^{n} w_j} \qquad \text{(Equation 3.5)}$$

- Maximizing average flow time ($\overline{F}$)

$$\overline{F}(\sigma) = \frac{1}{n}\sum_{j=1}^{n} C_j(\sigma) \qquad \text{(Equation 3.6)}$$

- Minimizing maximum lateness (L_{max}) :

$$L_{\max}(\sigma) = \max_j L_j(\sigma) \qquad \text{(Equation 3.7)}$$

- Minimizing maximum tardiness (T_{max})

$$T_{\max}(\sigma) = \max_j T_j(\sigma) \qquad \text{(Equation 3.8)}$$

- Minimizing maximum completion time, or make-span *(C_{max})*

$$C_{\max}(\sigma) = \max_j C_j(\sigma) \qquad \text{(Equation 3.9)}$$

- Total (weighted) flow time ($\overline{F}^w$)

$$\overline{F}^w(\sigma) = \sum_{j=1}^{n} w_j C_j(\sigma) \qquad \text{(Equation 3.10)}$$

- Maximizing machine utilization (*U%*)

Where, n is the number of jobs, i.e. products, $j \in \{1, 2, ..., n\}$, and σ is a possible sequence of jobs, i.e. possible schedule. Given the schedule σ, the starting time of job j in σ is denoted *a*s $S_j(\sigma)$, $C_j(\sigma)$ is used to denote its completion time, and d_j is its due date. Respectively, w_j is the weight of job j in terms of the importance of the job j. Besides, $L_j(\sigma)$ is the lateness of job j obtained from Equation 3.1, and $T_j(\sigma)$ is the tardiness of job j in σ calculated by Equation 3.2. The indicator function $U_j(\sigma)$ is used to identify whether job j is tardy (then $U_j = 1$) or on time (then $U_j = 0$) in σ. Correspondingly, $\overline{L}^w(\sigma)$ is the weighted average lateness, $\overline{T}^w(\sigma)$ is the weighted average tardiness, $\overline{F}(\sigma)$ is average flow time, $L_{\max}(\sigma)$ is maximum lateness, $T_{\max}(\sigma)$ is maximum tardiness, $C_{\max}(\sigma)$ is make-span, and $\overline{F}^w(\sigma)$ is total weighted flow time. Resource utilization (*U%)* is usually measured as the percentage of time that a resource is busy.

In addition to the aforementioned criteria, total earliness, which is defined in Equation 3.3, might be of interest due to inventory costs or limited inventory capacity. The emphasis on considering average earliness as an objective function started with the growing interest in *just-in-time* (JIT) production, which supports the idea that earliness should be discouraged (Baker and Trietsch 2009). In JIT production, a job that is completed earlier than its due date should be held in inventory and delivered on its due date. Therefore, finishing a job earlier than its due date results in inventory carrying costs. For example, spools that have been completed in a pipe spool fabrication shop should be usually delivered to the module yard. The due date of the spools is the start time of processes of the module yard. Consequently, spools that are ready earlier than their due date should be held in inventory until they can be used in module yard.

3.4.1 Primary Criteria Selection

The ultimate objective of every decision maker is to improve the performance of the shop floor in all aspects such as resource utilization, production throughput, and tardiness or lateness of the jobs. However, this objective is not practicable on the operational level of decision making in scheduling. Figure 3.5 and Figure 3.6 show examples of conflict between some criteria. In Figure 3.5, the performance of two conflicting criteria, including average flow time and maximum tardiness, using different dispatching rules are shown. Dispatching rules used in this illustration are shortest processing time (SPT), earliest due date (EDD), and minimum slack time (SLACK), all of which are explained in Chapter 2. As can be seen in Figure 3.5, minimizing the average flow time, which increases the production throughput, leads to a high maximum tardiness. Figure 3.6 illustrates the performance of average flow time and make-span using different dispatching rules. Dispatching rules in this example includes shortest remaining processing time (SRPT), shortest imminent processing time (SI), longest processing time (LPT), longest remaining processing time (LRPT), shortest remaining processing time per imminent processing time (RPT/I), fewest remaining operations (FRO), earliest due date (EDD), and minimum slack (SLACK). All aforementioned dispatching rules are explained in Chapter 2. Figure 3.6 shows that minimizing the average flow time results in a higher make-span. Therefore, it is difficult to simultaneously satisfy these conflicting criteria.

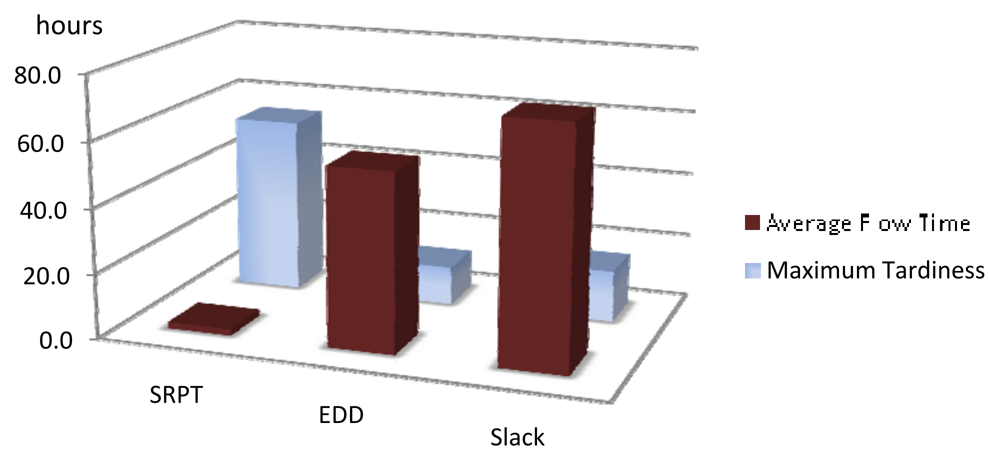

Figure 3.5 Simulation results of applying three simple dispatching rules on a spool fabrication shop (maximum tardiness vs. average flow time)

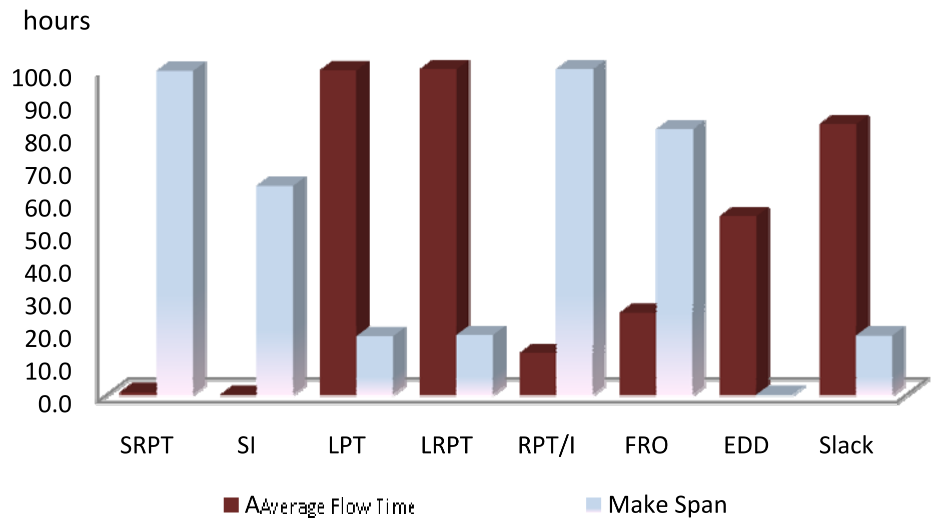

Figure 3.6 Simulation results of applying eight simple dispatching rules on a spool fabrication shop (make-span vs. average flow time)

Multiple runs of the simulation model of a pipe spool fabrication showed that the average flow time is correlated with the weekly production, which means that both of them can be optimized simultaneously. Correspondingly, make-span, total tardiness, and maximum tardiness are optimized concurrently. Table 3.1 shows the correlation matrix of criteria, which is calculated using the simulation results for different dispatching rules. In Table 3.1, the correlation coefficient indicates the strength and direction of a linear relationship between two criteria. In general statistical practice, correlation, or co-relation, refers to the departure of two variables from independence, although it does not imply causation. If two criteria are strongly correlated with each other, it is unnecessary to use both criteria in scheduling optimization since addressing one of them results in acceptable results for both criteria. The negative correlation between two criteria states that they are conflicting with each other. Based on the results shown in Table 3.1, the criteria are categorized into three groups, as shown in Table 3.2. Two criteria are in the same group if the correlation between them is more than 0.7. The criteria in each group are optimized simultaneously and therefore, one criterion from each category can represent all criteria for that category in the scheduling optimization problem.

Table 3.1 The Correlation Matrix of Scheduling Criteria for the Pipe Spool Fabrication

	Ave. Flow time	Make-Span	Max. Tardiness	No. of Tardy Jobs	Total Tardiness	Total Earliness	Mean Tardiness	Ave. Resource Usage
Ave. Flow time	-	-0.4	0.0	<u>0.8</u>	0.5	-0.9	0.2	<u>0.7</u>
Make-Span	-	-	0.6	-0.4	-0.2	0.5	0.2	-0.6
Max. Tardiness	-	-	-	0.1	<u>0.7</u>	0.1	<u>0.8</u>	-0.3
No. of Tardy Jobs	-	-	-	-	0.5	-0.9	0.3	0.6
Total Tardiness	-	-	-	-	-	-0.7	<u>0.7</u>	0.4
Total Earliness	-	-	-	-	-	-	0.0	-0.8
Mean Tardiness	-	-	-	-	-	-	-	-0.3
Ave. Resource Usage	-	-	-	-	-	-	-	-

In the first step of the first phase of the proposed scheduling framework, a sub-category of the criteria presented in the earlier section should be selected by the user. The user, who can be an industry practitioner or an academic researcher, can choose a subset of criteria to be used as the objective functions for the optimization problem. For example, minimization of maximum tardiness and minimization of average flow time are two main objectives that are important for the coordinator of a pipe spool fabrication shop. The total earliness is used when there are limitations in the inventory (such as limitation of the space or cost) and, therefore, JIT scheduling is of interest.

Table 3.2 Groups of Correlated Criteria

Group 1	Group 2	Group 3
Average Flow time Number of Tardy Jobs Average Resource Utilization	Make-Span Maximum Tardiness Total Tardiness Mean Tardiness	Total Earliness

3.4.2 Fuzzy Multiple Performance Measure

The fact that the value of each criterion belongs to a different range of variables makes it very difficult to evaluate and compare the solutions. For example, the value of resource utilization is normally measured in terms of the percentage of the time the resource is being used; therefore, it is shown by a number between '0' and '100,' while the value of make-span, average flow time, and maximum tardiness are measured in days and belong to different ranges. Table 3.3 shows an example of the range of values for pipe spool fabrication; the numbers in Table 3.3 are scaled for confidentiality purposes. In addition, some parameters, such as utilization, should be maximized, while some objectives, such as average flow time and make-span, should be minimized. Therefore, the concept of fuzzy sets (Bellman and Zadeh 1970) can be used to associate a membership degree with each value indicating the degree of satisfaction of the solution for the corresponding criterion.

Table 3.3 Range of Different Criteria for Pipe Spool Fabrication

	Average Flow time (Days)	Make-Span (Days)	Maximum Tardiness (Days)	Number of Tardy Jobs	Total Tardiness (Days)	Total Earliness (Days)	Average Resource Utilization (%)
Minimum Value	6	40	10	2	27	3156	70
Maximum Value	25	45	35	12	300	4094	95

Bellman and Zadeh (1970) used fuzzy sets to represent criteria and constraints to combine different performance measures in multi-attribute decision making. Let $D = \{D_1, D_2, \ldots, D_n\}$ be a set of alternative dispatching rules and $f = \{f_1, f_2, \ldots, f_c\}$ be a set of criteria (or objective functions), where c is the number of criteria, and f_q is the value of qth criterion. Considering A^q as the subset of the feasible values for the qth criteria, each dispatching rule in D, D_i, is associated with a vector $\mu(D_i)=(\mu_1(D_i), \mu_2(D_i), \ldots, \mu_q(D_i), \ldots, \mu_c(D_i))$, where $\mu_q(D_i)$ is interpreted as the degree to which the criterion q is satisfied by D_i in the subset A^q. Membership values $(\mu_q(D_i))$ are between 0 and 1, where a value of 0 indicates no membership, which is equivalent to no satisfaction, and a value of 1 indicates full membership, which is equivalent to full satisfaction.

The membership function of feasible values for each criterion is shown in Figure 3.7 and Figure 3.8. In this example trapezoidal membership functions are used (Zimmermann 1987). In Figure 3.7 and Figure 3.8, f_q^* is the ideal value of the criterion q, and f_q^H is the unacceptable value of criterion q. The membership function for fuzzy sets shown in Figure 3.7 and Figure 3.8 are formulated as shown in Equation 3.11 and Equation 3.12, respectively.

$$\mu_q(D_i) = \begin{cases} 1 & f_q \leq f_q^* \\ \dfrac{f_q^H - f_q}{f_q^H - f_q^*} & f_q^* \leq f_q \leq f_q^H \\ 0 & f_q \leq f_q^H \end{cases} \qquad \text{(Equation 3.11)}$$

$$\mu_q(D_i) = \begin{cases} 0 & f_q \leq f_q^H \\ \dfrac{f_q - f_q^H}{f_q^* - f_q^H} & f_q^H \leq f_q \leq f_q^* \\ 1 & f_q \leq f_q^* \end{cases} \qquad \text{(Equation 3.12)}$$

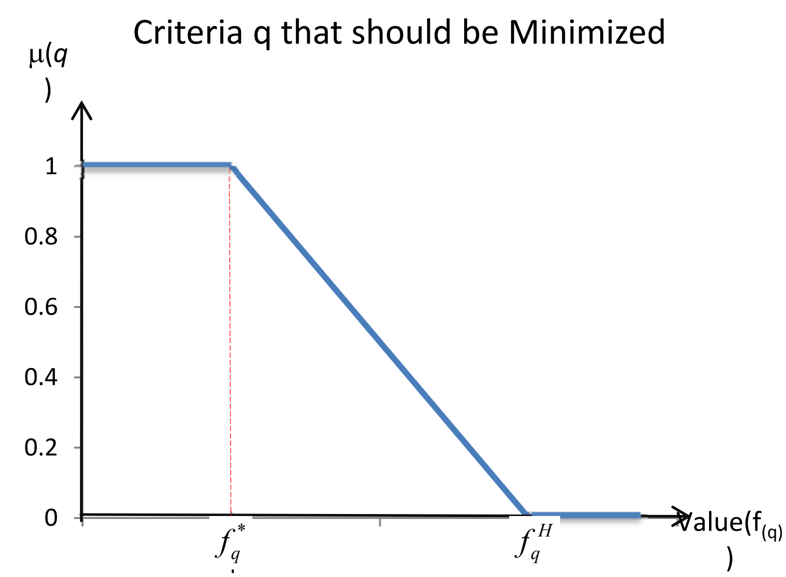

Figure 3.7 Membership function of acceptable values for minimization of criteria q

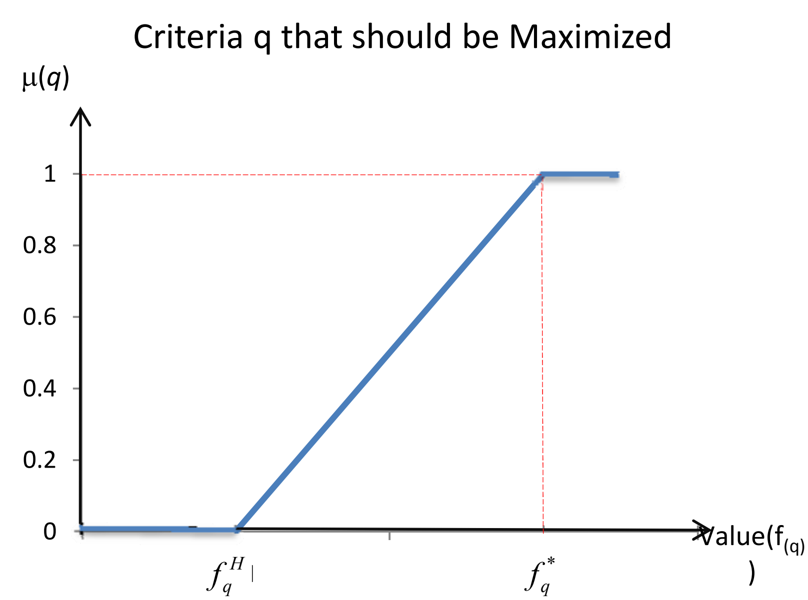

Figure 3.8 Membership function of acceptable values for maximization of criteria q

3.5 Phase 2: Combinatorial Dispatching Rules

The concept of combinatorial dispatching rules is to combine more than one parameter to produce better results. The parameter is usually referred to as the attribute of the job or station. Examples of parameters referring to attributes of the jobs are total processing time, due date, and slack. The average waiting time or queue length are examples of parameters referring to the attribute of a station. Simple dispatching are functions of a single parameter, which address one criterion. For example, as shown in Figure 3.5 and Figure 3.6, shortest imminent processing time (SI) optimizes average flow time, while earliest due date (EDD) and minimum slack (SLACK) rule optimize the maximum tardiness and make-span simultaneously. Studies on the combinatorial dispatching rule in construction project scheduling are limited. So far, two examples of combinatorial dispatching rule have been introduced in the literature (Bhaskaran and Pinedo 1992; Pinedo 2008): the cost over time (COVERT) rule and the apparent tardiness cost (ATC). The formulation of COVERT and ATC are given in Equation 3.13 and Equation 3.14 (Vepsalainen and Morton 1987). Both ATC and COVERT rules are a combination of slack and processing time parameters. In Equation 3.13 and Equation 3.14, processing time and slack of job *j* is denoted by t_j *and* u_j; respectively $\bar{t}$ represents average processing time. In these equations the scaling factor, *k*, is used to weight the slack parameter. Slack of job *j* is calculated by Equation 3.15, in which d_i *and p* represent the due date of job *j* and the present time.

$$Z_j = \frac{1}{t_j} \times \frac{k \times \bar{t} - (u_j)}{k \times \bar{t}} \qquad \text{(Equation 3.13)}$$

$$Z_j = \frac{1}{t_j} \exp\left(\frac{-(u_j)}{k \times \bar{t}}\right) \qquad \text{(Equation 3.14)}$$

$$u_j = d_j - t_j - p \qquad \text{(Equation 3.15)}$$

Scheduling performance of every combinatorial dispatching rule depends on their scaling factor values (Pfund et al. 2008; Chen et al. 2007). For example, the performance of ATC rule using different values of *k* is illustrated in Figure 3.9 for a spool fabrication shop. As shown in Figure 3.9, the satisfaction degree of each criterion varies for different *k* values in ATC rule. Small values of *k* make the slack parameter more influential and therefore it results in a high satisfaction degree for sum of the tardiness and low satisfaction degree for average flow time, while large values of *k* increase the weight of processing time and therefore make the SPT rule more important. Consequently, a large value of *k* results in a high degree of satisfaction for average flow time.

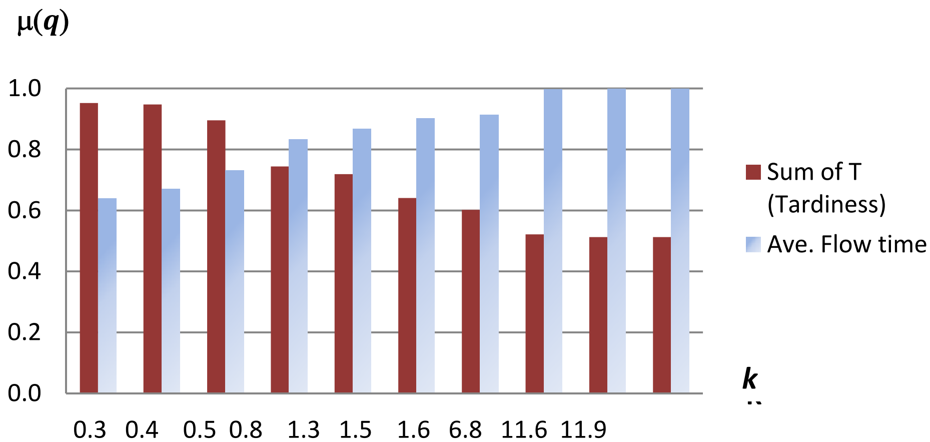

Figure 3.9 Performance of ATC rule with different k values

In addition to the two combinatorial rules in the literature, three new combinatorial rules are designed and introduced in this research by defining a combination of a set of parameters with relative weights as shown in Equation 3.16, Equation 3.17, and Equation 3.18. The relative weights, indicated by w_1 and w_2 in each equation, identify the contribution of different parameters in the rule; moreover, Z_j, indicates the priority of job j. The higher values of Z_j indicate the higher priority of the job j. Finally, processing time, due date, slack, and critical ratio of job j are denoted by t_j, d_j, uj, and CR_j. The critical ratio of job j, CR_j, is an index calculated by dividing the time remaining until due date by the work time remaining as shown in Equation 3.19. Each parameter should be normalized over interval [0, 1] to be applied in the same magnitude in the equation. Therefore, the exponential function is used to smoothly normalize each parameter based on the equation of the ATC rule (Vepsalainen and Morton 1987). Negative exponential function is a non-linear method for normalization that is used to smoothly normalize the data set (Lin et al 2005). Respectively, k_1 and k_2 are constant values for normalization.

$$Z_j = w_1 \times \exp(\frac{-(d_j)}{k_1}) + w_2 \times \exp(\frac{-(t_j)}{k_2}) \qquad \text{(Equation 3.16)}$$

$$Z_j = w_1 \times \exp(\frac{-(u_j)}{k_1}) + w_2 \times \exp(\frac{-(t_j)}{k_1}) \qquad \text{(Equation 3.17)}$$

$$Z_j = w_1 \times \exp(\frac{-(CR_j)}{k_1}) + w_2 \times \exp(\frac{-(t_j)}{k_2}) \qquad \text{(Equation 3.18)}$$

$$CR_j = \frac{d_i - p}{\sum_{j \in S} t_{ij}} \qquad \text{(Equation 3.19)}$$

As discussed earlier, due date in the scheduling criteria can be classified in three groups, and the criteria in each group can be optimized simultaneously. Equation 3.16, Equation 3.17, and Equation 3.16 are the weighted sum of two parameters, where the first parameter in each equation is usually used to satisfy the criteria in group1, including average flow time, number of tardy jobs, and average resource utilization. The second parameter in each equation is for satisfying criteria in group2, including make-span, maximum tardiness, total tardiness, and mean tardiness. Total earliness, which is in group3, is not of the interest in this study, because most industrial shops in Alberta do not have storage limitations.

Using ATC, COVERT, and the three new proposed combinatorial dispatching rules with different weights, four hundred rules are designed for scheduling.

Several simulation runs on the pipe spool fabrication showed that the ATC rule outperforms the COVERT rule, and the performance of the ATC rule is better than COVERT regarding to all criteria. Therefore, the COVERT rule was ignored and the number of rules was decreased to three hundred rules. Using the proposed dispatching rules and ATC rule together results in covering more compromise solutions on the Pareto- optimal frontier rather than using only ATC rule, as illustrated in Figure 3.10. Figure 3.10 shows that the proposed rules are more effective than ATC as they can span a wider area and stretch the Pareto frontier. The COVERT rule does not appear on the Pareto frontier, since its performance was dominated by the ATC rule.

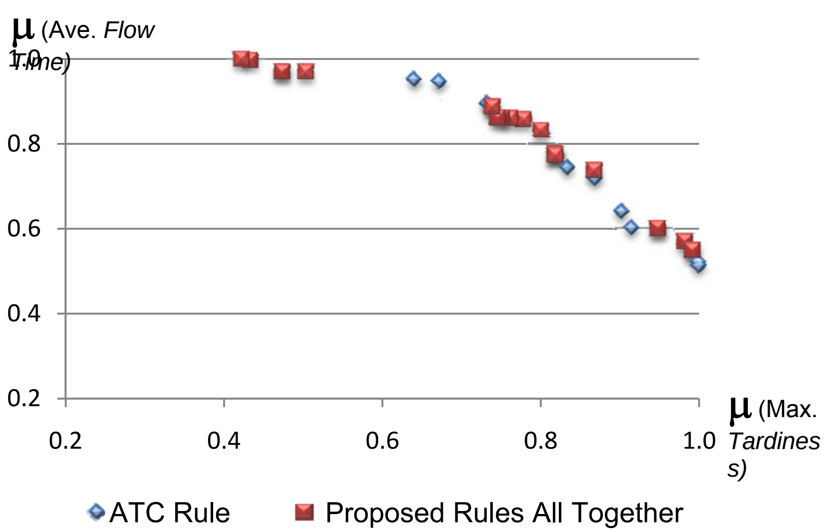

Figure 3.10 Performance of ATC rule and proposed dispatching rules for spool fabrication shop (Pareto frontier)

3.6 Phase 3: Identifying Candidate Rules

The principal of Pareto-optimality is used in multiple objective optimization problems. Consider a set of several criteria by $c = \{c_1, c_2, \ldots, c_n\}$; correspondingly, the satisfaction degree of the criteria is shown by $\mu = \{\mu_1, \mu_2, \ldots, \mu_n\}$, *where* μ_2 is the satisfaction degree of criterion c_2 indicating the performance value of criterion c_2. With respect to several, i.e. more than one, criteria, if it is not possible to increase the performance value of one criterion without decreasing the performance value of other criteria by applying each dispatching rule, a set of solutions that are feasible and not better than one another can be obtained. Although these solutions are better than each other with respect to identical criterion, no solution is superior to others with respect to all criteria. These solutions are Pareto-optimal and are called a Pareto-optimal set and establish the Pareto frontier. If a solution is Pareto optimal (Ehrgott 2005), it is called a non-dominated point. On the other hand, a solution is called dominated if some other solutions would make at least one criterion better off without compromising any other criterion. In order to identify the Pareto frontier, the non-dominated solution in set D, where D indicates the set of all solutions, should be identified. $\hat{d}$ is Pareto optimal if the following conditions are satisfied:

There is no $d \in D$ such that $\mu_q(d) \geq \mu_q(\hat{d})$ for $q = 1, \ldots, n$ and $\mu_i(d) > \mu_i(\hat{d})$ for some $i \in \{1, \ldots, q\}$

Figure 3.11 shows an example to illustrate the concept of Pareto-optimality graphically; c_1 and c_2 are two criteria considered in this example, the satisfaction degree of which are denoted by μ_1 and μ_2; as Figure 3.11 shows 'C' is not in the Pareto-optimal set because 'A' is superior to 'C' regarding both criteria as flows:

$\mu_{1(A)} > \mu_{1(C)}$, and $\mu_{2(A)} > \mu_{2(C)}$

Accordingly, 'C' is dominated by 'A'. On the contrary, 'A' and 'B' are both Pareto optimal. A is better than B with respect to c_2, while schedule B is better than A with respect to c_1.

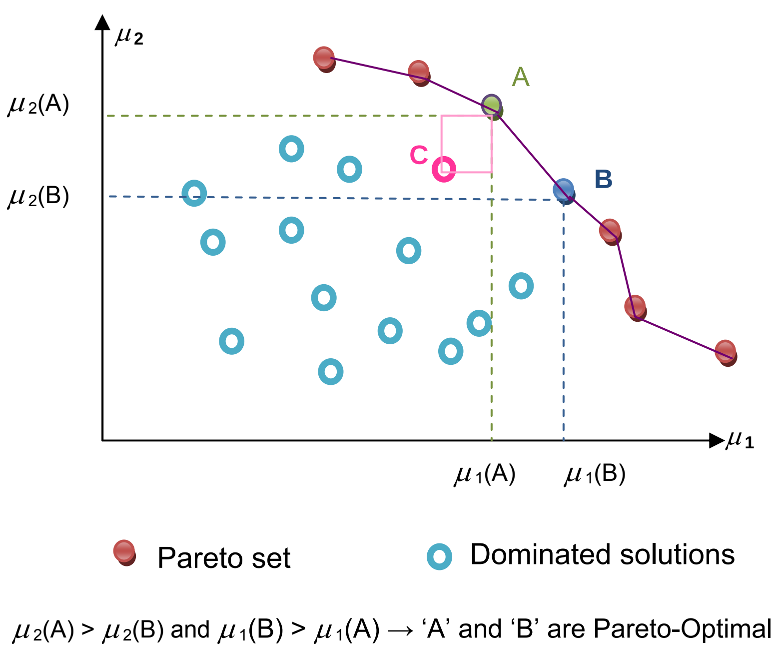

Figure 3.11 Example of Pareto-optimal set

Simulation models can be used to test different scenarios for a system. In this framework, simulation modeling is applied for identifying candidate rules. Candidate rules are rules that are in the Pareto frontier for each simulation experiment. The objective of this phase is to reduce the number of alternative dispatching rules by disregarding the rules that do not appear in the Pareto frontier set in any simulation experiment. In this step, a database consisting of a set of candidate dispatching rules and their performance values is constructed.

Figure 3.12 illustrates a summary of the proposed approach. As indicated in Figure 3.12, the approach includes two loops. The external loop models multiple scenarios by selecting different sets of spool in multiple time horizons of the shop. In each scenario, all alternative rules are tested, and their performance for each criterion is measured using proposed fuzzy sets (Equation 3.11 and Equation 3.12) through the internal loop. As a result, the rules in the Pareto optimal set are added to candidate rules.

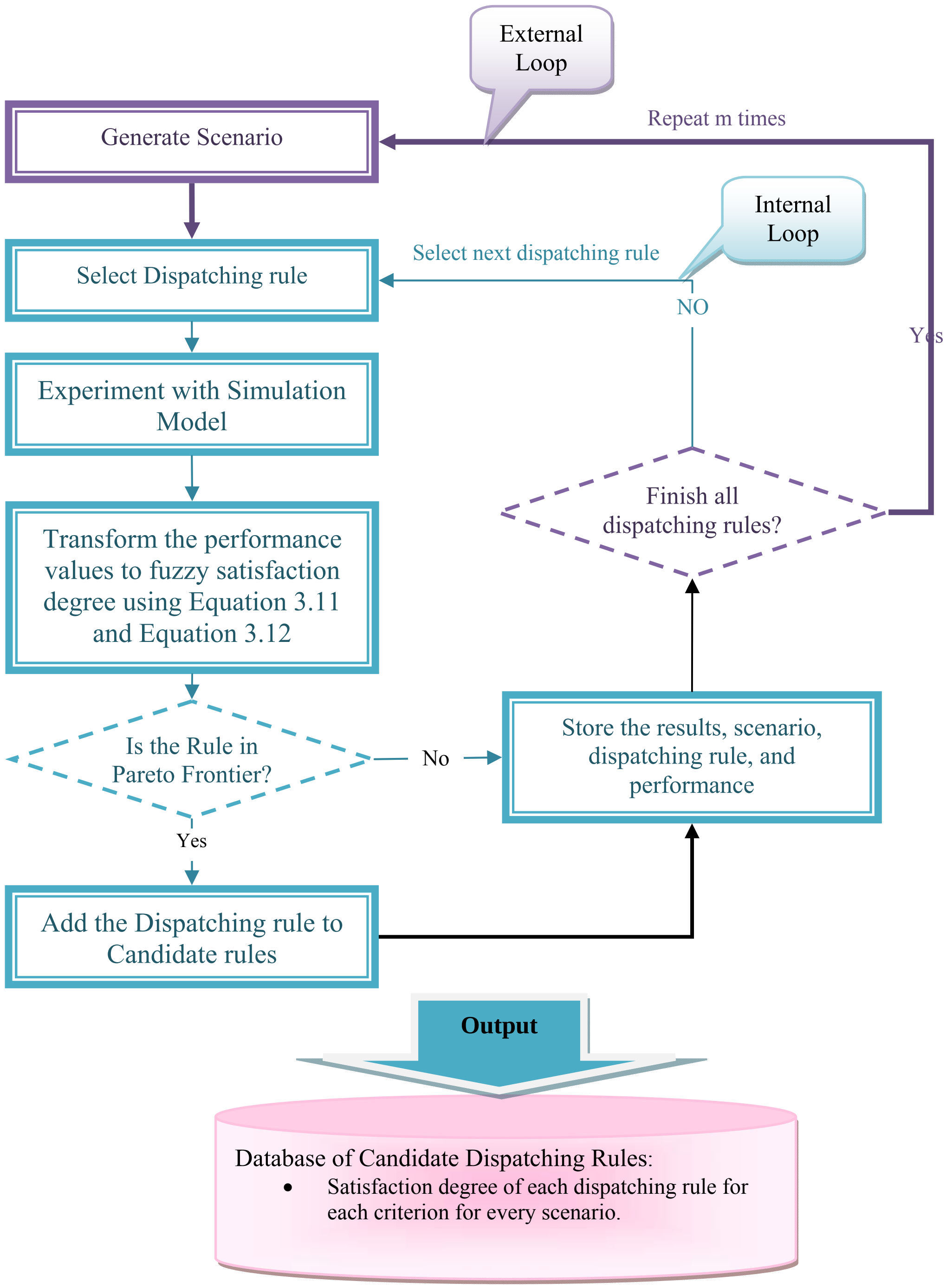

Figure 3.12 Generating candidate dispatching rules

Figure 3.13 illustrates the results of a sample scenario, which includes two objective functions. As a result of this phase, a knowledge base, including a set of candidate dispatching rules and the statistics of the performance of each rule under different scenarios, is developed. The framework of developing the simulation model is described in Chapter 2. This framework is applied using VB.NET programming and the simulation model, the development of which is explained in Chapter 2. The results of each simulation run are exported automatically to an Excel file. The Pareto-optimal set is automatically identified in the Excel sheets through a VBA macro. The program can determine the Pareto set with respect to the criteria selected by the user. The implementation of the algorithm will be explained through a case study in Chapter 4.

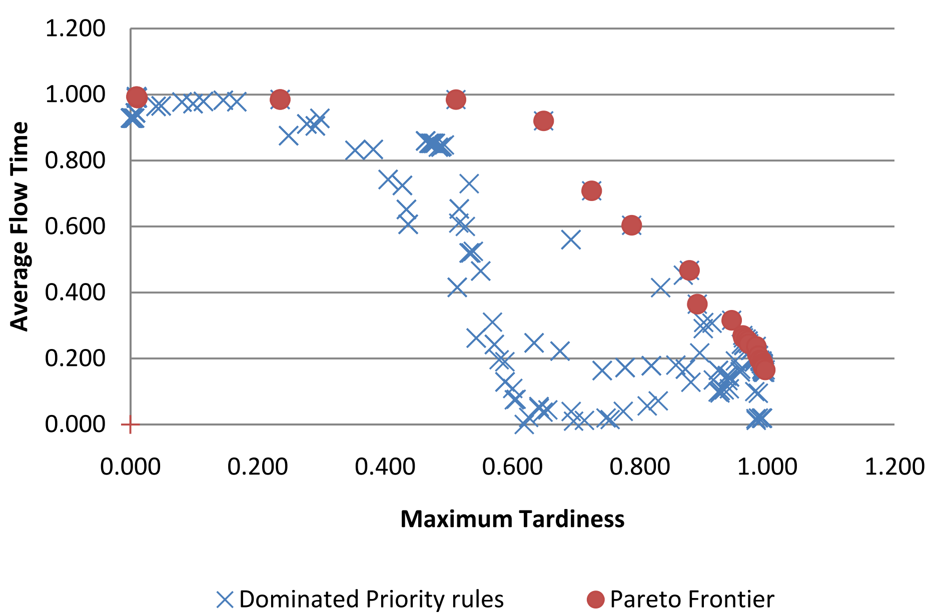

Figure 3.13 Pareto optimal set for a sample scenario

3.7 Phase 4: Selecting a Compromise Solution

In this phase of the framework, the structure of the data set that has been obtained in previous phases is identified in terms of the trade-off areas between the primary criteria. Each area represents a linguistic relationship between the solutions in that area and the corresponding criteria, i.e, the performance of each solution on the related criterion. Figure 3.14 graphically demonstrates the concept of trade-off area on a Pareto frontier for two criteria, c_1 and c_2, the performance of which are shown by μ_1 and μ_2. Five trade-off areas are considered as an example in Figure 3.14, including poor-good, fairly poor-fairly good, acceptable-acceptable, fairly good- fairly poor, and good-poor. This approach helps to consider changes in the performance of each dispatching rule in different scenarios when selecting the appropriate dispatching rule. Each trade-off area is represented by a linguistic term. The membership function of each linguistic term can be developed using expert judgment or numerical methods such as Fuzzy C-Means clustering (FCM) (Pedrycz and Gomide 2007). In this framework, FCM is used to group the Pareto frontier into the five aforementioned areas, and to determine the membership function of each linguistic term. The membership grade of each data point in each area is also determined using FCM.

Fuzzy clustering is commonly used to deliver comprehensive information about the structure in numeric data (Bezdek 1981; Pedrycz 2005; Pedrycz and Gomide 2007). Fuzzy clusters form a granular representation of data (Zadeh 1996, Zadeh 2005, Pedrycz 2009), which helps categorize the data into groups that better represent the distribution of the data. In fuzzy clustering, each data point is assigned a membership grade with respect to each cluster so that the sum of those membership grades for each data point equals one. The membership grade of an individual data point with respect to a cluster is an indicator of the position of that data point relative to the center of the cluster within the structure of the data.

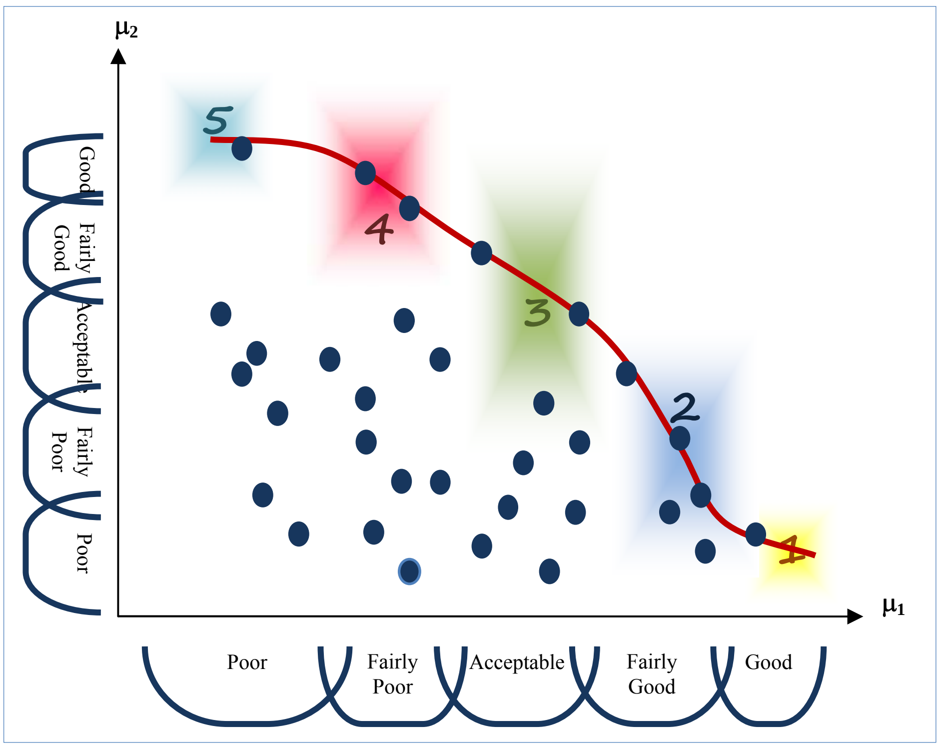

Figure 3.14 Trade-off areas on a Pareto frontier

There are two main reasons to use fuzzy clustering for the set of data that is the outcome of the previous phases of the proposed. The first is to convert the structure of the data into a linguistic representation with which the end-user in the industry can easily interface. The second reason is that each dispatching rule is represented by more than one data point, where each data point represents the performance of the dispatching rule in a different scenario (i.e. set of spool). In such a situation, the extent of belonging to the Pareto frontier cannot be represented by a crisp number or by a statistical moment, which only indicates the probability of being on the Pareto frontier without considering the proximity of the data points to the Pareto frontier. Using fuzzy C-means clustering together with probability of fuzzy event can help to address the aforementioned problem.

3.7.1 Fuzzy C-Means Clustering

Fuzzy C-Means clustering (FCM) is one of the most common methods for determining the structure of data. It is also used to determine membership functions based on numeric data. According to Pedrycz and Gomide (2007), with a collection of an N-dimensional data set, which in our case is a collection of alternative dispatching rules, $\{X_k\}$, $k= 1, 2, 3, \ldots, N$, Fuzzy C-Means clustering is used to identify the structure of the data set by determining a collection of C clusters with respect to minimization of the objective function formulated in Equation 3.20, representing the sum of the squared distances of each data point from cluster centers being regarded as prototypes.

$$Q = \sum_{i=1}^{C}\sum_{k=1}^{N} u_{ik}^{m} \left\| X_k - V_i \right\|^2 \qquad \text{(Equation 3.20)}$$

In Equation 3.20, $V= \{V_1, V_2, \ldots V_c\}$ are the n-dimensional prototypes of c clusters (or cluster center); || . || represents the distance between X_k and V_i, and m is the fuzzification coefficient, which is usually a number greater than ‘1’. The fuzzification coefficient determines the fuzziness of the resulting clusters. As m approaches ‘1’, the partition becomes hard, while by increasing m, m →∞, the partition becomes fuzzy. Respectively, $U=[u_{ik}]$ represents a partition matrix of allocating the data to corresponding clusters, which satisfies the following properties:

$$u_{ik} \in [0,1], \qquad \text{(Equation 3.21a)}$$

$$\sum_{i=1}^{c} u_{ik} = 1, \qquad \text{(Equation 3.21b)}$$

$$0 < \sum_{k=1}^{N} u_{ik} < n, \qquad \text{(Equation 3.21c)}$$

Where u_{ik} represents the membership degree of X_k to prototype V_i.

The FCM algorithm introduced by Pedrycz and Gomide (2007) is used to cluster the data points into a number of groups and determine the membership degree of each data point to each cluster. The algorithm includes the following steps:

1. Choose a value for c, m, and ε, a small positive constant.
2. Generate a random fuzzy C-partition U^0 and set the iteration number t= 0.
3. Given the membership values, U^0, the prototypes are calculated by Equation 3.22.

$$V_i^{(t)} = \frac{\sum_{k=1}^{N} (u_{ik}^{(t)})^m X_k}{\sum_{k=1}^{N} (u_{ik}^{(t)})^m} \qquad \text{(Equation 3.22)}$$

4. Given the new prototypes $V_i^{(t)}$ the updated membership values $u_{ik}^{(t+1)}$ are calculated by Equation 3.23.

$$u_{ik}^{(t+1)} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\left\| X_k - V_i^{(t)} \right\|^2}{\left\| X_k - V_j^{(t)} \right\|^2} \right)^{2/(m-1)}} \quad \text{(Equation 3.23)}$$

5. Repeat Step 3 and step 4 until the predefined number of iterations is reached or the following condition is satisfied:

$$\left\| U^{(t+1)} - U^{(t)} \right\| \leq \varepsilon \quad \text{(Equation 3.24)}$$

The aforementioned FCM algorithm is applied on the data points obtained in Phase 3 of the framework using a MATLAB program. As a result of performing FCM, a number of trade-off areas are identified. Moreover, every data point has a degree of membership to each area. Figure 3.15 shows five trade-off areas, which are obtained by implementing FCM on the dataset. The cluster centers (or prototypes) are identified in Figure 3.15. Each area in Figure 3.15 is defined linguistically, as shown in Table 3.4. The values of cluster centers determined from FCM are also shown in Table 3.4. For example, the linguistic term 'acceptable-acceptable' indicates that the performance of dispatching rules that lie in this area is acceptable regarding both criteria, which are average flow time and maximum tardiness. Correspondingly, the linguistic term 'fairly good-fairly poor' states that the performance of dispatching rules that are in this area is fairly good regarding to average flow time, and fairly poor regarding to maximum tardiness. Figure 3.16 shows the membership functions of linguistic terms obtained from FCM (Equation 3.23) (Pedrycz and Gomide 2007). The linguistic terms include good, fairly good, average, fairly poor, and poor, which are derived based on expert's oponin. As shown in Figure 3.16, the horizontal axis refers to performance value of a criterion, which is measured in terms of satisfaction degree of the criterion, and the vertical axis indicates the degree to which each value belongs to each linguistic term. For example, the performance value of a sample rule shown in Figure 3.15 is 0.6 with respect to maximum tardiness and 0.75 with respect to average flow time. Therfore, with respect to maximum tardiness, the rule is acceptable to degree of 0.5 and Fairly poor to degree of 0.5 (Figure 3.16), and with respect to Average flow time the rule is acceptable with degree of 1.0. The sample dispatching rule is in the 'acceptable-acceptable' trade-off area.

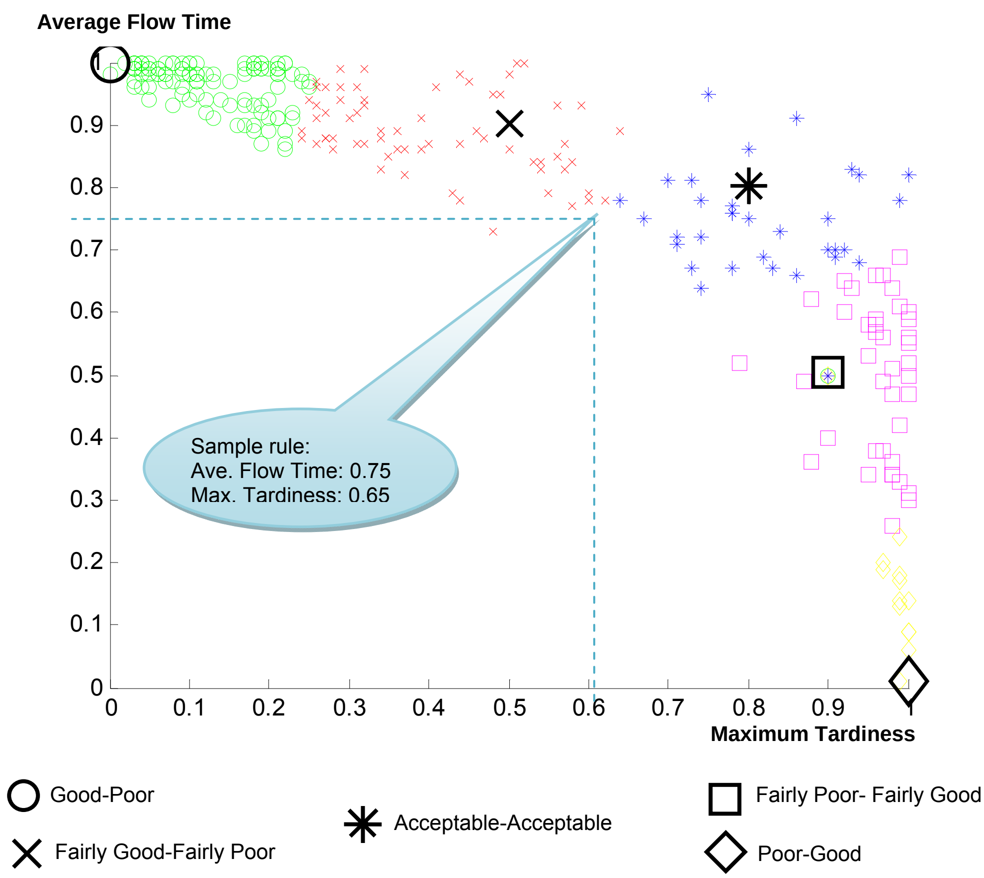

Figure 3.15 Linguistic trade-off areas for two criteria: average flow time and maximum tardiness

Table 3.4 Cluster Centers of Trade-off Areas

Trade-off Area	μ(Average Flow Time)	μ(Maximum Tardiness)
Good-Poor	1.00	0.00
Fairly Good-Fairly Poor	0.90	0.40
Acceptable-Acceptable	0.75	0.75
Fairly Poor-Fairly Good	0.40	0.90
Poor-Good	0.00	1.00

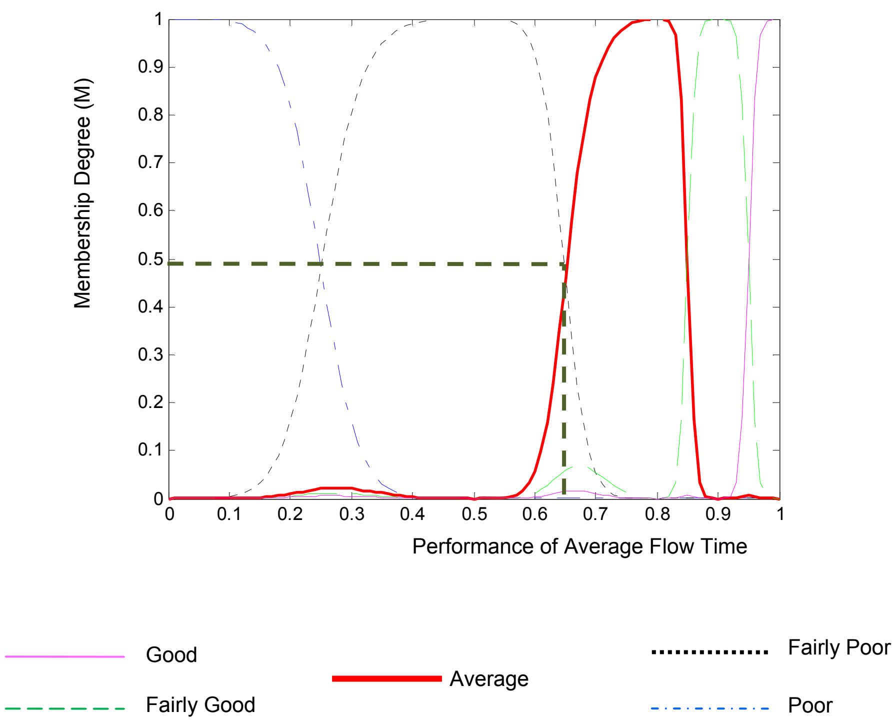

Figure 3.16 Membership functions of linguistic terms obtained from FCM

3.7.2 Statistical Analysis

Each dispatching rule is represented by several data points in the data structure, as shown in Figure 3.17. These data points represent the performance of the corresponding dispatching rule for different scenarios. Each data point is associated with a vector indicating its membership value to every cluster. Consequently, each dispatching rule has several membership degrees to each cluster because it is represented by several data points. Table 3.5 shows the satisfaction degree of two criteria (average flow time and maximum tardiness) for a dispatching rule and fifteen different scenarios, where one represents full satisfaction of the criteria and zero means no satisfaction. Each scenario constitutes a data point. This table also shows the membership degrees of each data point to clusters u1, u2, u3, u4 and u5.

The membership value of a data point to each cluster is calculated by Equation 3.25.

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\left\|X_k - V_i\right\|^2}{\left\|X_k - V_j\right\|^2}\right)^{2/(m-1)}} \qquad \text{(Equation 3.25)}$$

In Equation 3.25, $X = \{X_1, X_2, \ldots, X_N\}$ is the set of given data points, where X_k is a vector indicating the *k*th data point. $V = \{V_1, V_2, \ldots, V_N\}$ is the set of prototypes (or cluster centers), where V_j is a vector indicating the *j*th prototype. u_{ik} is the membership value of X_k to V_i.

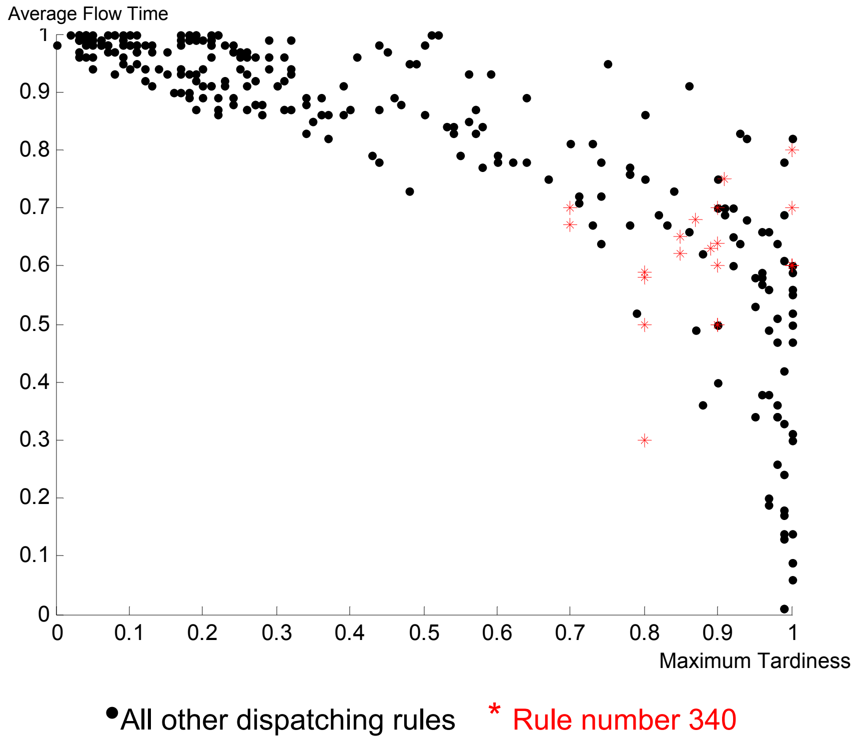

Figure 3.17 Data points represinting each dispatching rule

Table 3.5 Performance of an Example Rule for Fifteen Different Scenarios

Scenario	Avg. Flow time	Max. Tardiness	u1	u2	u3	u4	u5
1	0.3	0.8	0.01	0.04	0.09	0.66	0.2
2	0.3	0.7	0.07	0.18	0.19	0.37	0.19
3	0.5	0.9	0.00	0.00	0.00	1.00	0.00
4	0.3	0.7	0.02	0.08	0.13	0.57	0.21
5	0.4	0.8	0.01	0.02	0.06	0.86	0.05
6	0.4	1.0	0.00	0.02	0.05	0.87	0.06
7	0.6	0.9	0.00	0.02	0.11	0.86	0.01
8	0.6	1.0	0.01	0.02	0.14	0.81	0.02
9	0.5	0.8	0.00	0.02	0.06	0.91	0.01
10	0.6	1.0	0.01	0.02	0.14	0.81	0.02
11	0.5	0.9	0.00	0.00	0.00	1.00	0.00
12	0.7	0.9	0.01	0.04	0.67	0.28	0.01
13	0.3	0.8	0.01	0.04	0.09	0.66	0.2
14	0.8	1.0	0.01	0.07	0.68	0.22	0.02
15	0.6	1.0	0.01	0.02	0.14	0.81	0.02

Using the membership degree of each dispatching rule to a cluster for different scenarios, the concept of the probability of a fuzzy event (Zadeh 1968; Zadeh 1975) is used to calculate the expected membership value (Pedrycz and Gomide 2007) of each dispatching rule, *r*, to the *k*th cluster.

According to Zadeh (1968), an event is a precisely specified collection of points in a sample space in probability theory, while there are situations in which an event is a fuzzy collection of points, e.g. "it is a warm day." By using the concept of fuzzy sets and probability theory, the probability of a fuzzy event can be measured. Assuming that $P(x)$ is the probability measure of x, and $A(x)$ is the membership function of a fuzzy event, 'A', the probability of A can be measured by Equation 3.26 (Zadeh 1968). $E(A)$ is the probability of event 'A', which is also defined as the expected value of the membership function $A(x)$ (Zadeh 1968; Pedrycz and Gomide 2007).

$$E(A) = \int_{x} A(x)P(x)dx \qquad \text{(Equation 3.26)}$$

In a similar manner, data points representing a dispatching rule constitute a fuzzy collection of points or a fuzzy event. Therefore, the expected membership degree of a dispatching rule to a cluster can be calculated as the expected value of the membership degrees of all those data points using Equation 3.27, where n equals the number of data points or scenarios. Equation 3.27 is the discrete form of Equation 3.26, where the probability of each data point is equal to one over the total number of data points (n).

$$E(u_{rk}) = \frac{1}{n}\sum_{j} u_{rk}^{j} \qquad \text{(Equation 3.27)}$$

Where, $E(u_{rk})$ is the expected value of the membership degree of the *r*th dispatching rule to the *k*th cluster; j denotes the jth scenario and *n* is the total number of scenarios.

The expected membership value of a dispatching rule with respect to each cluster identifies the degree to which that rule belongs to that cluster. Given the fact that each cluster represents an area on the Pareto-optimal frontier where the satisfaction of each objective function or criterion is associated with a linguistic term (Table 3.4), the expected membership values calculated using Equation 3.27 assess the degree to which the associated rule can satisfy a criterion to the extent of that linguistic value.

Table 3.6 shows the expected membership values of a sample dispatching rule with respect to five clusters presented in Figure 3.15 and Table 3.4. The expected values in Table 3.6 clearly show that the sample dispatching rule has a higher degree of membership to cluster u4. This means that the sample dispatching rule has a fairly good performance in minimizing the maximum tardiness but it has a fairly poor performance in minimizing the average flow time.

Table 3.6 Expected Membership Value of an Example Rule to Five Different Clusters

Scenario	u1	u2	u3	u4	u5
Linguistic Value	Good-Poor	Fairly Good-Fairly Poor	Acceptable-Acceptable	Fairly Poor-Fairly Good	Poor-Good
Expected Membership	0.01	0.04	0.17	0.71	0.07
Variance	0.00	0.00	0.04	0.06	0.01

Zadeh (1968) also suggested calculating the variance of a fuzzy event, A, using Equation 3.28. The variance of a fuzzy event measures the dispersion of the data points in the fuzzy event A.

$$E^2(A) = \int [A\ (x) - E\ (A)]^2\, p(x)dx \qquad \text{(Equation 3.28)}$$

The variance of membership values of a dispatching similarly indicates the dispersion of the data points associated with that dispatching rule. A higher value for variance means less confidence in achieving the calculated expected membership degree by using a dispatching rule. In other words, the variance of membership degrees of a dispatching rule can be understood as a risk of using that dispatching rule. The variance of membership values for a dispatching rule can be calculated by Equation 3.29.

$$E^2(u_{rk}) = \frac{1}{n}\sum_j (u_{rk}^j - E(u_{rk}))^2 \qquad \text{(Equation 3.29)}$$

Table 3.6 also shows the variances of membership values of a sample dispatching rule's data points with respect to five clusters. The variance of the membership values with respect to cluster u4 is only 0.06, This low variance translates into a higher confidence and lower risk in achieving similar results by using the sample dispatching rule.

Dispatching rules can be compared using both their expected membership degree and variance of membership degrees. Rule A dominates rule B with respect to one cluster if rule A has a higher expected membership degree to that cluster and a lower variance of membership degrees to that cluster. When neither of the two dispatching rules dominates the other one, the user needs to choose the trade-off between expected membership value and variance. Table 3.7 shows two sample dispatching rules where sample rule 1 clearly dominates sample rule 2 with respect to cluster u4, however neither of the rules dominates the other one with respect to cluster u5.

Table 3.7 Expected Membership Values and Variances of Two Sample Dispatching Rules with Respect to Five Clusters

	Scenario	u1	u2	u3	u4	u5
	Linguistic Value	Good-Poor	Fairly Good-Fairly Poor	Acceptable-Acceptable	Fairly Poor-Fairly Good	Poor-Good
Sample rule #1	Expected Membership	0.01	0.04	0.17	0.71	0.07
	Variance	0	0	0.04	0.06	0.01
Sample rule #2	Expected Membership	0.01	0.02	0.05	0.12	0.8
	Variance	0	0	0.05	0.08	0.2

3.7.3 Selecting the Appropriate Rule

The decision making process based on the results of the statistical analysis and Fuzzy C-means clustering is comprise of two main steps.

First the decision maker should identify the desired compromise among the multiple objective functions initially introduced to the framework as all the objective functions cannot be fully satisfied by use of a single dispatching rule. This means that the decision maker has to choose a linguistic value or a trade-off zone on the Pareto optimal frontier. For example in the case presented in Table 3.7, the decision maker can select a trade-off zone or compromise solution, including “good-poor”, “fairly good-fairly poor”, “acceptable-acceptable”, “fairly poor-fairly good”, and “poor-good”. Each linguistic value represents a fuzzy cluster of data points. This fuzzy cluster is associated with a series of dispatching rules that have a high expected membership function with respect to that cluster.

In the second step of the decision making process, the decision maker should choose a dispatching rule from this group of dispatching rules by comparing their expected membership values and variances. Although ultimately one dispatching rule may have the highest expected membership value to the identified cluster, the decision maker may opt to use another dispatching rule with a lower expected membership and a lower variance to reduce the uncertainty (variance). The second step of the decision making process, like the first step, requires a choice by the decision maker on the trade-off between the expected membership value and the variance of membership values of the dispatching rules.

For example, Table 3.8 shows the linguistic performances of sample selected rules. In this table, the expected membership indicates the possibility to which the performance of the selected rule fits the linguistic term, and the variance indicates the confidence that the performance of the selected rules matches the linguistic terms. The expert can select the appropriate rule based on the linguistic performance of the rule and the expected membership and variance values. For instance, if the decision maker looks for good average flow time and poor maximum tardiness, he/she can select rule #1, rule #2, or rule #3. In case the confidence in the performance of the rule is important for the decision maker he/she can select rule#1, which has a lower variance.

Table 3.8 Linguistic performance of the ample dispatching rules

Rule (r)	Average Flow Time	Max Tardiness	Expected Membership	Variance
rule #1	Good	Poor	0.55	0.18
rule #2	Good	Poor	0.61	0.20
rule #3	Good	Poor	0.64	0.22
rule #4	Fairly Good	Fairly Poor	0.57	0.11
rule #5	Fairly Good	Fairly Poor	0.57	0.11
rule #6	Fairly Good	Fairly Poor	0.55	0.11
rule #7	Acceptable	Acceptable	0.75	0.05
rule #8	Acceptable	Acceptable	0.56	0.12
rule #9	Acceptable	Acceptable	0.58	0.12
rule #10	Fairly Poor	Fairly Good	0.69	0.08
rule #11	Fairly Poor	Fairly Good	0.56	0.09
rule #12	Fairly Poor	Fairly Good	0.74	0.06
rule #13	Poor	Good	0.62	0.02
rule #14	Poor	Good	0.64	0.00
rule #15	Poor	Good	0.62	0.00

3.8 Conclusions

In this chapter, a new framework for solving multi-criteria shop scheduling is developed. Using the proposed framework, the uncertainty incorporated with the shop environment can be captured by applying every dispatching rule to a set of different scenarios and utilizing statistical analysis to measure expected membership values and variances. In this chapter, new combinatorial dispatching rules are proposed in addition to existing combinatorial dispatching rules in order to address more than one criterion in schedule optimization. The significance of the proposed framework is in its ability to optimize a multi-criteria industrial shop scheduling problem while taking some other aspects into account:

1. The framework makes it possible to combine various dispatching rules with different weights to address multiple criteria in scheduling.
2. The framework provides the opportunity to evaluate different performance indices, which are in conflict with each other, using the concepts of fuzzy sets.
3. The framework uses fuzzy set theory to represent different trade-off areas between conflicting performance indices in the Pareto frontier (or Pareto optimal set).
4. The framework makes it possible to take into account the uncertainty of the performance of each dispatching rule through running each dispatching rule for different scenarios using the simulation model.

Furthermore, using Fuzzy C-Means clustering for analysis of the performance of dispatching rules makes it possible to convert the structure of the data, which is obtained from the simulation model, into a linguistic representation. Using that linguistic representation, the end-user in the industry can easily interpret the numerical results and choose the proper dispatching rule. Fuzzy C-Means clustering also accounts for the fact that each dispatching rule can satisfy a given criterion to a different degree, depending on the set of jobs being scheduled. Moreover, fuzzy clustering makes it possible to consider the quality of belonging of each dispatching rule to a Pareto frontier in the amalgamation of all the results of all scenarios, which cannot be represented by a crisp number or by a statistical moment. The statistical methods can only specify the probability of being on the Pareto frontier without considering the proximity of the data points to the Pareto frontier.

Finally, linguistic variables and statistical data are connected together by the concept of probability of a fuzzy event (Zadeh 1968; and Zadeh 1975), which is interpreted as the expected membership value by Pedrycz and Gomide (2007). Also using the variance of membership values (Pedrycz and Gomide 2007) of a dispatching rule, the confidence in the expected membership value of each dispatching rule with respect to each cluster can be determined.

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CHAPTER 4 - Case Study: Scheduling of Pipe Spool Fabrication Shop Using Simulation and Fuzzy Logic

4.1 Introduction

In this chapter, the proposed framework for simulation-based scheduling of industrial fabrication is implemented on a real case study of a pipe spool fabrication shop in Edmonton, Alberta. First, a simulation model is developed for the case study using the simulation modeling framework proposed in Chapter 2. Then the appropriate dispatching rule is identified using the multi-criteria scheduling framework proposed in Chapter 3. The simulation model presented here is developed for processes from the cutting station to the QC (Quality Check) station. Hydro-test, stress relief, painting, and shipping to the module yard are not considered in this model. Moreover, it is assumed that all materials and drawings are available when a spool is issued to the shop floor. The actual case study involves four bays, all of which are included in the simulation model. As shown in Figure 4.1, a bay is a production line including different stations through which spools are processed.

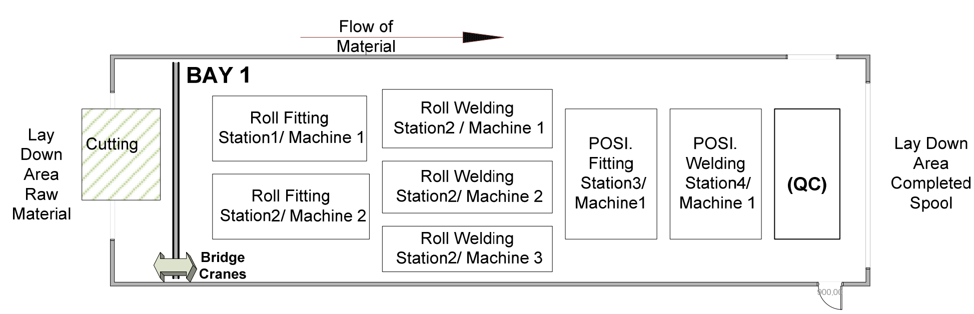


Figure 4.1 A schematic layout drawing of a bay in a pipe spool fabrication shop

Section 4.2 elaborates on the characteristics of the case study, as well as assumptions considered in developing this case study. Furthermore, the proposed simulation model is validated in Section 4.2. In Section 4.3, the proposed framework for multi-criteria scheduling is implemented on the case study. The results are then validated using test data.

4.2 Simulation Modeling of Pipe Spool Fabrication

The pipe spool fabrication processes are comprehensively described in Chapter 2. The case study includes 802 spools, which are sent to the shop floor over one month. As shown in Figure 4.2, after generating spools in the simulation model, spools are assigned to each bay based on their material group, weight, and size. Then, the spools are sent to the cutting station. In the next step of the simulation model, the model breaks down the spool into its assemblies based on the entity hierarchy (EH) of the spool, which is held in the central database. After roll welding and SAW welding of all the spool's assemblies are completed, the assemblies are then sent for position fitting and position welding. Quality check (QC) is the last process performed on the spool. Material handling is modeled between stations to calculate the utilization of cranes. As Figure 4.2 illustrates, the SAW welding process and the roll welding process are modeled separately.

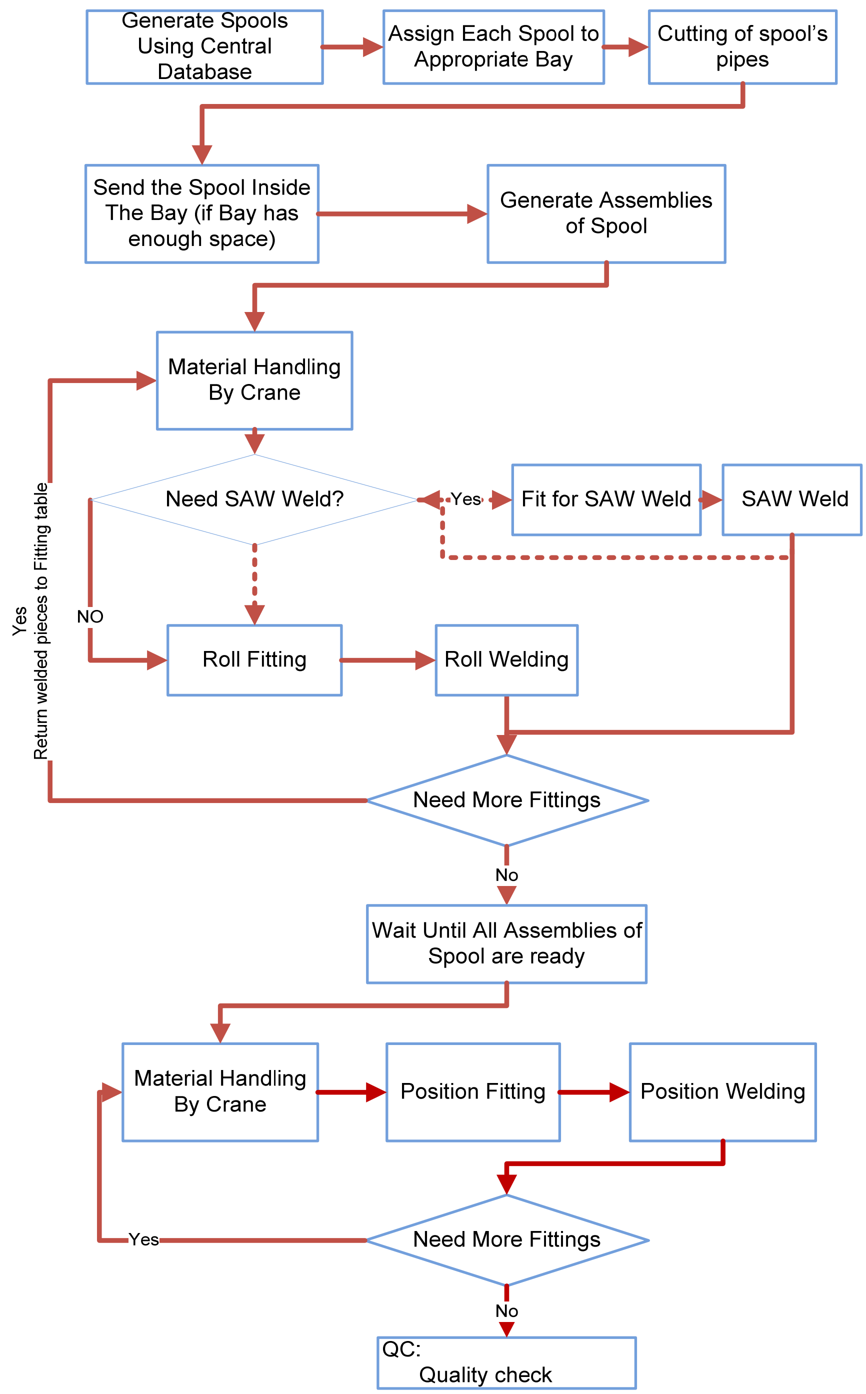


Figure 4.2 Structure of simulation model for case study

4.2.1 Assumptions

In order to simulate the fabrication shop, some assumptions have been made according to the experts' (shop foremen's Supervisor, Quality Assurance Coordinator, and Estimator) information. These assumptions help to speed up the development of the simulation model based on available data.

In this simulation model, only the following steps of spool fabrication are modeled: cutting, SAW welding, roll fitting, roll welding, position fitting, position welding, and QC. It is assumed that in the current configuration of the fabrication shop, bottlenecks are not due to tasks like hydro-testing and painting, so these activities do not directly affect the productivity of the fabrication shop.

Moreover, the simulation model is designed with the assumption that all materials are available for the spools while the model is run. In other words, it is assumed that the fabrication of a spool starts when all materials are available.

The processing time of each operation is estimated using the Equation 4.1:

$$\mathrm{t_{ij}} = \frac{\mathrm{Pr}_j \times (wu_i)}{nw_j} \qquad \text{(Equation 4.1)}$$

Where, t_{ij} the processing time of job i for the process j, Pr_j is man-hours required per unit of the work for process j (Equation 2.3), wu_i is the amount of work unit of job *i,* which is measured in diameter inches, and nw_j is the number of workers that are working on the product in process j.

Since the historical data do not specify different types of welds, e.g. position, SAW, and roll, the following assumptions are made about the durations of different types of welding methods according to the Operations Manager of the Ledcor fabrication shop:

- wall thickness<= 1.000" WT (Wall Thickness)
    - roll weld = base weld unit (diameter inches)
    - SAW = 0.8 × base weld unit
    - position = 1.75 × base weld unit
- wall thickness > 1.000" WT
    - SAW = base weld unit (diameter inches)
    - position = 1.5 × base weld unit

Pipes with wall thickness greater than 1.000" should be welded by the SAW machine.

Some assumptions were considered for calculating the duration of welding of different welds. These are explained in Appendix A, based on information available for butt welds (defined in Appendix A):

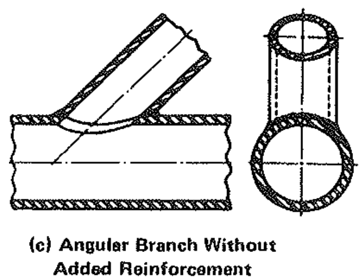
- Dummy legs are similar to butt welds if they are 90° to the header (Figure 4.3). The duration of welding 45° dummy legs (Figure 4.3) is close to butt welds.
- The duration of re-pad welds is considered to be 2.0 × duration of butt weld.

- o Re-pad welds are considered to be somewhere between 1.5 and 2.0 x duration of butt weld.

- The duration of welding for socket welds is 0.80 × duration for butt welds.

Finally, the available man-hour data do not include separate information for fitting and handling. Therefore, it is assumed that fitting and handling are done together. To calculate crane utilization, it is assumed that the crane supports the handling and fitting somewhere between 20 and 30 percent of the fitting time.

a) 90° Dummy leg

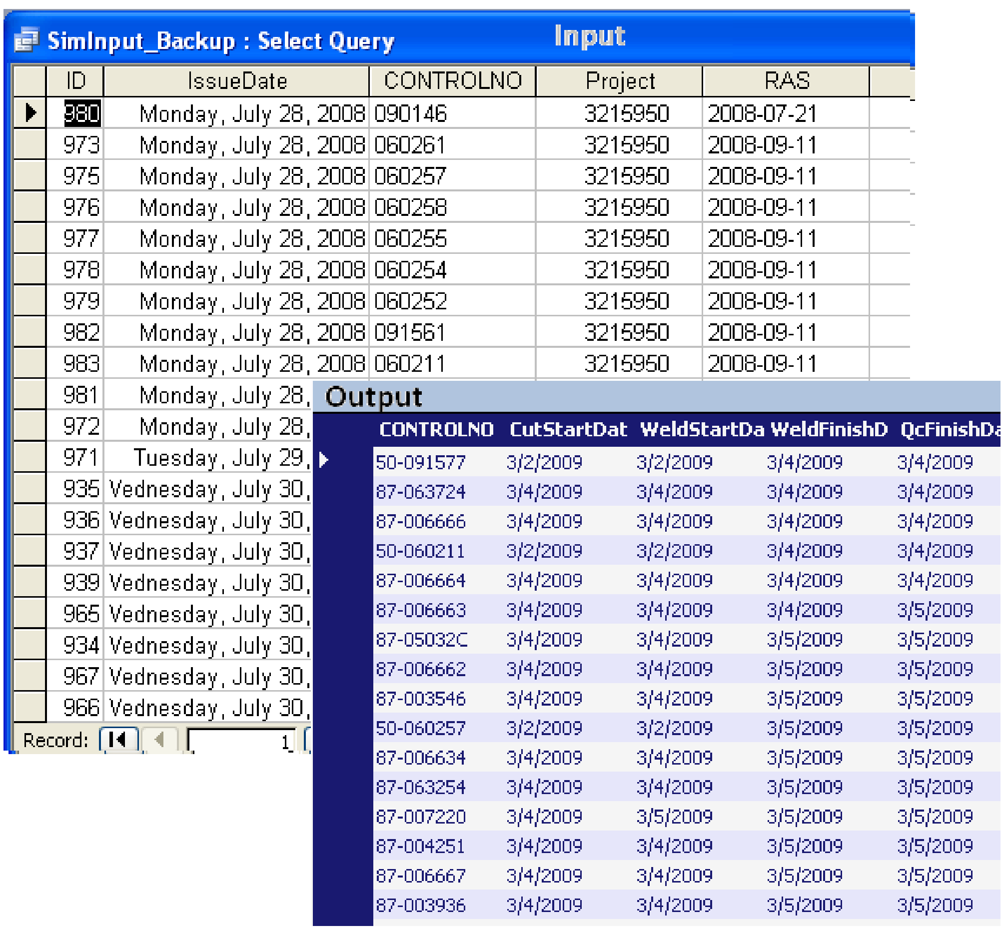


b) Angular Dummy leg

Figure 4.3 Dummy legs

4.2.2 Database

The central database holds the entity hierarchy (EH) information and is connected to the simulation model. The central database also holds the output results of the simulation model, which include the start and finish time of each process for every spool. Figure 4.4 shows the input table and the output table in the central database. The input table contains the entity hierarchy information. A special element is utilized in the simulation model to generate the entities using the input table in the central database. The central database is generated using the company's database and drawings of the pipe spool fabrication spool fabrication. It is connected to the simulation model through the user interface developed in VB.Net. The data in the central database, which are carried by entities in the simulation model as each entity's attributes, are listed in Table 4.1. In Table 4.1, a spool is the final product of the pipe spool fabrication shop. Respectively, an assembly is defined as the most basic element of a spool that does not need position welding, and components such as pipes, elbows, valves, etc. are the most basic elements of a spool. Chapter 2 contains a comprehensive explanation about pipe spool fabrication processes and the entity hierarchy model.


SimInput_Backup : Select Query

Input

ID	IssueDate	CONTROLNO	Project	RAS
980	Monday, July 28, 2008	090146	3215950	2008-07-21
973	Monday, July 28, 2008	060261	3215950	2008-09-11
975	Monday, July 28, 2008	060257	3215950	2008-09-11
976	Monday, July 28, 2008	060258	3215950	2008-09-11
977	Monday, July 28, 2008	060255	3215950	2008-09-11
978	Monday, July 28, 2008	060254	3215950	2008-09-11
979	Monday, July 28, 2008	060252	3215950	2008-09-11
982	Monday, July 28, 2008	091561	3215950	2008-09-11
983	Monday, July 28, 2008	060211	3215950	2008-09-11
981	Monday, July 28,			
972	Monday, July 28,			
971	Tuesday, July 29,			
935	Vednesday, July 30,			
936	Vednesday, July 30,			
937	Vednesday, July 30,			
939	Vednesday, July 30,			
965	Vednesday, July 30,			
934	Vednesday, July 30,			
967	Vednesday, July 30,			
966	Vednesday, July 30,			

Record: 1

Output

CONTROLNO	CutStartDat	WeldStartDa	WeldFinishD	QcFinishDa
50-091577	3/2/2009	3/2/2009	3/4/2009	3/4/2009
87-063724	3/4/2009	3/4/2009	3/4/2009	3/4/2009
87-006666	3/4/2009	3/4/2009	3/4/2009	3/4/2009
50-060211	3/2/2009	3/2/2009	3/4/2009	3/4/2009
87-006664	3/4/2009	3/4/2009	3/4/2009	3/4/2009
87-006663	3/4/2009	3/4/2009	3/4/2009	3/5/2009
87-05032C	3/4/2009	3/5/2009	3/5/2009	3/5/2009
87-006662	3/4/2009	3/4/2009	3/5/2009	3/5/2009
87-003546	3/4/2009	3/4/2009	3/5/2009	3/5/2009
50-060257	3/2/2009	3/2/2009	3/5/2009	3/5/2009
87-006634	3/4/2009	3/4/2009	3/5/2009	3/5/2009
87-063254	3/4/2009	3/4/2009	3/5/2009	3/5/2009
87-007220	3/4/2009	3/5/2009	3/5/2009	3/5/2009
87-004251	3/4/2009	3/4/2009	3/5/2009	3/5/2009
87-006667	3/4/2009	3/4/2009	3/5/2009	3/5/2009
87-003936	3/4/2009	3/4/2009	3/5/2009	3/5/2009

Figure 4.4 Input and output tables in central database

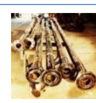
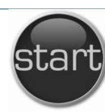
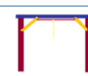
Table 4.1 List of Entities' Attributes in Central Database

	Spool	**Assemblies**	**Components**
Product Information	Spool ID Control Number Project ID Batch ID Issue date RAS (required at site date or due date) Material Type Total work units Length Weight Number of assemblies Number of pipes Number of Elbows Number of Tees Number of Valves Total number of fittings	Spool ID Control Number Project ID Batch ID Assembly ID Total work units Length Weight SAW welding work unit Roll welding work unit Number of assemblies Number of pipes Number of Elbows Number of Tees Number of Valves Total number of fittings	Spool ID Control Number Project ID Batch ID Assembly ID Component ID Length Weight Diameter Wall thickness Start Co-ordinate End Co-ordinate
Process Information	Processing time of the position fitting Processing time of position welding Processing time of quality check	Processing time of the roll fitting Processing time of the roll welding Processing time of the SAW fitting Processing time of SAW welding	Processing time of Cutting

4.2.3 Simulation Environment

A SPS template was developed to simulate the pipe spool fabrication shop in Simphony.Net©. The SPS template can be also used for other industrial fabrication facilities such as steel fabrication shops. The development of the SPS template is discussed in Chapter 2. In this section, the elements of this template used for modeling the case study are explained in detail. Also, the inputs and outputs of each element are introduced in this section. The input parameters can be changed through the developed user interface. The outputs of the elements can be viewed through the user interface after running the model. Table 4.2 summarizes the elements and the corresponding icons used in the model.

Table 4.2 Icons Used for Elements of Simulation Model

Element	**Icon**	**Element**	**Icon**
Fab-Shop		Working Station	
Start		Generate	
Dispatch controller		Assembly	
Bay		Crane	
Cutting Station		Material handling	
Worker		Bay	
Waiting file			

4.2.3.1 **Fab-Shop**

The Fab-Shop element contains all elements of a fabrication shop. The inputs of this element include database path, as well as the dispatching rule, which is used for scheduling the spools. The output includes work units produced per week.

4.2.3.2 **Start**

This element links the simulation model to the central database and produces spools based on entity hierarchy model in the central database. The start element fires the spools as entities according to their issue date in the central database. The issue date is the date that all materials and drawings of the spools are available and is pulled out of the fabrication status database of the shop.

4.2.3.3 **Bay**

All stations are child (sub) elements of this element. The input is the average number of spools can be in the bay. The outputs include production (produced work units) per week. The average number of spools is used to model the lay down area that is distributed through the fabrication shop.

The case study includes four bays. Two bays (Bay 2 and Bay 4) are for heavy wall and large diameter spools, and two bays (Bay 1 and Bay 3) are for standard wall and small diameter spools. According to fabrication shop foremen, stainless steel spools should be processed separately from carbon steel spools to prevent cross-contamination; therefore, stainless steel spools are processed in Bay 3 regardless of their weight and size (diameter).

4.2.3.4 **Dispatch Controller**

The dispatch controller element allocates spools to each bay based on their weight, diameter, and material group. The dispatch controller also checks the waiting time of spools in a bay and sends the spools to the appropriate bay with the lowest average waiting time in order to uniformly allocate the workload to the bays.

4.2.3.5 **Cutting Station**

This element represents a cutting station. The input is the number of stations. The outputs include work units produced per week, average waiting time for spools, and the utilization of a station.

4.2.3.6 **Worker**

This element represents the fitters and welders as a resource. The input of this element is the number of workers. The output includes utilization percentage of workers. Two types of workers are considered in the model: fitter and welder.

4.2.3.7 **Waiting File**

The waiting file element is for spools waiting for resources. The output of this element is the average waiting time for spools.

4.2.3.8 **Working Station**

This element represents a working station in which a specified process, such as roll fitting or roll welding, is performed on a spool. The input of this element is number of stations. The output of this element includes work units produced per week, average waiting time for spools, and utilization percentage of the station.

4.2.3.9 **Generate**

The generate element adjusts the entity to the required level of entity hierarchy by generating the assemblies for each spool based on the entity hierarchy model in the central database.

4.2.3.10 **Assembly**

The assembly element adjusts the level of the entity to the required level of the entity hierarchy model by gathering all the assemblies of spools together. The assembly element is developed by enhancing the methodology proposed by Wang (2006) and Sadeghi and Fayek (2008) using the information in the central database.

4.2.3.11 **Crane**

This element represents the bridge crane as a resource for material handling. Each bay includes a number of bridge cranes for handling material and spools between stations.

4.2.3.12 **Material handling**

This element represents the material handling between stations in fabrication shop. This element does not need any input.

4.2.4 User Interface

Using VB.net, the user interface is provided to control input to the simulation model and to develop an entity hierarchy model using the database and drawings of pipe spool fabrication shops as described in Chapter 3. Figure 4.5 illustrates the relationship between a pipe spool fabrication shop's database and the simulation model through Access and VB.net. The user interface of the model (Figure 4.6) consists of four sections. As shown in Figure 4.7, the first section is for revising the spools in the database and calculating man-hours and each type of weld for each spool to develop the entity hierarchy. Figure 4.7 also shows the second section, which allows the user to select the dispatching rule and to determine the working hours and shift hours of the fabrication. Figure 4.8 shows the third section, which can be viewed by clicking on "Revising Model" at the top of the interface. This section is for revising the layout and the configuration of the pipe spool fabrication shop in the simulation model. Examples of such revisions include changing the number of stations and resources. After running the simulation, the results for each station and bay appear in this section. The results of the simulation model for spool cycle time (in days) and delivery dates are saved in the database connected to the model. These results can be viewed through the interface in the third section by clicking on "spools cycle time" at the top of the user interface, as illustrated in Figure 4.9.

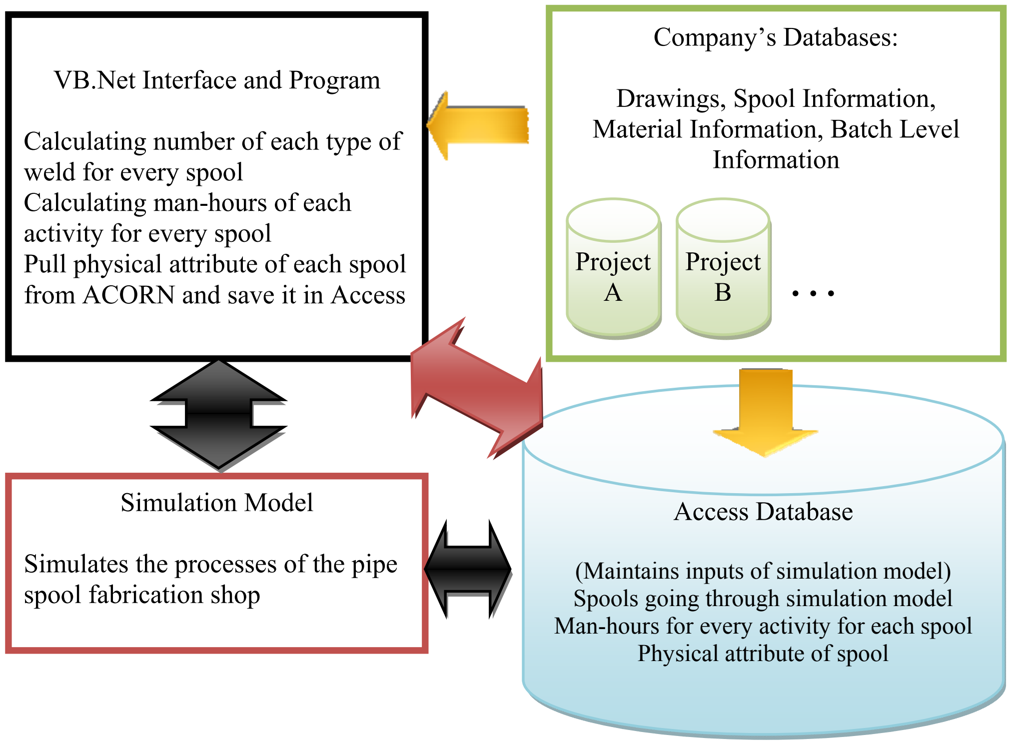


Figure 4.5 Relationships between company's databases and simulation model via VB.net and Access

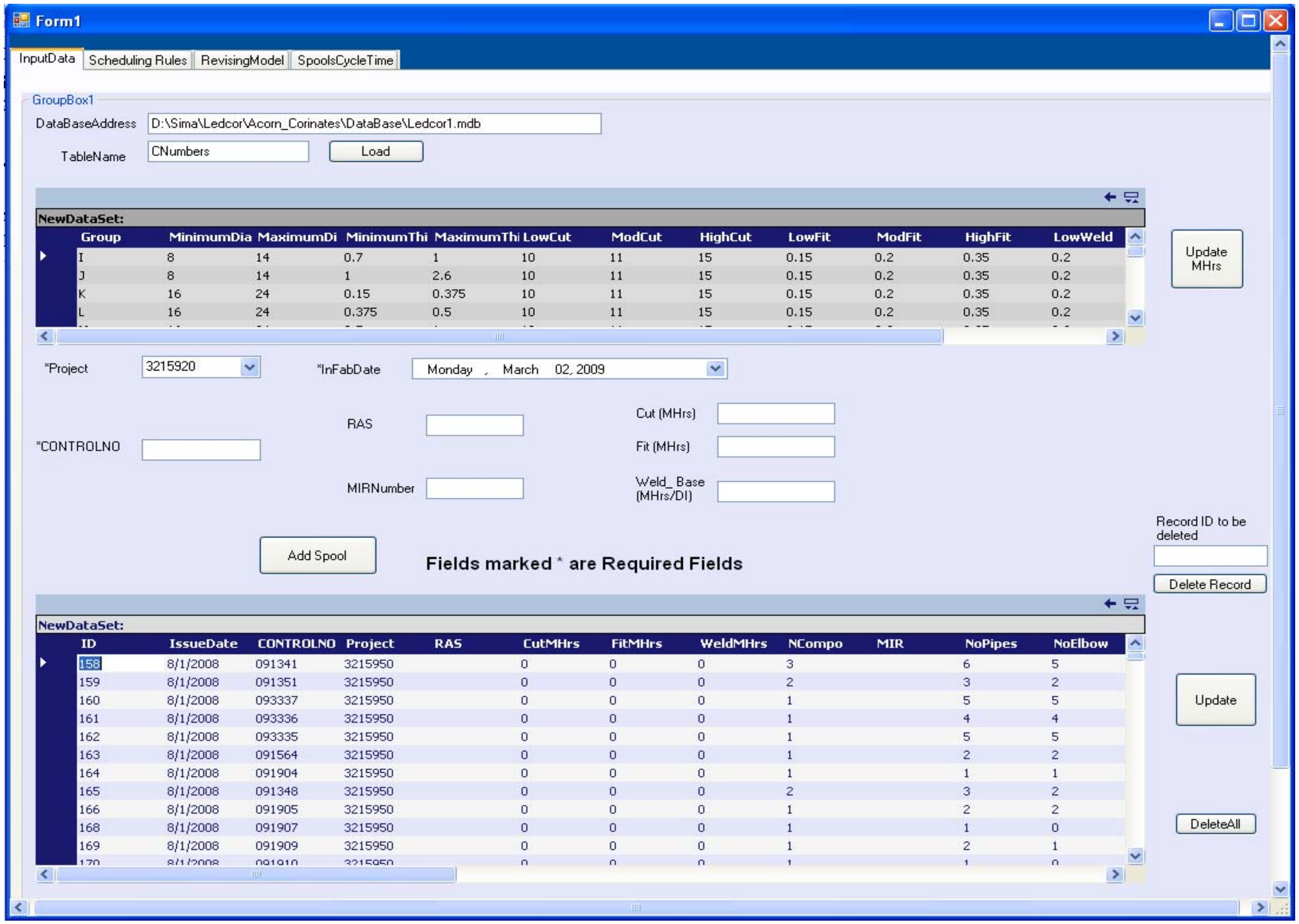


Figure 4.6 User interface for simulation model

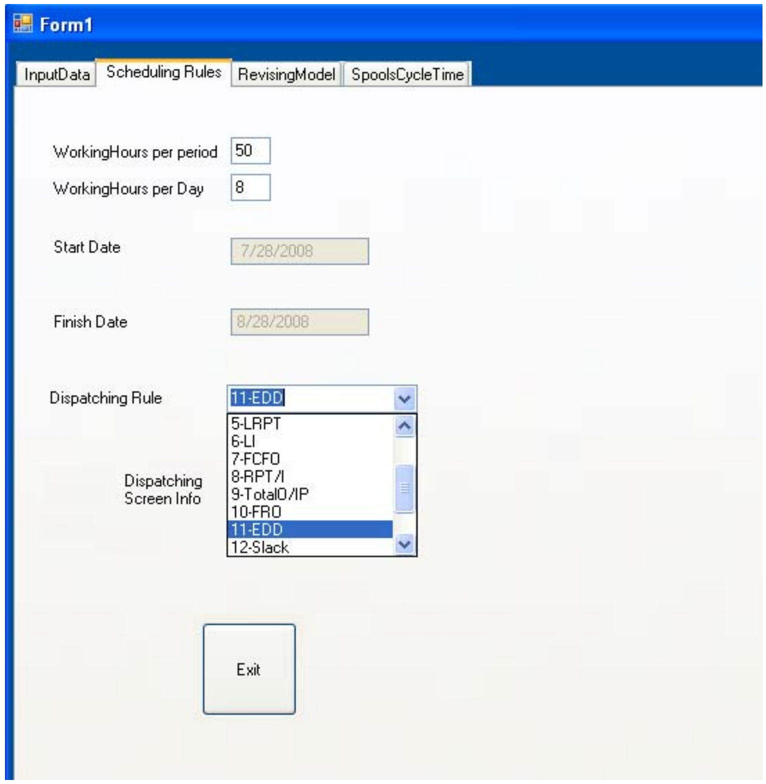


Figure 4.7 User interface for simulation model, selecting the scheduling rule

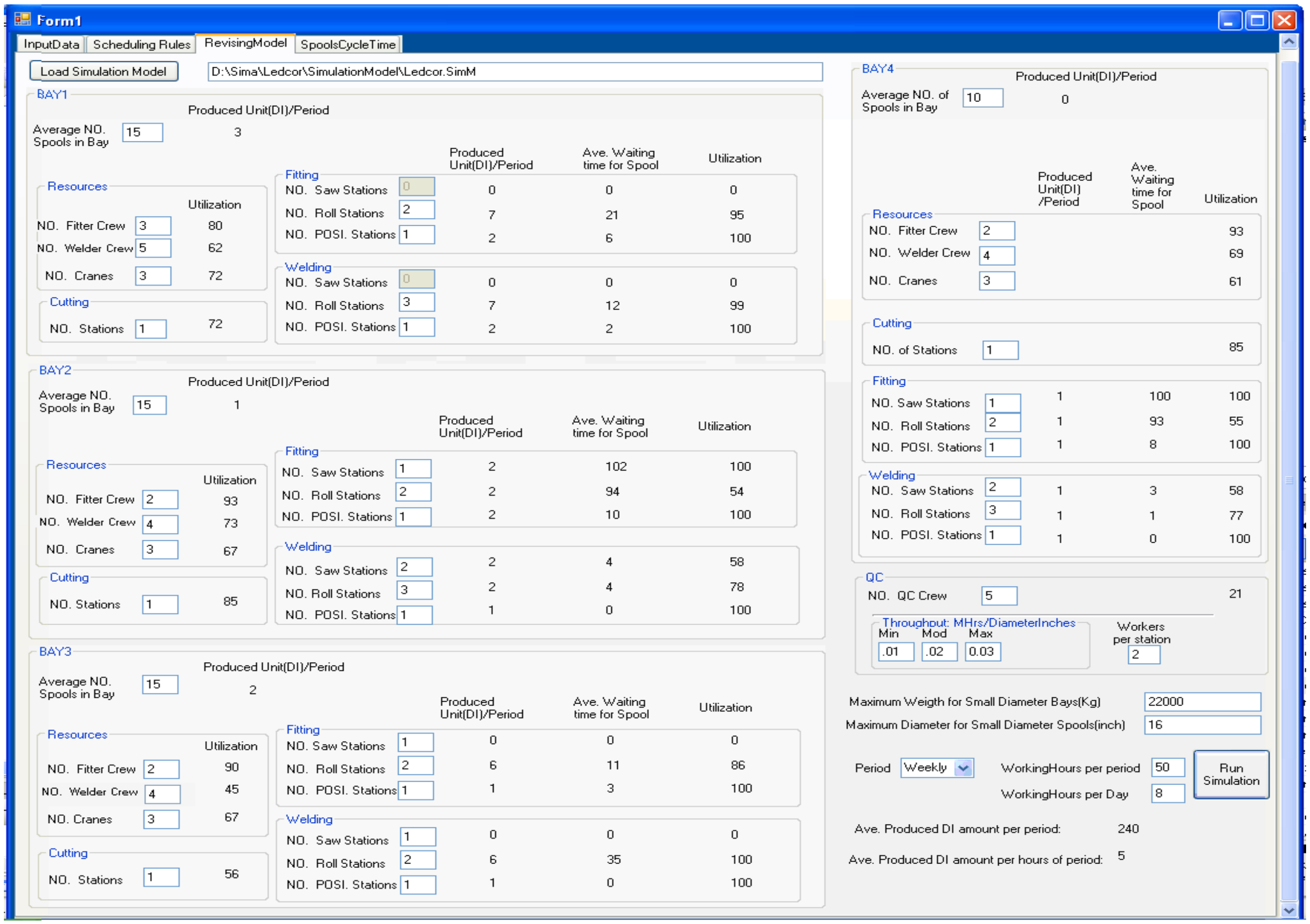
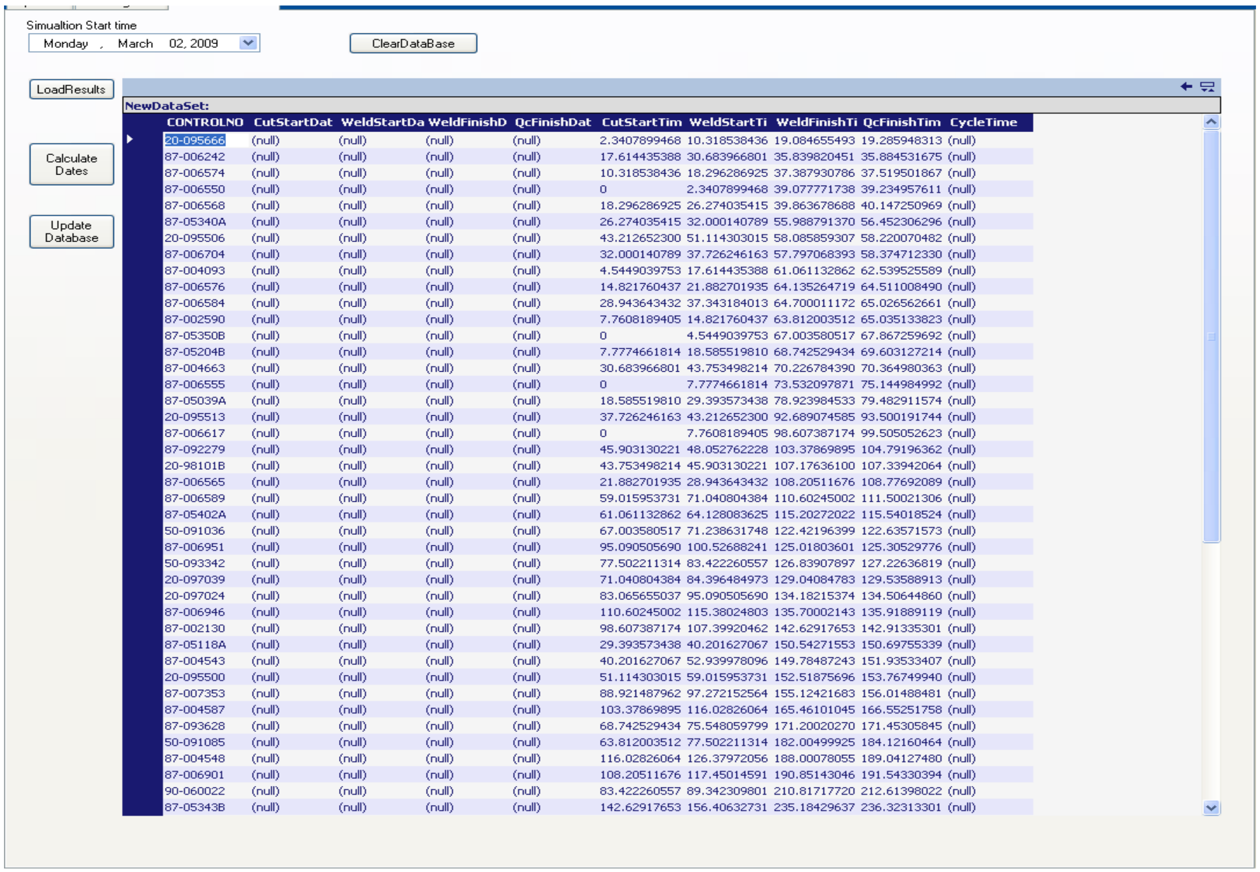


Figure 4.8 User interface for simulation model: revising the layout and shop configurations (inputs to simulation model)



CONTROLNO	CutStartDat	WeldStartDa	WeldFinishD	QcFinishDat	CutStartTim	WeldStartTi	WeldFinishTi	QcFinishTim	CycleTime
20-095666	(null)	(null)	(null)	(null)	2.3407899468	10.318538436	19.084655493	19.285948313	(null)
87-006242	(null)	(null)	(null)	(null)	17.614435388	30.683966801	35.839820451	35.884531675	(null)
87-006574	(null)	(null)	(null)	(null)	10.318538436	18.296286925	37.387930786	37.519501867	(null)
87-006550	(null)	(null)	(null)	(null)	0	2.3407899468	39.077771738	39.234957611	(null)
87-006568	(null)	(null)	(null)	(null)	18.296286925	26.274035415	39.863678688	40.147250969	(null)
87-05340A	(null)	(null)	(null)	(null)	26.274035415	32.000140789	55.988791370	56.452306296	(null)
20-095506	(null)	(null)	(null)	(null)	43.212652300	51.114303015	58.085859307	58.220070482	(null)
87-006704	(null)	(null)	(null)	(null)	32.000140789	37.726246163	57.797068393	58.374712330	(null)
87-004093	(null)	(null)	(null)	(null)	4.5449039753	17.614435388	61.061132862	62.539525589	(null)
87-006576	(null)	(null)	(null)	(null)	14.821760437	21.882701935	64.135264719	64.511008490	(null)
87-006584	(null)	(null)	(null)	(null)	28.943643432	37.343184013	64.700011172	65.026562661	(null)
87-002590	(null)	(null)	(null)	(null)	7.7608189405	14.821760437	63.812003512	65.035133823	(null)
87-05350B	(null)	(null)	(null)	(null)	0	4.5449039753	67.003580517	67.867259692	(null)
87-05204B	(null)	(null)	(null)	(null)	7.7774661814	18.585519810	68.742529434	69.603127214	(null)
87-004663	(null)	(null)	(null)	(null)	30.683966801	43.753498214	70.226784390	70.364980363	(null)
87-006555	(null)	(null)	(null)	(null)	0	7.7774661814	73.532097871	75.144984992	(null)
87-05039A	(null)	(null)	(null)	(null)	18.585519810	29.393573438	78.923984533	79.482911574	(null)
20-095513	(null)	(null)	(null)	(null)	37.726246163	43.212652300	92.689074585	93.500191744	(null)
87-006617	(null)	(null)	(null)	(null)	0	7.7608189405	98.607387174	99.505052623	(null)
87-092279	(null)	(null)	(null)	(null)	45.903130221	48.052762228	103.37869895	104.79196362	(null)
20-98101B	(null)	(null)	(null)	(null)	43.753498214	45.903130221	107.17636100	107.33942064	(null)
87-006565	(null)	(null)	(null)	(null)	21.882701935	28.943643432	108.20511676	108.77692089	(null)
87-006589	(null)	(null)	(null)	(null)	59.015953731	71.040804384	110.60245002	111.50021306	(null)
87-05402A	(null)	(null)	(null)	(null)	61.061132862	64.128083625	115.20272022	115.54018524	(null)
50-091036	(null)	(null)	(null)	(null)	67.003580517	71.238631748	122.42196399	122.63571573	(null)
87-006951	(null)	(null)	(null)	(null)	95.090505690	100.52688241	125.01803601	125.30529776	(null)
50-093342	(null)	(null)	(null)	(null)	77.502211314	83.422260557	126.83907897	127.22636819	(null)
20-097039	(null)	(null)	(null)	(null)	71.040804384	84.396484973	129.04084783	129.53588913	(null)
20-097024	(null)	(null)	(null)	(null)	83.065655037	95.090505690	134.18215374	134.50644860	(null)
87-006946	(null)	(null)	(null)	(null)	110.60245002	115.38024803	135.70002143	135.91889119	(null)
87-002130	(null)	(null)	(null)	(null)	98.607387174	107.39920462	142.62917653	142.91335301	(null)
87-05118A	(null)	(null)	(null)	(null)	29.393573438	40.201627067	150.54271553	150.69755339	(null)
87-004543	(null)	(null)	(null)	(null)	40.201627067	52.939978096	149.78487243	151.93533407	(null)
20-095500	(null)	(null)	(null)	(null)	51.114303015	59.015953731	152.51875696	153.76749940	(null)
87-007353	(null)	(null)	(null)	(null)	88.921487962	97.272152564	155.12421683	156.01488481	(null)
87-004587	(null)	(null)	(null)	(null)	103.37869895	116.02826064	165.46101045	166.55251758	(null)
87-093628	(null)	(null)	(null)	(null)	68.742529434	75.548059799	171.20020270	171.45305845	(null)
50-091085	(null)	(null)	(null)	(null)	63.812003512	77.502211314	182.00499925	184.12160464	(null)
87-004548	(null)	(null)	(null)	(null)	116.02826064	126.37972056	188.00078055	189.04127480	(null)
87-006901	(null)	(null)	(null)	(null)	108.20511676	117.45014591	190.85143046	191.54330394	(null)
90-060022	(null)	(null)	(null)	(null)	83.422260557	89.342309801	210.81717720	212.61398022	(null)
87-05343B	(null)	(null)	(null)	(null)	142.62917653	156.40632731	235.18429637	236.32313301	(null)

Figure 4.9 User interface for simulation model: cycle time for each spool

4.2.5 Validation of Simulation Model

After developing any simulation model or tool, that simulation model or tool should be validated. In this study, the validation of the model was performed using 802 spools from the company's database. The percentage error of the simulation model was calculated by comparing the estimated average spools' cycle time by the simulation model with the actual spools' average cycle time collected from the fabrication material tracking system. Equation 4.2 is used to calculate the percentage error of the simulation model.

$$\text{Average Error\%} = \frac{\sum_{1}^{n}\left(\frac{C_{Actual} - C_{\text{Predicted}}}{C_{Actual}}\right)\times 100}{n} \qquad \text{(Equation 4.2)}$$

Where, C_{Actual} is the actual average cycle time obtained from company's material tracking system, $C_{Predicted}$ is the average cycle time estimated by the simulation model, and n is number of spools. For validation of simulation model, earliest due date (EDD) is used for prioritizing and sequencing of spools in the model which is the same rule used in the actual shop. The average percentage error found using 802 spools was 4.5%, and the variance of errors was 3.1. The average cycle time estimated by the simulation model was shorter than the actual average cycle time.

The simulation model can also be validated by comparing estimated produced work units by the simulation model with actual produced work unit of the shop in a specific period of the time. The model was run for a period of time (a month), and the estimated weekly produced units were compared to the actual weekly produced units that were obtained from the company's weekly production reports. The percentage error was calculated using Equation 4.3.

$$\text{Error\%} = \frac{\sum_{i=1}^{n} \left| \frac{\text{Actual}_{\text{i}} \text{ - Predicted}_{\text{i}}}{\text{Actual}_{\text{i}}} \right|}{n} \times 100 \qquad \text{Equation 4.3}$$

Where, Actual is the actual weekly produced units in the shop; Predicted is the weekly produced units estimated by the simulation model, i is equal to the individual week number, and *n* equals the total number of weeks. The percentage error obtained from Equation 4.3 was 4.1%, which is acceptable.

The possible explanation for this discrepancy is that the rework was not simulated. In addition, it was assumed that all materials and drawings of the spools issuing to the shop are available, whereas sometimes, there are material shortages and changes in the drawings in reality. Furthermore, the simulation model cannot model many dynamic changes of the shop floor, such as rush orders or shop managers' decisions. As explained in chapter 2, the simulation model can be improved busing following developments:

- The percentage of rework is not modeled in the current study due to lack of information for rework. One of the further developments of the model could include modeling rework in simulation studies using probabilistic distributions in the simulation model.

- The productivity values used for calculating the duration of activities are obtained from estimation department which is not accurate. Additional data collections, such as time study, must be

- Because the spool fabrication shop is labour-intensive, productivity is highly affected by the skill of the labourers in the shop. Since the skill of labourers is a subjective factor, a fuzzy expert system is one of the best models for calculating productivity, because it is capable of considering both qualitative and quantitative factors in estimating productivity. The important factors that affect the productivity of pipe spool fabrication processes are introduced in Chapter 2. These factors can be used to developed fuzzy rules based on experts' judgment to develop a fuzzy expert system for determining the productivity of pipe spool fabrication processes.

4.2.6 Experimenting with Different Scheduling Rules

The performance of different heuristic rules for a two week schedule is shown in Table 4.3, as an example. The values used in Table 4.3 are not the actual numbers from the experiment, due to the confidentiality issue. The heuristic rules used in Table 4.3 are explained in Chapter 2. As shown in Table 4.3, EDD reduces the maximum tardiness, average tardiness, and number of tardy jobs, while SI reduces the average flow time and increases the weekly production of the shop. Usually, the criteria related to tardiness, such as maximum tardiness and average tardiness, are more important to the shop managers because of the importance of customer satisfaction. However, when the shop is heavily loaded with several projects, reducing the flow time would be of interest.

Table 4.3 Sample Results of Scheduling Heuristic for Two Weeks

Heuristic Rule	Average Flow time (Hr)	Make- Span (Hr)	Max Tardiness (Hr)	Number of Tardy Jobs	Total Tardiness (Hr)	Total Earliness (Hr)	Average Resource Utilization (%)	Average weekly Produced work units (Diameter Inches)
SRPT	13	89	47	4	186	8177	94	**5416**
SI	**13**	86	44	4	177	8187	**94**	**5416**
LPT	50	82	70	18	596	6316	91	4456
LRPT	50	82	62	18	599	6312	92	4456
LI	54	85	58	19	709	6223	94	4456
FCFO	22	77	61	9	297	7740	92	5216
RPT/I	18	89	61	6	231	7945	87	3816
TotalO/IP	53	85	58	19	710	6272	91	3816
FRO	22	88	58	10	216	7648	87	3880
EDD	33	**77**	**21**	**5**	**54**	6804	90	3816
Slack	44	82	23	4	304	6404	93	3816
Slack / OPN	45	82	29	14	304	6361	92	3840
Slack / TotalP	51	82	53	20	538	6218	93	3816

4.3 Implementation of Multi-Criteria Scheduling Framework on the Case Study

In this section, the multi-criteria scheduling framework described in Chapter 3 is implemented on the case study. According to the Operations Manager of the spool fabrication shop, the maximum tardiness and average flow time are usually the most important criteria in the fabrication shop. Since the cost of storage does not have a remarkable effect on the total cost of the projects, the earliness is not considered in the scheduling of this case study. As discussed in Chapter 3, the average flow time, average resource utilization, and number of tardy jobs are correlated with each other and can be improved simultaneously. Also, The make-span, maximum tardiness, total tardiness, and mean tardiness of the pipe spool fabrication shop can be improved simultaneously. Therefore, by addressing average flow time and maximum tardiness, other criteria improve at the same time, although they are not as important as the two selected criteria. Combinatorial dispatching rules are used in this case study, which are described in Chapter 3. Using the dispatching rules introduced in Chapter 3, three hundred rules are constructed to be used in this framework. Thirty scenarios are generated by selecting random sets of spool from the fabrication shop database for different time horizons, e.g. the first week of August or second week of August, to experiment with the rules and implement the framework.

As discussed in Chapter 3, for each scenario a set of candidate dispatching rules is obtained. The candidate dispatching rules are the rules that are in the Pareto-optimal set when running each scenario. A program is developed in VB.Net to automatically run a simulation model for every scenario and export the performance value of criteria into an Excel sheet. The flow chart of the program is shown in Figure 4.10.

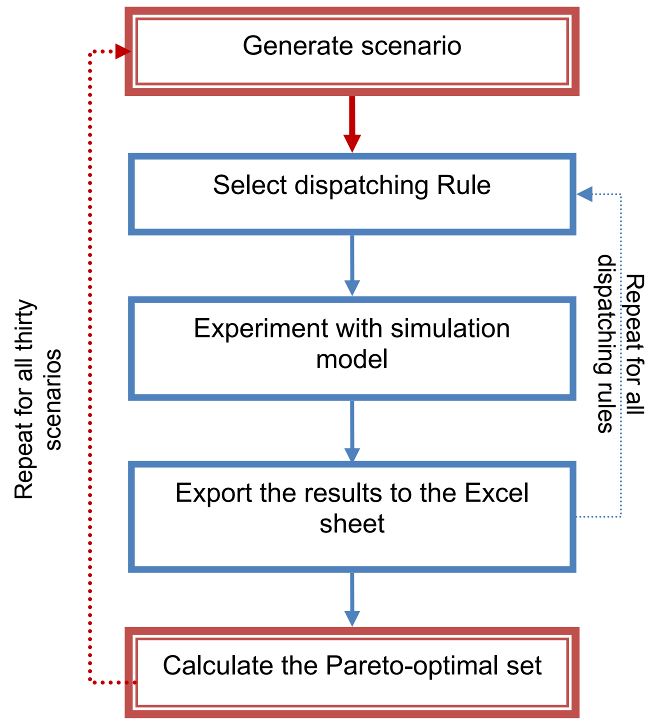


Figure 4.10 The process of identifying the Pareto optimal set for case study

The results of the first scenario are shown in Figure 4.11. In Figure 4.11, the each criterion is marked by 'Yes' or 'No'; if it is marked as 'Yes,' the criterion is considered in calculating the Pareto-optimal set. By clicking on the calculate button, the Pareto optimal set is calculated based on the selected criteria. If a dispatching rule is Pareto-optimal, the corresponding cell is changed to '1'. Also the performance values are fizzified in terms of satisfaction degree using Equation 3.11 and Equation 3.12, which are introduced in Chapter 3.

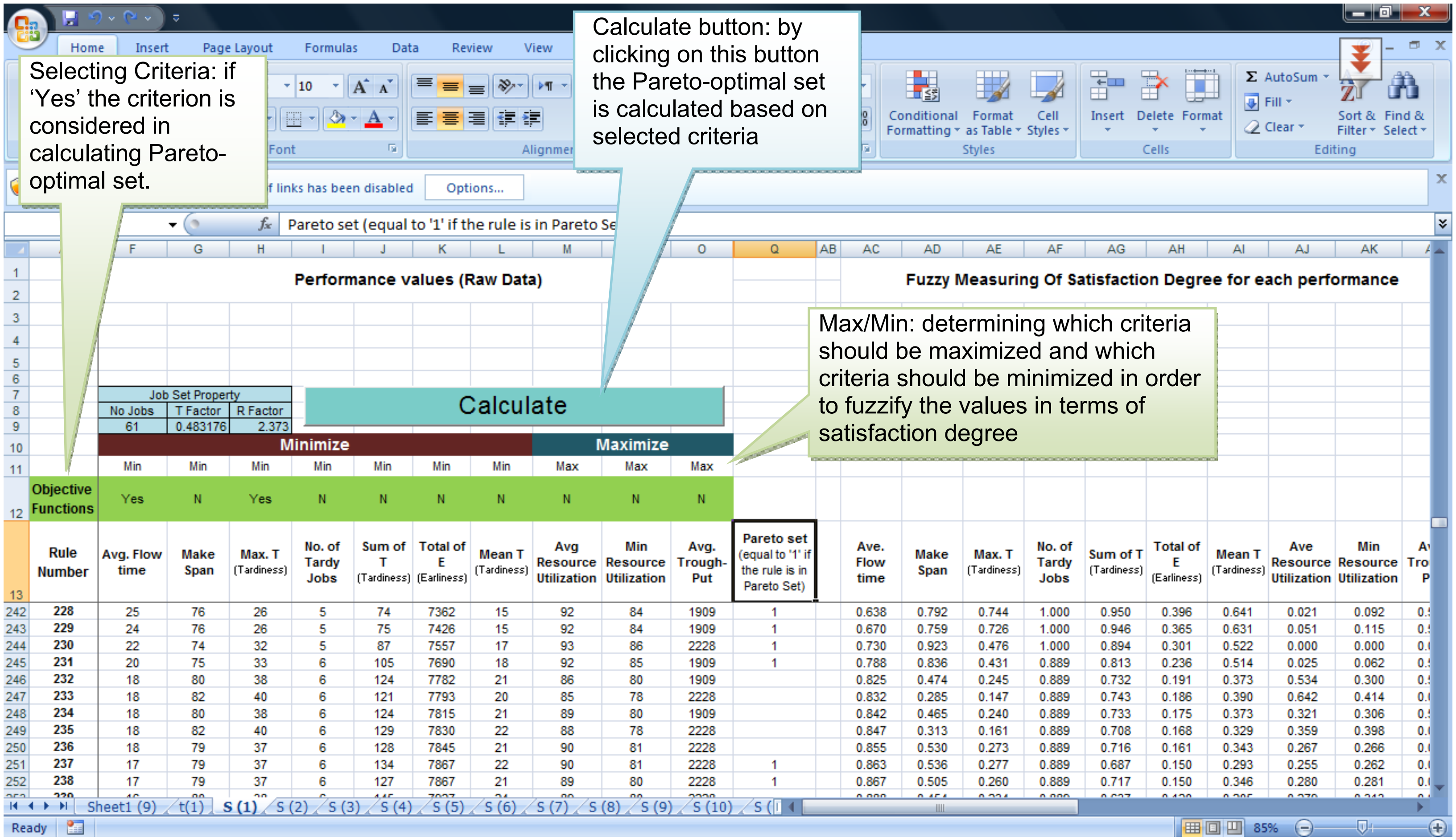
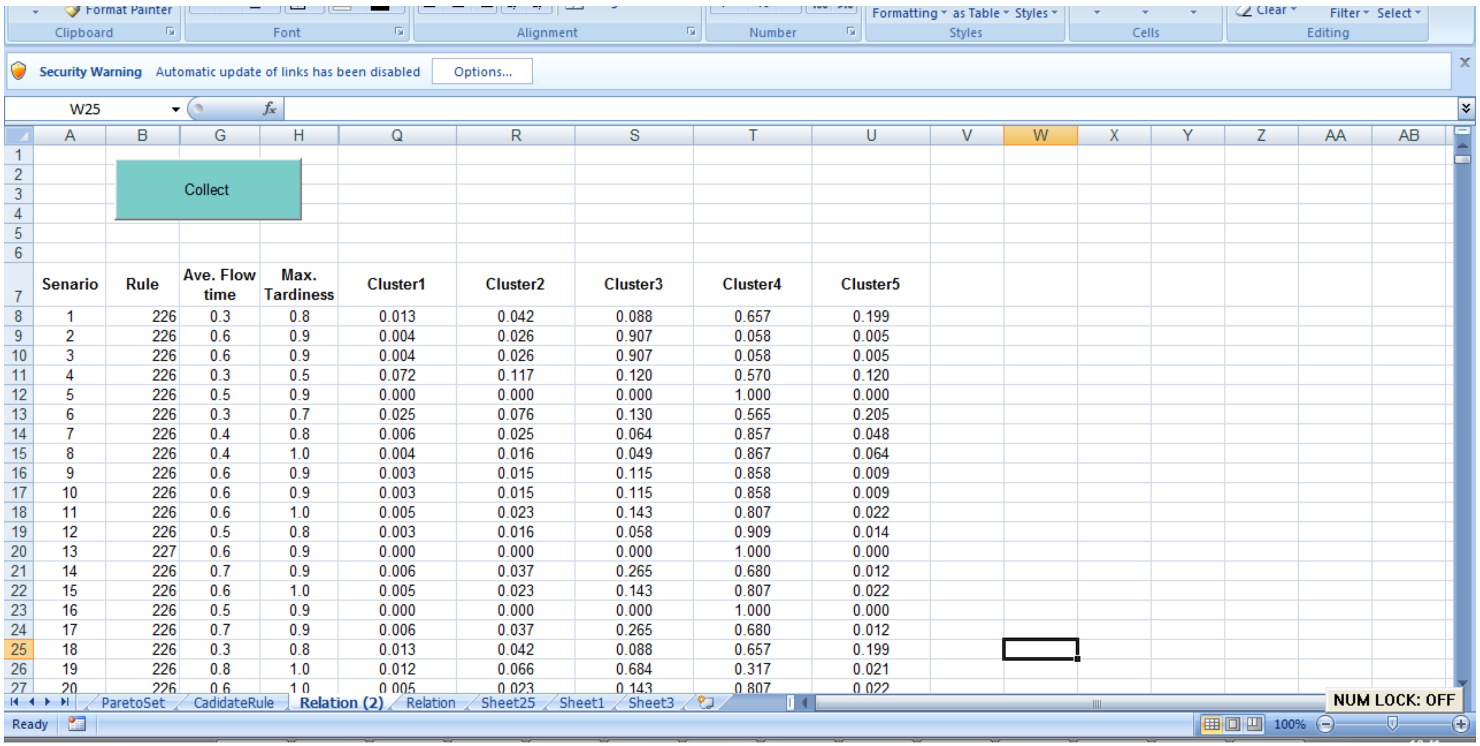


Figure 4.11 Performance values of different dispatching rules for the first scenario

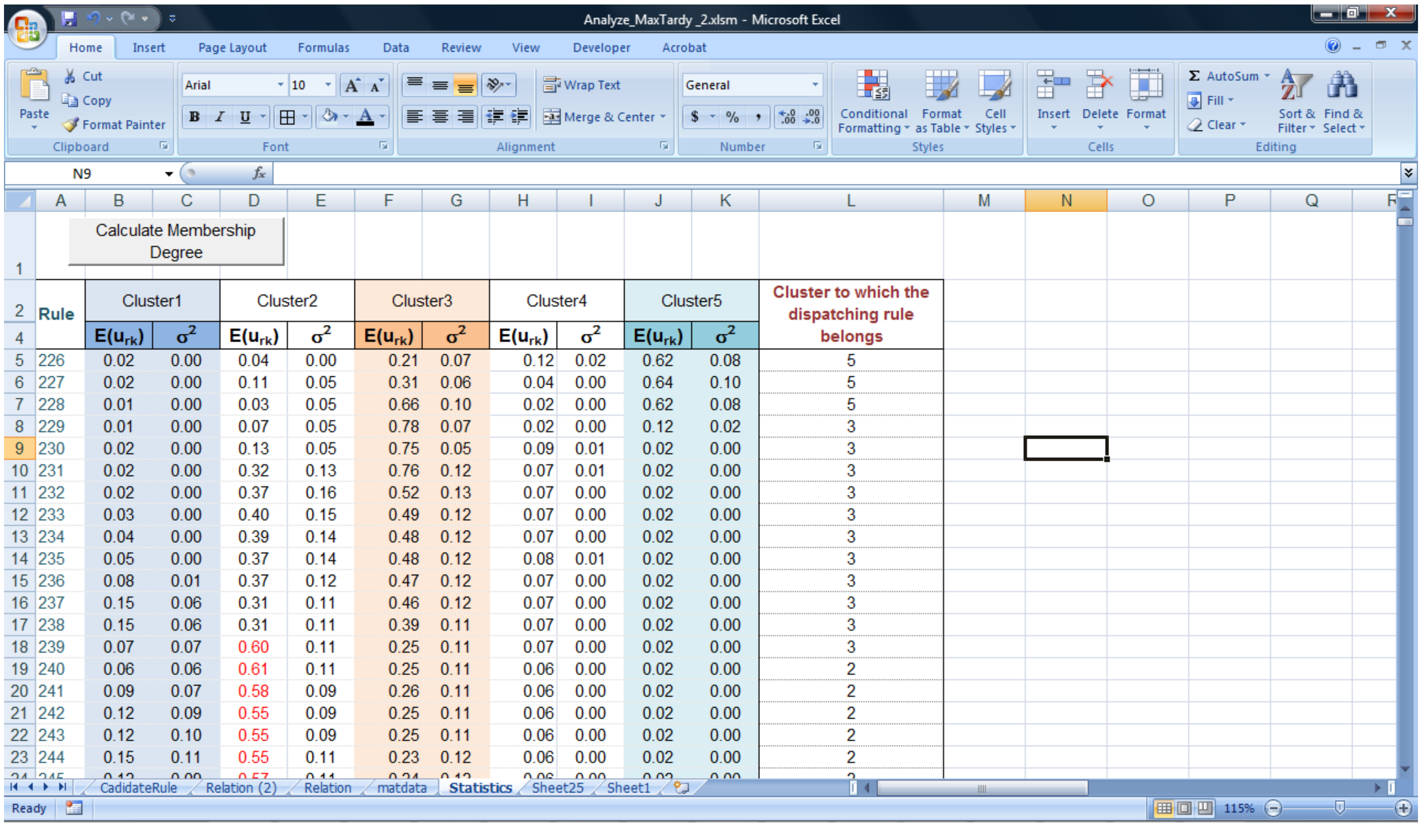
Figure 4.12 shows the performance values of different dispatching rules for all scenarios, which are automatically collected from multiple spreadsheets by clicking on 'Collect'. The data set then is used in MATLAB for Fuzzy C-Means clustering (FCM). Next, the membership degree of every data point to each trade-off area (cluster) is exported to the Excel sheet, which is shown in Figure 4.13. The expected membership degree of each cluster then is calculated according to Equation 3.27, which is described in Chapter 3.



Senario	Rule	Ave. Flow time	Max. Tardiness	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
1	226	0.3	0.8	0.013	0.042	0.088	0.657	0.199
2	226	0.6	0.9	0.004	0.026	0.907	0.058	0.005
3	226	0.6	0.9	0.004	0.026	0.907	0.058	0.005
4	226	0.3	0.5	0.072	0.117	0.120	0.570	0.120
5	226	0.5	0.9	0.000	0.000	0.000	1.000	0.000
6	226	0.3	0.7	0.025	0.076	0.130	0.565	0.205
7	226	0.4	0.8	0.006	0.025	0.064	0.857	0.048
8	226	0.4	1.0	0.004	0.016	0.049	0.867	0.064
9	226	0.6	0.9	0.003	0.015	0.115	0.858	0.009
10	226	0.6	0.9	0.003	0.015	0.115	0.858	0.009
11	226	0.6	1.0	0.005	0.023	0.143	0.807	0.022
12	226	0.5	0.8	0.003	0.016	0.058	0.909	0.014
13	227	0.6	0.9	0.000	0.000	0.000	1.000	0.000
14	226	0.7	0.9	0.006	0.037	0.265	0.680	0.012
15	226	0.6	1.0	0.005	0.023	0.143	0.807	0.022
16	226	0.5	0.9	0.000	0.000	0.000	1.000	0.000
17	226	0.7	0.9	0.006	0.037	0.265	0.680	0.012
18	226	0.3	0.8	0.013	0.042	0.088	0.657	0.199
19	226	0.8	1.0	0.012	0.066	0.684	0.317	0.021
20	226	0.6	1.0	0.005	0.023	0.143	0.807	0.022

Figure 4.12 Performance values of different dispatching rules for all scenarios

Figure 4.13 shows the spreadsheet that contains the expected membership value of each dispatching rule to every cluster. The expected membership value is used to determine the cluster to which a dispatching rule belongs. Furthermore, the expected membership value determines the proximity of a dispatching rule to the center of a cluster, which represents an area on the Pareto-optimal frontier, where the satisfaction of every objective function or criterion is associated with a linguistic value, which is shown in Table 4.4. Therefore, the higher value of expected membership indicates that the performance of the corresponding dispatching rule is closer to the linguistic description of the cluster. On the other hand, the variance of the membership degree refers to the robustness of the dispatching rule, which indicates the consistency of the performance of the dispatching rule in different scenarios. Therefore, the ideal situation for each trade-off area is selecting the dispatching rule with the highest expected membership value and the lowest variance. High expected membership value indicates that the possibility that the rule fits the linguistic description is high, and therefore it shows that the corresponding rule satisfies the linguistic preference of the decision makers.



Calculate Membership Degree

Rule	Cluster1 E(u_rk)	Cluster1 σ^2	Cluster2 E(u_rk)	Cluster2 σ^2	Cluster3 E(u_rk)	Cluster3 σ^2	Cluster4 E(u_rk)	Cluster4 σ^2	Cluster5 E(u_rk)	Cluster5 σ^2	Cluster to which the dispatching rule belongs
226	0.02	0.00	0.04	0.00	0.21	0.07	0.12	0.02	0.62	0.08	5
227	0.02	0.00	0.11	0.05	0.31	0.06	0.04	0.00	0.64	0.10	5
228	0.01	0.00	0.03	0.05	0.66	0.10	0.02	0.00	0.62	0.08	5
229	0.01	0.00	0.07	0.05	0.78	0.07	0.02	0.00	0.12	0.02	3
230	0.02	0.00	0.13	0.05	0.75	0.05	0.09	0.01	0.02	0.00	3
231	0.02	0.00	0.32	0.13	0.76	0.12	0.07	0.01	0.02	0.00	3
232	0.02	0.00	0.37	0.16	0.52	0.13	0.07	0.00	0.02	0.00	3
233	0.03	0.00	0.40	0.15	0.49	0.12	0.07	0.00	0.02	0.00	3
234	0.04	0.00	0.39	0.14	0.48	0.12	0.07	0.00	0.02	0.00	3
235	0.05	0.00	0.37	0.14	0.48	0.12	0.08	0.01	0.02	0.00	3
236	0.08	0.01	0.37	0.12	0.47	0.12	0.07	0.00	0.02	0.00	3
237	0.15	0.06	0.31	0.11	0.46	0.12	0.07	0.00	0.02	0.00	3
238	0.15	0.06	0.31	0.11	0.39	0.11	0.07	0.00	0.02	0.00	3
239	0.07	0.07	0.60	0.11	0.25	0.11	0.07	0.00	0.02	0.00	3
240	0.06	0.06	0.61	0.11	0.25	0.11	0.06	0.00	0.02	0.00	2
241	0.09	0.07	0.58	0.09	0.26	0.11	0.06	0.00	0.02	0.00	2
242	0.12	0.09	0.55	0.09	0.25	0.11	0.06	0.00	0.02	0.00	2
243	0.12	0.10	0.55	0.09	0.25	0.11	0.06	0.00	0.02	0.00	2
244	0.15	0.11	0.55	0.11	0.23	0.12	0.06	0.00	0.02	0.00	2

Figure 4.13 The expected membership value of each dispatching rule to every cluster

In Table 4.4, μ(Average Flow Time) and μ(Maximum Tardiness) indicate the satisfaction degree associated with the linguistic variables, which describes the performance of the corresponding rules . For example, the performance of rules in cluster 1 is good with respect to average flow time and poor with respect to maximum tardiness. The satisfaction degree of ‘1’ indicates full satisfaction, or a linguistic term of “good” performance. The satisfaction degree of ‘0’ represents no satisfaction, or a linguistic term of “poor” performance.

Table 4.4 Linguistic Description of Each Trade-off Area and the Prototypes of Each Cluster

Cluster		1	2	3	4	5
Linguistic Trade-off area	**Average Flow Time**	Good	Fairly Good	Acceptable	Fairly Poor	Poor
	Maximum Tardiness	Poor	Fairly Poor	Acceptable	Fairly Good	Good
μ(Average Flow Time)		1.00	0.85	0.75	0.40	0.00
μ(Maximum Tardiness)		0.00	0.40	0.75	0.85	1.00

Table 4.5 shows the selected rules for each cluster. $E(u_{rk})$ in Table 4.5 refers to the expected membership value of dispatching rule ‘r’ to the kth cluster. Table 4.5 includes the linguistic value of the performance of the selected rules. Based on the results of Table 4.5, the user can select the appropriate rules in the user interface of the simulation model, which was shown in Figure 4.7, to generate the schedule of the fabrication shop. The appropriate rule is selected by the decision maker

using the linguistic description given in Table 4.5. The decision maker may consider the variance and expected membership value to determine how well the rule fits the linguistic description, and how robust the performance of rule is in different scenarios.

As explained in Chapter 3, in the first step of decision making, the decision maker selects a trade-off area (cluster) using Table 4.4. Then the decision maker chooses an appropriate rule from the corresponding group of dispatching rules by comparing their expected membership values and variances. The expected membership degree is used to rank the dispatching rules based on how well they fit the corresponding linguistic description, while the variance is used to rank the dispatching rules regarding the robustness and the confidence level of their performance.

For example, if the decision maker selects “fairly poor-fairly good” (cluster 4) as the trade off area from Table 4.4, the decision maker can select rules 372, 376, 422, from Table 4.6. The decision maker can select either the rule with highest expected membership value, rule 376, or the rule with the lowest variance, rule 422 or rule 372, based on his/her preferences. The higher expected membership value is equivalent to a better match between the performance of the rule and the corresponding linguistic descriptions, while the lower variance is equivalent to greater confidence that the performance of the rule will match the linguistic descriptions.

Table 4.5 Linguistic Performance of the Selected Dispatching Rules

Rule (*r*)	**Average Flow Time**	**Maximum Tardiness**	**Cluster (*k*)**	**Expected Membership Value $E(u_{rk})$**	**Variance (σ^2)**
253	Good	Poor	1	0.55	0.18
263	Good	Poor	1	0.61	0.20
282	Good	Poor	1	0.64	0.22
290	Good	Poor	1	0.63	0.21
291	Good	Poor	1	0.63	0.21
292	Good	Poor	1	0.61	0.20
308	Good	Poor	1	0.52	0.15
245	Fairly Good	Fairly Poor	2	0.57	0.11
246	Fairly Good	Fairly Poor	2	0.57	0.11
247	Fairly Good	Fairly Poor	2	0.55	0.11
249	Fairly Good	Fairly Poor	2	0.52	0.10
310	Fairly Good	Fairly Poor	2	0.44	0.16
358	Fairly Good	Fairly Poor	2	0.33	0.08
408	Fairly Good	Fairly Poor	2	0.33	0.08
229	Acceptable	Acceptable	3	0.78	0.07
230	Acceptable	Acceptable	3	0.75	0.05
231	Acceptable	Acceptable	3	0.56	0.12
363	Acceptable	Acceptable	3	0.58	0.12
364	Acceptable	Acceptable	3	0.60	0.09
366	Acceptable	Acceptable	3	0.65	0.09
413	Acceptable	Acceptable	3	0.58	0.12
416	Acceptable	Acceptable	3	0.65	0.09
417	Acceptable	Acceptable	3	0.55	0.09
372	Fairly Poor	Fairly Good	4	0.74	0.06
376	Fairly Poor	Fairly Good	4	0.76	0.07
422	Fairly Poor	Fairly Good	4	0.74	0.06
226	Poor	Good	5	0.62	0.02
227	Poor	Good	5	0.64	0.00
228	Poor	Good	5	0.62	0.00
350	Poor	Good	5	0.66	0.09
395	Poor	Good	5	0.55	0.10
398	Poor	Good	5	0.68	0.10
445	Poor	Good	5	0.71	0.10
448	Poor	Good	5	0.69	0.10

Table 4.7 shows the performance of selected rules with respect to different criteria for pipe spool fabrication shop. The values shown in the table are factored due to the confidentiality issues. As shown in the table the productivity of the shop (diameter inches per week) can be most improved by minimizing average flow time using rules in cluster 1. Also, the maximum tardiness of spools can be most improved using the rules in cluster 5. For example, using rule 253 in cluster 1, the average productivity of the shop can be improved by 23% , as shown in Equation 4.4, comparing to the results of current heuristic rule used in the shop, earliest due date (EDD).

$$\text{Improvement } \% = \frac{2959 - 2403}{2403} \times 100 = 23\% \qquad \text{(Equation 4.4)}$$

Consequently, the productivity of shop can be improved by 556 diameter inches per week (Equation 4.5). Assuming that completing one diameter inches takes 0.5 man-hours, the total saving in man-hours would be 278 hours in a week (Equation 4.6).

$$\text{Improvement } (DI/week) = 2959 - 2403 = 556 \qquad \text{(Equation 4.5)}$$

$$\text{Total Saving } (man - hours/week) = 556 \times 0.5 = 278 \qquad \text{(Equation 4.6)}$$

In Equation 4.5, DI refers to diameter inches, which is spool fabrication shop's work unit.

Table 4.6 Performance of the Selected Dispatching Rules for the Case Study

Rule	Cluster	$E(\mu(\text{Avg. Flow Time}))$	$E(\mu(\text{max. Tardiness}))$	Avg. Flow time (days)	Max. Tardiness (days)	Avg. Productivity (diameter inches/week)
EDD		-	-	69	25	2403
SPT		-	-	39	32	2527
253	1	0.89	0.34	8	12	2959
263	1	0.91	0.3	8	13	2973
282	1	0.92	0.46	7	10	2980
290	1	0.92	0.45	7	10	2980
291	1	0.92	0.45	7	10	2980
292	1	0.92	0.35	7	12	2980
308	1	0.92	0.58	7	8	2980
245	2	0.9	0.63	8	7	2966
246	2	0.9	0.63	8	7	2966
247	2	0.87	0.6	8	8	2944
249	2	0.82	0.57	9	8	2908
310	2	0.89	0.5	8	9	2959
358	2	0.8	0.6	9	8	2893
408	2	0.89	0.6	8	8	2959
229	3	0.72	0.76	10	5	2835
230	3	0.66	0.73	11	5	2792
231	3	0.87	0.7	8	6	2944
363	3	0.72	0.7	10	6	2835
364	3	0.78	0.81	9	4	2879
366	3	0.74	0.85	10	4	2850
413	3	0.72	0.7	10	6	2835
416	3	0.74	0.8	10	4	2850
417	3	0.72	0.77	10	5	2835
340	4	0.54	0.9	12	3	2705
370	4	0.64	0.9	11	3	2777
372	4	0.58	0.9	12	3	2734
376	4	0.5	0.88	13	3	2676
422	4	0.58	0.9	12	3	2734
423	4	0.56	0.89	12	3	2719
426	4	0.5	0.88	13	3	2676
226	5	0.51	0.89	13	3	2683
227	5	0.64	0.91	11	2	2777
228	5	0.69	0.9	10	3	2814
350	5	0.5	0.88	13	3	2676
395	5	0.06	0.95	19	2	2357
398	5	0.02	0.97	19	1	2328
445	5	0.06	0.96	19	2	2357
448	5	0.02	0.97	19	1	2328

4.3.1 Validation of the Results

The results of implementing the multi-criteria scheduling framework shown in Table 4.5 and Table 4.6 are obtained through generating different scenarios, i.e. random sets of spools, and applying dispatching rules on these scenarios. Therefore, the results may be sensitive to the attributes of the generated scenarios. To verify the extent of such sensitivity a validation is required. For validation of the presented results, ten scenarios were generated by selecting random spools as testing scenarios. The selected dispatching rules shown in Table 4.6 were performed on the testing scenarios using the simulation model. The membership value of each dispatching rule to the corresponding trade-off area was calculated and compared to the expected membership value in Table 4.8. The average percentage of error for each dispatching rule (e_r %) is calculated using Equation 4.7.

$$e_r\% = \frac{\sum_{1}^{n}\left|E(u_{rk}) - u_{rk}^{j}\right|}{n} \qquad \text{(Equation 4.7)}$$

Where, $E(u_{rk})$ is the expected membership value of rth dispatching rule to the kth cluster based on Table 4.6, u_{rk}^{j} is the actual membership value calculated for jth scenario, and n is number of scenarios. The results are shown in Table 4.8. As shown in Table 4.8, the average error is 2.7%, which means that in average the membership value of each dispatching rule to each cluster is different from the expected membership values by 2.7% percent. The maximum error is 7.3%, and the percentage of mis-clustered dispatching rules for the validation data is 5%, which means that the linguistic terms assigned to 5% of dispatching rules are different for the validation scenarios.

Table 4.7 Validation Results

Rule (r)	**Original results**	**Validation Results**	e_r**%**	**Original results**	**Validation Results**
	$E(u_{rk})$	$Ave.(u_{rk})$		**Cluster**	**Cluster**
253	0.55	0.51	5.8	1	1
263	0.61	0.62	1.6	1	1
282	0.64	0.67	4.5	1	1
290	0.63	0.59	6.8	1	1
291	0.63	0.60	5.0	1	1
292	0.61	0.60	1.7	1	1
308	0.52	0.50	4.0	1	1
245	0.57	0.60	5.0	2	2
246	0.57	0.55	3.6	2	2
247	0.55	0.53	3.8	2	2
249	0.52	0.54	3.7	2	2
310	0.44	0.47	7.3	2	1
358	0.33	0.36	5.7	2	2
408	0.33	0.32	3.1	2	2
229	0.78	0.76	2.6	3	3
230	0.75	0.74	1.4	3	3
231	0.56	0.57	1.8	3	3
363	0.58	0.60	3.3	3	3
364	0.60	0.58	3.4	3	3
366	0.65	0.66	1.5	3	3
413	0.58	0.59	1.7	3	3
416	0.65	0.65	0.0	3	3
417	0.55	0.55	0.0	3	3
340	0.69	0.67	3.0	4	4
370	0.56	0.55	1.8	4	4
372	0.74	0.79	6.3	4	4
376	0.76	0.77	1.3	4	4
422	0.74	0.76	2.6	4	4
423	0.75	0.74	1.4	4	4
426	0.76	0.76	0.0	4	4
226	0.62	0.63	1.6	5	5
227	0.64	0.65	1.5	5	5
228	0.62	0.62	0.0	5	5
350	0.66	0.67	1.5	5	4
395	0.55	0.56	1.8	5	5
398	0.68	0.68	0.0	5	5
445	0.71	0.70	1.4	5	5
448	0.69	0.70	1.4	5	5
Error	Average Error (%)		2.7	Percentage of Mis-Clustered Data (%)	5%
	Maximum Error (%)		7.3		

4.4 Conclusion

This chapter presents the implementation of the scheduling frameworks on a pipe spool fabrication shop in Edmonton, Alberta as a case study. Firstly, the simulation-based scheduling framework developed in Chapter 2 was implemented in the case study. An executable toolkit was created for simulation-based scheduling of the pipe spool fabrication shop using VB.Net programming. The model was validated using the data collected from company's database and productivity reports. The error of the model was calculated by comparing the actual weekly production of the case study to the weekly production estimated by the simulation model. The error of the model was 4.1%, which is acceptable. Moreover, the average error of estimating cycle time of the spools, calculated using 802 spools, was 4.5%.

Furthermore, the multi-criteria scheduling framework developed in Chapter 3 was implemented on the same case study. Through this framework, appropriate dispatching rules for optimizing two objective functions, i.e. minimizing average flow time and maximum tardiness, were identified. By means of Fuzzy C-Means clustering, the dispatching rules were linked to the objective functions through fuzzy rules. The results were validated by comparing the performance of the selected dispatching rules on the test data with the expected performance, which was estimated by the model. The average error obtained from validation was 2.7%, which is acceptable for the pipe spool fabrication shop.

4.5 References

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CHAPTER 5 - Conclusions

5.1 Research Summary

Industrial fabrication has a great impact on construction projects through reducing time and cost of the projects due to decreased uncertainty in a controlled environment. Therefore, the success of a project depends on effective planning and scheduling of the industrial fabrication process. Today's complex shop environments, diverse products, and many potential influencing factors make it difficult for the human mind to process the information required for an accurate analysis of such a production system. Therefore, developing a scheduling technique to analyze and capture all these complexities would contribute to the better planning and scheduling of fabrication shops and consequently reduce the cost of the construction projects.

In this thesis, a new framework for optimizing industrial shop scheduling, specifically pipe spool fabrication shop scheduling, was developed. The methodology provides the opportunity to capture the uncertainty of the industrial shop, while coping with the linguistic vagueness of the decision makers' preferences by using simulation modeling and fuzzy set theory. Additionally, a scheduling toolkit was developed as a decision support system for the spool fabrication shop. This toolkit provides decision makers with the ability to select an appropriate scheduling solution based on fuzzy goals. The content of the thesis presents the process and outcomes of the performed research in three phases.

The first phase of the research, presented in Chapter 2 of this thesis, focuses on the development of an enhanced framework for simulation-based scheduling of industrial construction. The proposed framework is developed based on the integration of a relational database management system, product modeling, simulation modeling, and heuristic approaches to streamline the scheduling process of industrial fabrication shops, particularly pipe spool fabrication shops. In this phase, first, the concepts of production scheduling and the simulation modeling were reviewed. Next, the spool fabrication shop processes, stages that each spool should go through during the fabrication, the constraints and limitations of resources, and the configurations and constraints of the shop were identified. A product model was then developed for spools to identify jobs and model the spool fabrication processes. The product model was designed to incorporate the 3-D relational geometric attributes of the spools, the type and shape of the spool components, the relationship between the spool components, shop process information, and constraints of the shop. Subsequently, a set of heuristic rules were introduced for use in scheduling in the simulation model. Finally, a Special Purpose Simulation (SPS) template for pipe spool fabrication was developed in Simphony.Net©, which is an object-oriented environment for building SPS templates using VB.net programming language. The SPS template is connected to the central database to use the developed product model for generating the entities of the simulation model. The SPS template is also capable of incorporating different heuristic rules for the scheduling of the fabrication shop.

The second phase of the research, presented in Chapter 3 of this thesis, focuses on optimizing the scheduling of industrial fabrication. Given that real life industrial scheduling problems usually consist of multiple criteria, in this phase, a framework for optimization of the industrial shop scheduling with respect to multiple criteria was developed. Fuzzy set theory was used to linguistically assess different levels of satisfaction for the selected criteria. New combinatorial dispatching rules were established by combining and weighting multiple parameters, such as processing time, due date, and slack of the spools. The performance of each rule with respect to different criteria was estimated for different scenarios using the simulation model. Fuzzy membership functions were used to evaluate the satisfaction degree of each conflicting criterion, the value of which was estimated by the simulation model. The data set obtained from the simulation results for different scenarios was analyzed using the concept of Pareto-optimality and Fuzzy C-Means clustering (FCM). The linguistic trade-offs between the criteria were identified using the concepts of fuzzy set theory. In addition, FCM was used to categorize the performance values obtained from the simulation model for different scenarios. The probability and possibility analyses were performed on the results to identify the most efficient and robust rules for each linguistic trade-off between conflicting criteria.

The last phase of the research, presented in Chapter 4 of this thesis, focuses on developing a simulation-based scheduling model for a real case study. The multi-criteria scheduling framework proposed in phase 2 was implemented on the case study. A scheduling toolkit, which enables the decision maker to select an appropriate scheduling solution based on fuzzy goals, was developed as a decision support system for a spool fabrication shop. The toolkit has been developed using VB.NET and Simphony.Net as an underlying simulation environment. The validation of the simulation model and the proposed optimization methodology were performed in this phase using actual data. Comparison of the results showed an acceptable accuracy of the outputs of the simulation model and the multi-criteria scheduling framework.

5.2 Research Contributions

This thesis introduces a framework for micro-modeling of pipe spool fabrication processes at the operational level. The methodology incorporates the relational geometry of the spools at different levels of the product model. The processing time of each activity can be calculated accurately because of the detailed product model developed in this framework. This methodology facilitates the assignment of different levels of product modelling to different processes. It is capable of capturing the uniqueness of the products of the pipe spool fabrication process. As a result, the effect of the characteristics of each component of a product on the duration of different activities is considered for use in discrete event simulation.

The simulation model that is developed for pipe spool fabrication is connected to the database of the company to read the exact information of the pipes from the database and create more accurate Product Models (PM) for the entities in the simulation model. A heuristic search algorithm was developed for creating the product model of pipe spool fabrication shops using CAD drawings and the database of the company. The heuristic search algorithm considers 3-D geometric attributes of the product, the type and shape of the product components, relationships between the product components, shop process information, and constraints of the shop. Moreover, the framework includes a scheduling engine to help the decision maker produce feasible schedules by using an appropriate scheduling heuristic.

The proposed multi-criteria scheduling framework captures the uncertainty inherent in the shop environment, by applying every dispatching rule to a set of different scenarios and utilizing statistical analysis to measure expected membership values and variances. The significance of the proposed framework is in its ability to optimize a multi-criteria industrial shop scheduling problem while taking the following aspects into account:

1. New combinatorial dispatching rules are proposed in addition to existing combinatorial dispatching rules in order to address more than one criterion in scheduling optimization.
2. The framework provides the opportunity to evaluate different performance indices, which are in conflict with each other, using the concepts of fuzzy sets.
3. The framework uses fuzzy set theory to represent different trade-off areas between conflicting performance indices in the Pareto frontier (or Pareto-optimal set).

4. The framework makes it possible to take into account the uncertainty of the performance of each dispatching rule through running each dispatching rule for different scenarios using the simulation model.
5. Using Fuzzy C-Means clustering for analysis of the performance of dispatching rules, the structure of the data, which is obtained from the simulation model, is converted into a linguistic representation. Using that linguistic representation, the end-user in the industry can easily interpret the numerical results and choose the proper dispatching rule. Fuzzy C-Means clustering also accounts for the fact that each dispatching rule can satisfy a given criterion to a different degree depending on the set of jobs being scheduled.
6. Fuzzy C-Means clustering makes it possible to consider the quality of belonging of each dispatching rule to a Pareto frontier in the amalgamation of all the results of all scenarios, which cannot be represented by a crisp number or by a statistical moment. Statistical methods can only specify the probability of being on the Pareto frontier without considering the proximity of the data points to the Pareto frontier.
7. The decision maker can express his/her preferences linguistically.
8. Linguistic variables and statistical data are connected together by the concept of probability of a fuzzy event, which is interpreted as the expected membership value. Also, using the variance of membership values of a dispatching rule, the confidence in the expected membership

value of each dispatching rule with respect to each cluster can be determined.

The industrial contributions of this research include developing a simulation-based scheduling toolkit, which can be used as a decision support system by coordinators and superintendants of pipe spool fabrication shops for automated scheduling. This application improves the performance of the shop in terms of increasing productivity, throughput, and the shop's works in progress, and also reduces the tardiness of the spools, by applying the appropriate dispatching rule and optimizing the schedule of the pipe spool fabrication shop. Moreover, the toolkit can be used to explore if- then scenarios to determine possible improvements in the shop, such as improving number of resources or working stations. Finally, the developed scheduling tool can be used as a tool for better planning and control of the shop floor. The multi-criteria scheduling framework enables the decision makers to develop different objective functions to suit the requirements of company, while considering different levels of satisfaction for each objective function.

5.3 Recommendations for Future Research

The limitation of simulation model developed in this thesis is that it is more static than the shop floor and cannot consider the changes and mangers' decision making during the fabrication. Moreover, the product model can be improved by performing a more accurate data collection, including time study for different types of welds. Furthermore, the proposed for multi-criteria scheduling does not produce a quite optimum answer, but gives the best answer from a set of rules.

The following are numerous areas that have the potential for future research:

1. The percentage of rework is not modeled in the current study due to lack of information for rework. One of the further developments of the model could include modeling rework in simulation studies using probabilistic distributions in the simulation model.

2. Because the spool fabrication shop is labour-intensive, productivity is highly affected by the skill of the labourers in the shop. Since the skill of labourers is a subjective factor, a fuzzy expert system is one of the best models for calculating productivity, because it is capable of considering both qualitative and quantitative factors in estimating productivity. The important factors that affect the productivity of pipe spool fabrication processes are introduced in Chapter 2. These factors can be used to developed fuzzy rules based on experts' judgment to develop a fuzzy expert system for determining the productivity of pipe spool fabrication processes.

3. To use the output of fuzzy expert systems in the simulation model and to appropriately model the subjective uncertainty of the shop, such as skill of the labourers, the output of the fuzzy expert systems should be transformed to fuzzy set and be used in simulation models for modeling the duration of the activities.

4. A combined fuzzy and probabilistic discrete event simulation framework can be developed to consider the fuzzy durations of the activities, which are obtained from experts' judgment or fuzzy expert systems.

5. The simulation-based scheduling framework can be extended to facilitate the integration of the scheduling toolkit with other shop information systems and planning tools for simulation output analysis. This integration will help to the development of a fully digitized fabrication environment for advanced project planning and control.

6. The suggested framework for multi-criteria scheduling can be extended to optimize the resource allocation and the site layout of the fabrication shop, such as the number of resources, and the number of stations by integrating fuzzy set theory and meta-heuristic searches such as genetic algorithms (GA).

Appendix A Definitions and Illustrations of Welds

Figure A1 and Figure A2 illustrate the shape of welds according to the American Society of Mechanical Engineers (ASME) (www.asme.org).

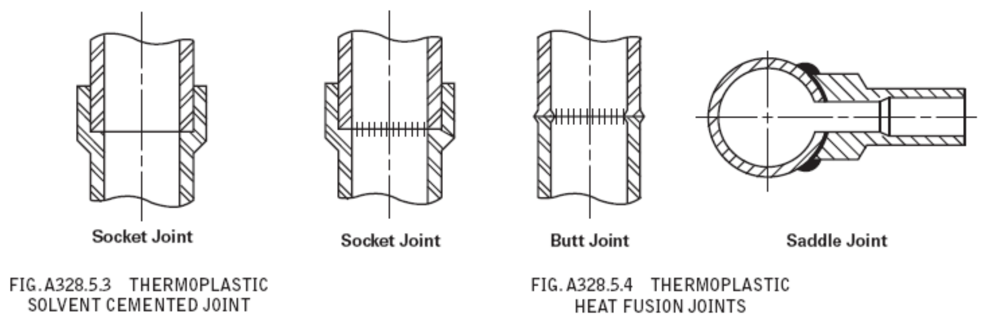

Figure A1 Socket weld and butt weld

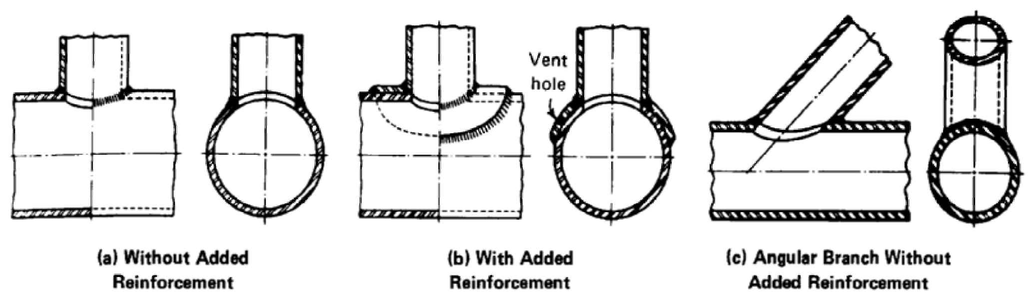

Figure A2 Re-pads and dummy leg

Butt Weld: Butt welding is welding a joint by fastening its ends together without overlapping.

Socket Weld: A socket weld is a pipe attachment detail in which a pipe is inserted into a recessed area of a valve or fitting, and then fillet welded between its outside diameter and the fitting end. Generally, it is used for piping whose nominal diameter is 2 inches (50 mm) or smaller.

Re-Pad weld: Re-pad is reinforcement to the dummy leg or nozzle weld**.**

Dummy Leg (Figure A6): The dummy leg is a piece of open pipe welded to the outside of an elbow or pipe.

Nozzle: A short length of pipe which is welded to a vessel at one end and is chambered at the other end for butt welding.