DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

MULTI-CRITERIA REAL-TIME SCHEDULING APPROACHES FOR DUAL RESOURCE CONSTRAINED MANUFACTURING SYSTEMS

by
Özlem UZUN ARAZ

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İZMİR

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Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"MULTI-CRITERIA REAL-TIME SCHEDULING APPROACHES FOR DUAL RESOURCE CONSTRAINED MANUFACTURING SYSTEMS"** completed by **ÖZLEM UZUN ARAZ** under supervision of **ASST. PROF. DR. LATİF SALUM** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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MULTI-CRITERIA REAL-TIME SCHEDULING APPROACHES FOR DUAL RESOURCE CONSTRAINED MANUFACTURING SYSTEMS

ABSTRACT

Scheduling is a crucial issue that can have a deep impact over the performance of a manufacturing system and its efficiency. Due to such disturbances as in part arrivals, and in states of machines, tools, and operators, manufacturing systems have uncertain and dynamic nature, which requires real-time scheduling approaches.

Up to date, numerous real-time scheduling approaches have been proposed for machine-only constrained systems. However, real-time scheduling of dual resource constrained (DRC) systems, which share a significant portion of manufacturing systems, is not common in scheduling literature. In DRC systems, the number of workers is typically less than the number of machines. Therefore, assignment of these workers to the machines in real time is also crucial as the worker capacity is a critical resource in completing jobs.

Increased attention towards responsive manufacturing systems not only raises the importance of real-time scheduling of manufacturing systems, but also increases the significance of considering multiple performance measures in this decision making process. However, in the literature, there is no sufficient effort on multi-criteria scheduling of DRC systems.

This research proposes three multi-criteria real-time scheduling approaches for DRC manufacturing systems to address the issues mentioned above. The first two approaches focus on the dynamic selection of appropriate set of rules, and use artificial neural networks (ANNs) and some multi-criteria decision making techniques to reduce computational complexity and cope with multiple performance measures. The first approach uses a fuzzy inference system (FIS), while the second utilizes a well-known multi-criteria decision making technique, PROMETHEE. The third uses a fuzzy-based real-time scheduling approach for DRC manufacturing systems.

In order to show the effectiveness of the proposed approaches, a number of experimental studies are performed. Their results show that the proposed approaches can be used in practice and provide satisfactory solutions for real-time scheduling of DRC systems.

Keywords: Dual resource constrained (DRC) systems, Real-time scheduling, Multi-criteria scheduling, Artificial Neural Network, Fuzzy Logic.

ÇİFT KAYNAK KISITLI İMALAT SİSTEMLERİ İÇİN ÇOK KRİTERLİ – GERÇEK ZAMANLI ÇİZELGELEME YAKLAŞIMLARI

ÖZ

Çizelgeleme üretim sisteminin performansında ve verimliliğinde derin etkileri olan önemli bir konudur. Üretilen parçaların gelişlerinde ve üretimde kullanılan makina, teçhizat ve operatörlerin durumlarında meydana gelen bazı düzensizliklerden dolayı, üretim sistemleri belirsiz ve dinamik bir yapıya sahiptir ve bu yapı gerçek zamanlı çizelgeleme yaklaşımlarının kullanılmasını zorunlu kılar.

Bugüne kadar, yalnızca makina kısıtlı üretim sistemleri için pek çok gerçek zamanlı çizelgeleme yaklaşımları geliştirilmiştir. Fakat üretim sistemlerinin önemli bir kısmını oluşturan çift kaynak kısıtlı (ÇKK) sistemlerin gerçek zamanlı çizelgelenmesi literatürde sıkça rastlanan bir alan değildir. ÇKK sistemlerde, genellikle işçi sayısı makina sayısından daha azdır. Bu yüzden, işçi kapasitesi işlerin tamamlanmasında kritik bir kaynak olduğunda, bu işçilerin makinalara gerçek zamanlı atanmaları da hayati bir karardır.

Çevik imalat sistemlerine olan artan ilgi, bugünlerde yalnızca üretim sistemlerinin gerçek zamanlı çizelgelenmesinin önemini artırmakla kalmamakta, aynı zamanda karar verme sürecinde çoklu performans ölçütlerini dikkate almanın önemini de artırmaktadır. Fakat literatürde ÇKK sistemlerin çok kriterli çizelgelenmesi ile ilgili yeterince çaba sarf edilmemiştir.

Bu çalışma ÇKK imalat sistemleri için üç çok kriterli gerçek zamanlı çizelgeleme yaklaşımı önermektedir. İlk iki yaklaşım uygun çizelgelenme kurallarının dinamik olarak seçimi üzerine odaklanmaktadır ve işlemsel karmaşıklığı azaltmak ve birden fazla performans ölçütünü dikkate alabilmek için yapay sinir ağları ile bazı çok kriterli karar verme teknikleri kullanmaktadır. İlk yaklaşım bir bulanık çıkarsama sistemi kullanırken, ikincisi çok bilinen bir çok kriterli karar verme tekniği olan PROMETHEE'yi kullanmaktadır. Diğer bir taraftan, ÇKK imalat sistemleri için bulanık mantık tabanlı bir gerçek-zamanlı çizelgeleme yaklaşımı da önerilmektedir.

Önerilen yaklaşımların etkinliğini göstermek için, bir takım deneysel çalışmalar gerçekleştirilmiştir. Bu çalışmaların sonuçları önerilen gerçek zamanlı çizelgeleme yaklaşımlarının pratik olarak kullanılabileceğini ve ÇKK imalat sistemlerinin gerçek-zamanlı çizelgelenmesinde tatmin edici sonuçlar sağlayacağını göstermiştir.

Anahtar Kelimeler: Çift kısıt kaynaklı (ÇKK) sistemler, Gerçek zamanlı çizelgeleme, Yapay sinir ağları, Bulanık mantık.

CONTENTS

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CHAPTER ONE
INTRODUCTION

In this chapter, the background, motivation and objectives of this thesis are introduced, and its organization is outlined.

1.1 Background and Motivation

Scheduling in a manufacturing environment is the process of deciding *what* happens *when* and *where*. That is, a schedule is a subset of the Cartesian product of three sets; there is a set of tasks (what) that must be done, there is a set of time periods or intervals (when), and there is a set of resources (where) that the tasks occupy as they execute (Parunak, 1991). Scheduling is a crucial issue that can have a deep impact over the performance of a (manufacturing) system and its efficiency (Petroni and Rizzi, 2002).

Static scheduling approaches are used for almost deterministic systems. However, due to such disturbances as in part arrivals, and in states of machines, tools, and operators, manufacturing systems have uncertain and dynamic nature, which requires real-time scheduling approaches.

The speed at which a control system makes production decisions affects the performance of the production system. Hence, scheduling and control actions need to occur quickly, i.e. they need to be done in 'real-time'. Traditionally, real-time refers to the immediate response to some event in a system, such as process completions, part arrivals, or machine breakdowns. Responses include selecting parts for a machine, starting a machining process, and re-routing a part. The speed needed for a response may actually depend on system parameters such as the magnitude of part processing times and the flexibility of the system. For example, if part processing times are of the order of an hour, a response within five minutes may be considered ‘real-time’. On the other hand, if they are of the order of fifteen minutes, a decision within one minute may be considered ‘real-time’ (Harmonosky and Robohn, 1991).

Various real-time scheduling approaches have been proposed so far. One of the most common approaches to real-time scheduling is to use dispatching rules (DPRs) (Pierreval and Mebarki, 1997). Although numerous DPRs have been developed over the years, with different levels of complexity and capability, there is no DPR that is globally better than all the others (Blackstone et al., 1982; Pierreval, 1992). Pierreval and Mebarki (1997) state that the efficiency of DPRs depends on the performance criteria as well as on the operating conditions. Under certain configurations of manufacturing systems and the performance criteria, some DPRs may perform better than the others. Hence, instead of using a single DPR for a long time, changing a DPR over successive short-time periods based on the current system state could improve the performance (Ishii and Talavage, 1991). Therefore, for flexible and dynamic scheduling decisions, an effective tool is required to help the decision maker in selecting the best rule for each particular state of the system.

Simulation-based adaptive control approaches are commonly used to select the DPR that gives the best performance for each particular state of the system (e.g. see, Wu and Wysk (1989); Ishii and Talavage (1991); Kim and Kim (1994); Kutanoglu and Sabuncuoglu, 2001, Singh et al., 2007). In all these studies, the system state variables are periodically tested, and then analyzed by a simulation model which selects, from a large number of possible DPRs, the best scheduling rule which would be used in the system until the next scheduling point. The next scheduling point, i.e., rescheduling point, can be determined either by random events or discrete time periods (Sabuncuoglu and Kizilisik, 2003). Although simulation is a highly flexible tool that can be used analyzing complex systems (Chan and Chan, 2001) and can be efficiently used to represent the dynamic and stochastic manufacturing environment (Sabuncuoglu and Kizilisik, 2003), one of its most important shortcomings is that it is time consuming, since a number of simulation runs must be carried out before finding the best DPR.

Alternatively, artificial intelligence (AI) based approaches are used which necessitate prior and lesser simulation runs to determine the best DPR for each possible system state (Priore et al., 2006). Some researchers exploit such AI based approaches as machine learning and rule based to select the best DPR (e.g. Pierreval and Mebarki, 1997; Priore et al., 2006; Shnits and Sinreich, 2006), while some others utilize evolutionary heuristics to determine appropriate rules based on the current system configuration (e.g. Kunnathar et al. 2004; Piramuthu et al., 2000; Kim and Lee, 1996). Some attempts have also been made to combine simple DPRs through fuzzy logic to improve their efficiency (e.g. Grabot and Geneste, 1994; Fanti et al., 1998; Chan et al., 2003).

Besides DPRs and the approaches that select them dynamically as the state of the shop changes, a considerable amount of research have been directed to develop predictive/reactive scheduling approaches to deal with uncertain disruptions (e.g. Kim and Jeong, 1998; Sabuncuoglu and Karabuk, 1999; Sabuncuoglu and Kizilisik, 2003). In such approaches, a predictive schedule is first generated. This schedule is then updated during the execution to cope with unexpected events (Sabuncuoglu and Kizilisik, 2003; Aytuğ et al., 2005). On the other hand, many authors have proposed robust scheduling methods that aim to obtain a schedule which minimizes the effects of disruptions on the primary performance measure of the schedule (Aytuğ et al., 2005).

Regardless of which type of real-time scheduling approach is developed, most of the studies in the literature are developed for FMSs and job shops. These approaches consider single resource (i.e. machine) constraints in general. Yet, dual resource constrained (DRC) systems also share a significant portion of manufacturing systems. In DRC systems, the number of workers is typically less than the number of machines. Therefore, assignment of these workers to the machines in real time is also crucial as the worker capacity is an essential resource to complete jobs.

Scheduling in DRC systems is more complex, as not only machines, but also operators should be considered in the scheduling (Bokhorst et al., 2004). The scheduling is performed by two primary types of worker assignment rules: "when" and "where" rules. The when-rule determines when a worker is considered to be transferred between work centres, while the where-rule determines to which work centre a worker is to be transferred (Bokhorst et al., 2004).

As discussed earlier, with respect to machine-only constrained scheduling, most of the early research focus on the job DPRs (Liao and Lin, 1998). However, these DPRs alone are not adequate in worker-limited DRC environments (Kher and Fry, 2001). In DRC systems, in addition to job DPRs, making right decisions on the timing of worker transfers ("when" rules) and the selection of the next task ("where" rules) are necessary to improve the shop performance. Some researchers have indicated that the worker assignment rules have a significant bearing on the performance of a DRC system (Weeks and Fryer, 1976; Malhotra and Kher, 1994; Bobrowski and Park, 1993). In such environments, poor decision making becomes more severe.

Numerous "when" and "where" rules exist in the DRC literature. There are also numerous studies that propose different worker assignment rules, analyze their performances and select the best one via simulation according to the performance criterion selected (e.g. Fryer, 1973; Gunther, 1979; Nelson, 1967; Treleven and Elvers, 1987; Weeks and Fryer, 1976; Malhotra and Kher, 1994; Kher, 2000). In almost all these studies, a simulation model is used to represent the DRC system.

Similar to job DPRs in machine-only constrained manufacturing systems, it has been indicated that the efficiency of these worker assignment rules are highly dependent on the performance criteria of interest and on system state conditions. Therefore, just as job DPRs, there is no worker assignment rule that is globally better than the others. When the operating conditions or the performance criteria are changed, the worker assignment rules currently used can become ineffective. Therefore, dynamic selection of worker assignment rules or some combination of them through AI techniques is required to improve a DRC system performance. There are three important points in this respect.

First, although various real-time scheduling approaches have been developed for machine-only constrained manufacturing systems, studies on real-time scheduling of DRC systems are not common in the literature.

Second, most researchers have paid considerable attention to evaluate different DPR and worker assignment rule combinations in the DRC context. Many single-performance measures have been studied, e.g. mean flow time and mean tardiness. Although all these applications are inherently multi-criteria decision making problems, there is no effort on the multi-criteria scheduling of DRC systems, except for the use of aggregated cost functions. However, several, and possibly conflicting, criteria might come about in the decision process, which makes it difficult to determine the right criterion. Moreover, because of the difference in the evaluation of each objective, it is difficult to define the unit cost for them. As a result, the overall objective function (aggregated cost function) applied to evaluate the performance of the schedules cannot be constructed reasonably (Lee et al., 2002). Therefore, a multi-criteria aggregation scheme for DRC scheduling is required.

Third, although job dispatching, worker assignment and route selection decisions have been extensively studied in the DRC literature, almost no research has been dedicated to solve these problems simultaneously.

Consequently, effective tools are needed to help shop managers efficiently schedule machines and workers. These tools should consider real-time and multi-criteria nature of DRC shops that generate job, worker and route schedules dynamically based on the state changes of the shop, which is the major motivator of this study.

1.2 Research Objectives

Motivated by the fact that scheduling decisions in DRC systems must be taken into consideration in real-time, this research proposes adaptive real-time DRC schedulers capable of reacting to the changes in the system in a timely manner and satisfying the multiple objectives simultaneously.

Considering these facts, this research proposes three multi-criteria real-time scheduling approaches for DRC manufacturing systems. The first two approaches focus on the dynamic selection of appropriate set of rules, and use artificial neural networks (ANNs) and some multi-criteria decision making techniques to reduce computational complexity and cope with multiple performance measures. Specifically, these two approaches

i. determine the appropriate rule set dynamically, which includes the part dispatching rule, routing policy and “when” and “where” rules, over successive time periods as the state of the shop changes,
ii. evaluate each competing rule set through ANNs that predict the performance of rule sets for a look-ahead window,
iii. utilize multi-criteria decision making techniques to aggregate the multi-criteria performance. The first approach uses a fuzzy inference system (FIS), while the second utilizes a well-known multi-criteria decision making technique, PROMETHEE.

The third is a novel fuzzy-based real-time scheduling approach for DRC manufacturing systems. Specifically, this approach

i. makes real-time decisions about the part dispatching, the route selection and worker assignment rules each time a scheduling decision has to be made,
ii. aggregates dispatching rules, part routings and “where” rules through fuzzy arithmetic to obtain a compromise solution for each rule type,
iii. decides the part to be processed next, the routing alternative to be selected and the alternative machine which needs a worker through fuzzy priority indexes instead of using combinations of traditional rules,
iv. determines when a worker should be transferred to another machine via Sugeno type FIS instead of traditional “when” rules,

v. improves the system performance through a reverse ANN module by updating the parameters of fuzzy functions considering the decision maker's preferences.

To summarize, the main objectives of this research are twofold. The first one is to develop novel adaptive real-time scheduling approaches for DRC manufacturing systems which focus on dynamic selection of traditional rules under multiple performance measures. The second one is to develop a fuzzy-based real-time scheduling approach for DRC systems to cope with the disadvantages of pre-determined myopic traditional rules.

1.3 Novel Contributions

This research contributes to the DRC and real-time scheduling literature in various ways.

- It proposes three real-time scheduling approaches for DRC manufacturing systems. Although the real-time manufacturing approaches have extensively been studied for machine-only constrained systems, studies on real-time scheduling of DRC systems are not common in the literature.

- To the best of the author's knowledge, multiple performance criteria are taken into consideration in scheduling DRC systems for the first time, except for the use of some cost functions. The literature review reveals that various researchers have paid considerable attention to evaluate different dispatching rule and worker assignment rule combinations in DRC context. Although all these applications are inherently multi-criteria decision making problems, there is no effort on the multi-criteria scheduling of DRC systems.

- It is clear from the literature review that most researches on DRC scheduling are based on discrete event simulation. Although, in recent years, numerous AI techniques have been successfully applied to other scheduling problems, little research has been devoted to the use of AI techniques, such as ANN and fuzzy logic, for DRC scheduling. This research uses such techniques.

- To the best of the author’s knowledge, a fuzzy-based real-time scheduling approach has been proposed for the first time in the DRC literature. Up to date, various approaches based on fuzzy logic have been developed for machine-only constrained systems. Most of them deal with the scheduling problem of flexible manufacturing systems (FMSs) and focus on part dispatching and routing selection. Furthermore, to the best of the author’s knowledge, there is no effort on the use of fuzzy sets in DRC scheduling.

- In DRC systems, some “where” rules are used to select the department to which the worker will be transferred next. This research proposes a novel fuzzy “where” rule for DRC systems, which combines various traditional “where” rules into a single fuzzy rule. On the other hand, the frequency of worker transfers is generally dictated by centralized, decentralized or parametric “when” rules. This research also proposes a novel fuzzy “when” rule based on Sugeno type FIS which lies in between the decentralized and centralized “when” rules in terms of flexibility.

- Although job dispatching, worker assignment and route selection decisions have significant impact on the performance of DRC systems, there has been little research on investigating their interactions and obtaining best combinations for the current system state. The proposed approaches deal with all these decisions simultaneously.

- Although real-life scheduling problems need to consider multiple objectives, only little research has been directed to use multi-criteria decision making techniques in scheduling problems. To the best of the author’s knowledge, the PROMETHEE multi-criteria decision making method is used to solve the scheduling problem for the first time.

- Different from the other fuzzy-based approaches, the proposed fuzzy approach offers an adaptive control scheme to update the system parameters during the scheduling period in order to achieve a decision maker's changing aspiration levels and to adapt to the prevailing shop conditions. Although some researchers propose optimization algorithms to optimize these parameters for the entire scheduling period, to the best of the author's knowledge, none of them use an adaptive control scheme which updates these parameters periodically.

1.4 Organization of the Thesis

The organization of the dissertation is as follows.

Chapter 2 gives an overview of DRC manufacturing and real time scheduling, and a detailed literature review. An overview of solution approaches for real-time scheduling of machine-only constrained systems is also provided in this chapter.

In Chapter 3, a brief overview is given on ANNs and fuzzy sets, and their use in scheduling problems.

Chapter 4 introduces the proposed DRC real-time scheduling methodology that consists of three modules; simulation, ANNs, and FIS. By means of a DRC scheduling example, its performance under different system variation levels is also evaluated. The results are compared with single-pass and multi-pass simulation based real time scheduling methodologies.

Chapter 5 proposes another integrated DRC real time scheduling methodology that incorporates simulation, ANNs and PROMETHEE approaches. The proposed methodology is tested in a hypothetical manufacturing system to prove its effectiveness over single-pass, multi-pass and the previously proposed approaches.

In Chapter 6, a real-time scheduling system incorporating an adaptive fuzzy system is proposed. This approach, instead of using standard dispatching rule sets, uses fuzzy priorities for parts dispatching and fuzzy routes considering multiple performance measures. An adaptive control mechanism that incorporates simulation and ANNs is then presented. Effectiveness of the proposed methodology is tested through several experimental analyses.

Chapter 7 contains concluding remarks and identifies future research directions.

CHAPTER TWO
LITERATURE REVIEW ON DUAL RESOURCE CONSTRAINED MANUFACTURING SYSTEMS AND REAL-TIME SCHEDULING

2.1 Introduction

The main goal of the thesis is to develop novel real-time scheduling methodologies for dual resource constrained (DRC) manufacturing systems. Thus, this chapter introduces DRC manufacturing systems with an emphasis on their scheduling. This chapter also gives a detailed review on the real-time scheduling literature.

2.2 DRC Manufacturing Systems

Scheduling is a decision-making process that plays an important role in most manufacturing industries (Pinedo and Chao, 1999). There are various scheduling approaches depending on the manufacturing environment. Vast majority of the scheduling literature is devoted to machine-only constrained manufacturing systems. In such environments, generally, it is assumed that machines on the shop floor are fully staffed. However, in practice, it may not always be the case. Manufacturing environments in which machines and workers are the constraining recourses are called dual resource constrained (DRC) manufacturing systems. In a DRC setting, the number of workers is typically less than the number of available machines, and workers are cross-trained so that they can process jobs in different machines (Treleven, 1989). Shop floor management then addresses not only the scheduling of the parts to be processed, but also the workers needed to make machines available to reduce manufacturing costs caused by the inefficient use of workers.

In one of the pioneering work of DRC literature, Nelson (1967) first considered operators as an additional constraint. With the increasing impact of multifunctional workers on shop performance, approaches to traditional machine-only constrained scheduling has been changed to reflect the new requirements according to the role of workers in DRC systems. Some researches focus on the inclusion of the worker as a second constraint and indicate that shop floor performance is strongly affected by the efficiency of the machine/part, as well as that of the operator (Elvers and Treleven, 1985; Huang et al., 1984; Treleven, 1989; Fryer, 1975, Chen, 1995). This situation becomes more severe in DRC shops (Treleven and Elvers, 1985). Since DRC systems necessitate worker assignment decisions besides job assignments to machines, these decisions are crucial when worker capacity is a critical resource in completing the job (Mosier and Mahmodi, 2002).

In DRC systems, generally, the scheduling of workers is handled by two primary types of worker assignment rules, “when” and “where”. The when-rule determines when a worker is considered to be transferred between work centers while the where-rule determines to which work centre the worker should be transferred (Bokhorst et al., 2004). Therefore, the scheduling of a DRC manufacturing system is more complicated than the scheduling of a machine-only constrained system.

There are various studies that investigate the performance of DRC manufacturing systems under different operating conditions. In an early review paper, Treleven (1989) categorizes the researches on DRC systems into two groups addressing the design and operating issues. While worker flexibility is considered to be the most important design factor in the study, decisions on dispatching rules and worker assignment rules are listed as the operating issues. In another review paper, Hottenstein and Bowman (1998) categorized sixteen simulation studies of DRC systems according to five main dimensions: worker flexibility, centralization of control, worker assignment rules, queue disciplines and the cost of transferring workers.

Since the analytical models include simplifications that are not always valid in practice, hence they are not efficient for large-scale DRC scheduling, researchers have paid considerable attention to develop heuristic based approaches for the DRC scheduling problem. Several simulation based scheduling studies have investigated dynamic worker assignment heuristics which include decisions on when and where to move the workers, i.e., when-where rule pairs, (Yildiz and Tunali, 2007). Studies indicate that the importance of choosing the appropriate assignment policy depends on the certain shop characteristics (Fryer, 1973; Gunther, 1979; Nelson, 1967; Treleven and Elvers, 1985; Weeks and Fryer, 1976; Malhotra and Kher, 1994; Kher, 2000).

In the next section, simulation based DRC scheduling studies are classified according to five dimensions by adopting and updating the classification scheme proposed by Hottenstein and Bowman (1998).

2.2.1 Worker Flexibility

The concept of worker flexibility or cross training plays a major role in the success of DRC systems. Worker flexibility in general refers to the responsiveness of a system to variations in the supply and demand of workers (Yue, et al., 2007). The use of multitasking workers helps in reacting to unbalanced work loads where the bottleneck location changes from period to period (Cochran and Horng, 2007).

There are two levels of worker flexibility (Felan and Fry, 2001): single-level flexibility and multi-level flexibility. In the case of the single level flexibility, every worker is trained to operate a machine in the same number of departments (Felan and Fry, 2001). Figure 2.1 illustrates a different type cross-training level for a simple five-worker five-task system (Inman et al., 2004). In the no-cross-training case, each worker is trained to perform only one task type. In the total cross-training, all workers can perform all task types. On the other hand, the multi-level flexibility can be regarded as the situation in which workers are trained to work in a different number of departments (Yildiz, 2003). A multi-level flexibility could occur because some workers, regardless of seniority, are motivated to learn new tasks more than other, less motivated, workers (Felan and Fry, 2001).

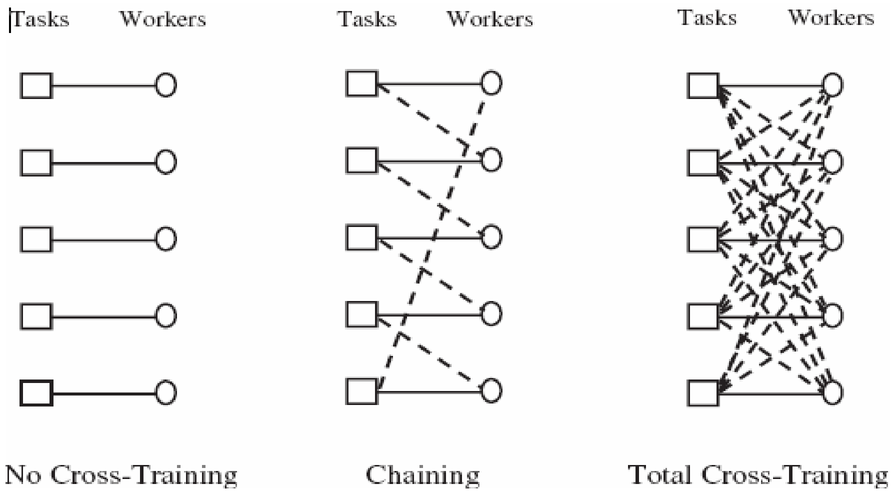

Figure 2.1 Schematic representation of cross-training strategies (Inman, et.al., 2004)

Worker flexibility can also be characterized by another type of flexibility: homogeneous or heterogeneous. Homogeneous worker flexibility can be regarded as the situation in which workers have the same level of proficiency at performing their assigned tasks (Felan and Fry, 2001). Although workers provide the same level of cross training in the heterogeneous worker flexibility case as well, they have different level proficiency when performing their assigned tasks (Bokhorst et al., 2004). The worker flexibility has been studied in numerous studies; e.g. see Allen, 1963; Nelson, 1967; Malhotra et al., 1993; Brusco and Johns, 1998; Kher et al., 1999; Molleman and Slomp, 1999; Felan and Fry, 2001; Slomp and Molleman, 2002; Hopp et al., 2004; Bokhorst et al., 2004; Inman et al., 2004; Yue et.al., 2007.

Allen (1963), being first to introduce multi-level flexibility, showed that by cross-training workers, DRC systems can utilize their workforce more efficiently. Then, Nelson (1967, 1970) investigated the effects of homogeneous and heterogeneous worker flexibility on the performance of DRC systems. The results showed that single level flexibility with both homogeneous and heterogeneous workers can improve the system performance.

Some researchers investigated the effects of worker flexibility with homogeneous workers (e.g. Fryer, 1973, 1974a, 1974b, 1975, 1976; Hogg et al., 1975a, 1975b; Elvers and Treleven 1985; Treleven and Elvers 1985, Scudder 1986; Park 1991), and heterogeneous workers (e.g. Rochette and Sadowski, 1976; Hogg et al., 1977;

Malhotra et al., 1992). The results show that significant improvement on the performance can be achieved by a minimal level of flexibility rather than total worker flexibility.

Park and Bobrowski (1989) studied on single-level worker flexibility with homogeneous workers. Although the main aim of the study was to investigate the job release mechanisms in DRC manufacturing, the effects of the degree of worker flexibility were also investigated by considering it as an experimental factor. The results indicate that when workers have more than two skills, performance cannot be significantly improved anymore. In another study, Bobrowski and Park (1993) considered heterogeneous workers. The research showed that worker assignment rules which consider the worker efficiency perform better than all the other rules which do not take into account worker flexibility.

Felan, Fry and Philipoom (1993) evaluate the impact of varying levels of worker flexibility and worker staffing on the performance of a DRC hybrid job shop. This comparison is based on two alternatives: i) implementing an extensive training programme to develop cross trained workers ii) hiring more workers. The results showed that the shop performance can be improved by using both strategies. Although hiring new workers is a more effective strategy in terms of shop performances, it is more costly than implementing a training programme. They also point out that increasing the degree of worker flexibility is more effective when the cost is the major criterion.

Although it has been confirmed by numerous researchers that worker flexibility improves the system performance under a variety of different shop designs, the cost of gaining this flexibility has not been studied extensively. In order to evaluate the cost of worker flexibility alternatives, the following criteria are commonly used in the DRC literature: the total number of worker transfers, server transfer delays, and heterogeneous efficiencies of the transferred worker (Malhotra et al., 1995).

Worker transfer delays are firstly considered by Gunther (1979) to show the effects of these delays on the system performance. In this study, the workers are not considered as productive while they are moving. Besides, dispatching rules, when rules, where rules, and worker transfer delays are considered as the experimental factors in the study. The results show that any increment in time required for the transfers increases the mean flow time. In another study, Gunther (1981) expanded his earlier model by including information access delays. An information access delay can be defined as the amount of time that is required for a worker to obtain the updated information necessary to make the appropriate transfer decision (Treleven, 1989).

Firstly, Malhotra et al. (1993) considered the cost of gaining flexibility in terms of worker attrition and learning effects during the cross training phase. They assumed that workers do not have full efficiencies in their new workstations and can only reach full efficiency after a learning process. The worker attrition and learning effects are evaluated under different scenarios. The experimental results indicate that the greatest benefits are achieved when interdepartmental worker flexibility is incrementally introduced into the system. Additionally, gaining flexibility is affected by the learning environment, which depends on the initial processing time of jobs and the learning rate of workers. In another study, Kher and Malhotra (1994) extended this study by considering worker transfer delay. Afterwards, Fry, Kher and Malhotra (1995) modeled the case of gaining workforce flexibility in DRC job shops that have high learning costs and the presence of the worker attrition. The results show that the combination of worker flexibility and attrition rate significantly affects the shop performance. An increment in the worker flexibility causes much greater improvement on the system performance, while it results in increments in the cost as well. On the other hand, decreasing attrition results in much less dramatic improvement on the system performance. Kher et al. (1999) extended the work of Malhotra et al. (1993) by including forgetting. The results of this study show that if the worker attrition and forgetting rates is high in the system, which means that the workers never gain full flexibility, to train a worker for even two different kinds of skills may not improve the performance of the system as expected.

Felan and Fry (2001) investigate the effects of the mixture of cross training in a DRC job shop. It is indicated that it is better to have a mix of workers with no flexibility and some workers with very high flexibility rather than all workers with equal flexibility.

Bokhorst, Slomp and Gaalman (2004) present a “WHO” rule used to select one worker out of several available workers to be transferred to a work centre. In order to investigate the effects of “who” rules on the system performances, the cases of homogeneous and heterogeneous workers were considered. The results showed that the characteristics of the DRC shop influence the impact of the ‘WHO’ rule.

Yue, Slomp, Molleman and Zee (2007) investigated the effects of cross-training policies in a DRC parallel job shop where new part types are frequently introduced into the system. Different cross-training policies related to the level of multifunctionality, the pattern of skill overlaps, and the distribution of skills among workers are considered. The results show that the frequency of new part type introduction should be considered in the selection of a cross-training policy.

Several researchers have studied on the worker flexibility in cellular manufacturing. Some of them investigate the effects of worker allocation on the shop performance, e.g., Askin and Iyer (1993); Russell et al. (1991) and Wirth et al. (1993). Some others indicate that worker assignment policy and cross training of workers have important impacts on the performance of cellular manufacturing systems, e.g., Morris and Tersine (1994); Suresh (1994), Shafer and Charnes (1995), Chen (1995).

Jensen (2000) investigated the relationship between staffing level and shop layout. The results indicate that strict cell shops provide superior flow time and tardiness performance under conditions of moderate and low staffing levels. Kannan and Jensen (2004) investigate the effects of worker assignment on the performance of a DRC cellular manufacturing system. It is assumed that processing time decreased with the operator task repetition. Results show that worker assignments significantly influence the shop performance in the presence of worker learning. Slomp, Bokhorst and Molleman (2005) developed an integer programming model to select workers to be cross-trained for particular machines in a cellular manufacturing environment. In the model developed, the training costs are traded off the workload balance among workers in a manufacturing cell. Djassemi (2005) investigates the performance of a cellular manufacturing system with a variable demand and flexible work force through simulation. The results indicate that the flexibility of cellular manufacturing in reacting to unbalanced work load can be improved by using flexible cross trained workers.

In summary, all the studies above show that a DRC shop with a flexible workforce can have better performance in terms of almost all criteria than a shop with no cross-trained workers. Despite these benefits, some of the studies highlight that worker flexibility may cause some additional costs such as learning and forgetting costs (Yue et al., 2007).

2.2.2 Centralization of Control

The centralization of control is defined in DRC system research with the decision about when a cross trained worker is eligible for transfer to another work center (Hottenstein and Bowman, 1998). The centralized and decentralized rules are the most commonly used “when” rules. The centralized rule means that a worker is eligible for transfer after each job he has finished in a work centre. The decentralized rule means that a worker is only eligible for transfer after finishing the job if the work centre becomes idle (Bokhorst et al., 2004). Many researches have investigated the effects of these rules under different DRC manufacturing environments (Hottenstein and Bowman, 1998). Some researchers only consider centralized control (Gunther, 1979, 1981; Malhotra et al., 1993; Treleven, 1987), while some others use only decentralized control (Elvers and Treleven, 1985; Treleven and Elvers, 1985; Treleven, 1988).

Nelson (1970) and Gunther (1979) investigate worker assignment rules in DRC shop with heterogeneous resources and homogeneous resources, respectively. While worker transfer delays are not considered in the earlier study, the later considers transfer delay times. The results of both studies show that the selection of the "when" rule affects the system performance. Different from Nelson (1970), Gunther (1979) indicates that the decentralized rule performs better than the centralized control when transfer delay times are considered.

Fryer (1973) showed that interdivisional and intradivisional transfers with centralized control are more effective than interdivisional and intradivisional transfers with decentralized control. In another study, Fryer (1974b) investigates the performance of a new parametric when-rule which allows the worker to be transferred to another work center, only if the number of jobs in queue is below a certain level.

Weeks and Fryer (1976) investigates the effects of dispatching rules, "when-where" rules and due date assignment rules on the system performance. Similar to previous studies, the centralized and decentralized rules are selected as "when" rules. The results of the study show that the centralized rule performs better than the decentralized rule.

Treleven (1987) studies three "pull" variations of the "when" worker assignment rule for DRC manufacturing systems. Three parametric "when" rules are defined, which consider the number of parts in queue. Experimental results indicate that "when" rules have impacts on the performance of a DRC system. In this study, the centralized control is suggested to be used when the transfer times are significant. The results also confirmed that the proposed rules have superior performances than the traditional when rules.

Park and Bobrowski (1989) studied four experimental factors, which are two release mechanisms, three levels of worker flexibility, two "when" rules and two levels of due date tightness. The effects of centralized and decentralized "when" rules on the system performance are investigated under different situations with full and partial cross trained homogeneous workers. During the experiments, the system performance is measured as a cost function with cost terms related to the inventory, the late penalty, and worker transfers. Results of the experiments show that the worker cross-training does not have a significant effect on the system performance in the case of the centralized control. Also, the centralization policy with a lower cross training performs better than the decentralization policy with a higher cross training. Among the alternatives with lower worker cross training, the centralized control ensures the maximum benefit.

In another study, Bobrowski and Park (1993) work on the assignment of heterogeneous workers to work centers. Five "when" rules are investigated in this study to determine when a worker is available for transfer to another machine: *"i) centralized ii) decentralized iii) efficiency rule: move immediately if the worker can move to the work center where the worker is more efficient iv) follower rule: move when the worker finishes the number of jobs which were there at arrival v) normalized queue rule: move when normalized queue length is less than the target value, which is estimated through a prior simulation."* The five when rules and seven where rules are simulated in order to minimize the flow time for each job. Results show that "efficiency when" rule provides superior system performance.

Malhotra and Kher (1994) investigated worker assignment policies in DRC job shops with heterogeneous workers. They also consider transfer delay times. It should be noted that these features are simultaneously modeled firstly in the DRC literature. Two "when rules" (centralized and decentralized) and five "where" rules are tested in such environments. Results indicate that decentralized "when" rule improves the system performance in the DRC shops considered.

Kher (2000) evaluated the relative importance of worker assignment and dispatching rules in offering a near-perfect delivery performance to vital customers served by the firm. Three different "when" rules are used, *i)* centralized *ii)* decentralized *iii)* a modified version of the decentralized rule. The modified rule incorporates information about high priority jobs in the current department, and does not allow a worker to be transferred until all high priority jobs in the current department have been processed. Results of the study show that a relatively high level customer service can be achieved for high priority orders only when the proposed rules are used.

Suresh and Slomp (2005) compared the performance of virtual cellular manufacturing systems with functional layouts and physical cellular layout in a DRC context. They studied four experimental factors which are worker flexibility, lot size, set-up reduction and worker assignment rules. While the centralized and decentralized “when” rules were used, the LNQ rule was used as the “where” rule. Flow time and WIP were selected as the performance measures. Transfer delays are also considered. The results of experimental analysis show that the centralized rule is marginally better than the decentralized rule.

Yildiz and Tunali (2007) proposed a novel methodology that integrates the response surface methodology and simulation to develop a worker assignment policy for CONWIP controlled DRC manufacturing systems. A two stage simulation optimization procedure that involves response surface methodology (RSM) is developed to determine on the length of periodic controls for evaluating the current system status. To evaluate the alternatives, a cost based performance measure and the number of worker transfers are considered. The results of this study show that the proposed methodology outperforms other flexibility control approaches with respect to the mean cycle time and the unit penalty cost especially in systems with fewer numbers of machines.

Although the decentralized “when” rule is less flexible than the “centralized” rule (Kher and Fry, 2001), many researches recommended its use because any increment in worker transfers will results in a deterioration in the effective worker capacity. The centralized rule causes more number of worker transfers than the decentralized rule. However, when transfer delays are considered, the flow times increase in centralized control due to the frequent worker transfers (Suresh and Slomp, 2005).

Additionally, the centralized rule could give superior performance in the case of heterogeneous workers.

2.2.3 Where Rules

Besides the "when" rule, the "where" rule that helps to determine where the worker should be reassigned when a worker is eligible for transfer is an important decision for scheduling of DRC manufacturing systems (Hottenstein and Bowman, 1998). Commonly used "where" rules are random, to the work center first come first served (FCFS), to the work center with shortest operation time (SOPT), to the work center with largest number in queue (LNQ) (Fryer, 1973; Weeks and Fryer, 1976; Gunther, 1979; Treleven and Elvers, 1985; Park Bobrowski and Park, 1993; Kher, 2000). The appropriate use of "where" rules leads to substantial improvement in the shop performance and this decision depends on the scheduling of machines (Hottenstein and Bowman 1998).

Up to date, the effects of "where" rules on the system performance have been investigated by many researchers and different conclusions can be drawn from these studies. In one of the earliest work of DRC literature, Nelson (1967) reports that the use of different "where" worker assignment rules could improve the mean and variance of flow time simultaneously. However, Fryer (1973), Weeks and Fryer (1976), and Treleven and Elvers (1985) indicate that these rules do not have significant effects on the shop performance, except for flow/queue time variance criterion (Treleven, 1989). Fryer (1973) analyzed effects of LNQ and LWT (work center with the job in the queue which has been in the system the longest period of time) "where" rules on the system performance. In one of the most comprehensive studies in DRC literature, Treleven and Elvers (1985) analyzed eleven "where" rules in the DRC shop with homogeneous partial cross trained workers. The classical "where" rules, FCFS, SOPT, EDD (work center whose queue has the job with the earliest due date), CR (work center whose queue has the job with the smallest critical ratio), LST and LNQ (i.e., classical "where" rules), were used in this study. Additionally, the new five where rules that use an average priority value of all jobs in queue were proposed and their effects on the performance of the DRC shop were evaluated. These are AFISFS (earliest average entry into the system of all jobs in queue), ASOPT (shortest average processing time of all jobs in queue), AEDD (earliest average due date of all jobs in its queue), ACR (lowest average critical ratio of all jobs in its queue), AST (lowest average slack per remaining number of operations of all jobs in its queue). The experimental results show that none of the "where" rules performs significantly better than the others. Kher and Malhotra (1994) studied two "where" rules: FISFS and LST. Results of the study confirmed prior studies which report that the "where" rules do not have a significant impact on shop performance.

On the other hand, some researchers report that the appropriate choice of "where" rules affect the performance of DRC systems with respect to shop characteristics. Weeks and Fryer (1976) examined the impact of LNQ, LWT and LST (work center whose queue has the job with the least slack time per operation remaining) rules on the performance of a DRC job shop. The results indicate that the rule which considers the time in the system of the jobs in queue is the optimal assignment rule in terms of all performance measures.

Hogg, Phillips and Maggard (1977) investigated the performance of two where rules in a DRC shop with heterogeneous workers. These are "first arrived in the system first served (FASFS)" and "most efficient (MEF)" rules. In their study, three different types of worker efficiency schemes were modeled. When comparing the performance of the "where" rules, it is assumed that the centralized control is selected as the "when" rule. The results of the study illustrate that the FASFS performs superior in the case of homogeneous workers. On the other hand, MEF gives better results for heterogeneous workers.

Gunther (1979) examined the impact of SOPT, LNQ and FISFS rules. In his study, SOPT and LNQ are modified by including worker transfer times. He reports that the SOPT rule improves the mean flow time performance even when transfer delay times are considered.

Treleven (1987) compares the performance of the proposed "pull" worker assignment rules that integrate "when" and "where" rules with those of traditional push rules. The results of this study show that the new rules perform well in comparison to the traditional "push" rules.

Bobrowski and Park (1993) analyzed the effects of "where" rules on the mean flow time performance of DRC systems with heterogeneous workers besides the effects of "when" rules. In the research, seven "where" rules are tested: LNQ, MLNQ (modified queue length by efficiency of the worker at the work center), NQL (normalized queue length; move to the work centre with the NQL value closest to the target value, which is estimated through a prior simulation), MEF, SOPT, LTST (least total slack loss rule), and LAST (Least aggregate slack rule). Results indicated that the MEF rule performs better than the others. Malhotra and Kher (1994) performed a similar study to show the impacts of five where rules on performance of DRC systems. In their study, it is assumed that the workers are heterogeneous and significant transfer delay times exist. The "where" rules used are: *i)* FISFS, *ii)* SOPT1 (smallest processing time and transfer time), *iii)* SOPT2 (modified version of SOPT1 by processing time by efficiency of the worker), *iv)* LNQ, *v)* MEF. Similar to the results of Bobrowski and Park (1993), the rules that use worker efficiency information provide better results than the other traditional "where" rules.

Liao and Lin (1998) studied a real life production system in a manufacturing company producing sewing machine parts. The production system is a DRC job shop with sequence-independent set-up times, a make-to-order policy, and equal-sized transfer batches. The performance measure is the mean absolute lateness. Two worker assignment rules are: (*i*) longest number in queue and (*ii*) a novel method. In the novel method, the priority is given by considering the amount of investment, set-up time and unit processing time. Results of the experimental studies show that the combination of modified due date rule for dispatching and the LNQ rule for the "where" rule gives a superior performance.

Cochran and Horng (1999) and Horng and Cochran (2001) introduced multitasking workers in Just-in-Time (JIT) environments. Different from other studies, the performance of the traditional "when –where" rule combinations were investigated in the DRC-JIT environment. While the centralized and decentralized control were used as "when" rules, FISFS, LNQ, MEF, SOPT1 and SOPT2 were considered as the "where" rules. In addition to the traditional rules, novel "when" and "where" rules were proposed for the JIT production system. The proposed "when" rule, called the bottleneck rule, allows the worker transfer when the number of unsatisfied production kanbans of the station drops to a predetermined level after a job is completed. The novel "where" rule assigns the multitasking worker to the bottleneck station which is the closest one to the last station. Additionally, a decision support system that integrates simulation and response surface methodology is developed. Results showed that the new rule-pairs perform well in the JIT production system.

Kher (2000) analyzed the effects of three worker assignment rules. These rules include customer identity based information to allocate workers to different departments. LNQ, longest queue of high priority jobs and the high priority job with the earliest due date rules are used as the "where" rules. The experimental results show that the "where" rules that consider customer information give superior performance for high priority jobs. Kher and Fry (2001) extend this study by considering additional tools that can be used by managers in DRC shops such as worker flexibility and worker assignment rules. They studied four experimental factors that include two different percentages of high-priority orders, six levels of flexibility, two "when" rules, two "where" rules and two part dispatching rules. The first "where" rule is EDD which assigned the worker to the work center that contains the job with the earliest due date. The second "where" rule, EDDP, selects a work center that contains vital customer orders with earliest due dates. Results show that the "when" rule has more impacts on the performance of the system than the "where" rules. Experimental results also show that there were insignificant differences between the two "where" rules.

Jensen (2000) examined the performances of LNQ, EDD and CYC (cyclic) worker assignment rules on a DRC job shop, in a hybrid cell layout and in a strict cellular configuration. Experimental results show that EDD gives better performance than the other rules under the centralized control rule. Similar results have been obtained by the work of Suresh and Gaalman (2000). This study compares the performance of the functional layout with those of the cellular manufacturing. Worker flexibility, lot size, set-up reduction, worker assignment rules and scheduling rules are considered as the experimental factors. The results indicate that the LNQ rule with centralized control gives significantly lowest flow ratios.

Chen (1995) developed heuristic approaches for the single operator scheduling problem in Group Technology (GT) cells. The heuristic consists of Cycle Switching Rules (CSR) to deal with production environments covering a longer decision horizon and (2) Dynamic Scheduling Rules (DSR) to deal with environments covering the shorter decision horizon. The implementation of the CSR and DSR is performed by some IF-THEN-ELSE rules considering the changing dynamic situations. The results indicate that both CSR and DSR outperform the internal rules. However, the proposed heuristics can only deal with the single-operator scheduling problem. Therefore, the author stated that the operator's scheduling for multi operator problem should be developed; however, the combinatorial explosion makes this problem difficult to solve.

Mosier and Mahmoodi (2002) studied the group scheduling heuristics in a DRC, automated manufacturing cell. In this study, it is assumed that the workers are only responsible for set-up, tear-downs and loads/unloads. Three worker scheduling policies are used to determine which work centers need a worker: *i)* select the workstation with the largest total number of jobs in all of the subfamily queues, *ii*) select the workstation whose next job requires the least amount of set-up time, *iii)* select the workstation whose next job entered the shop first. Three performance measures are considered as mean tardiness, mean flow time, and average proportion of jobs tardy. The results of the experiments indicate that, in a DRC cell environment, policies for allocating workers to tasks have very little impact on the system performance.

Kannan and Jensen (2004) examined the impact of worker assignments in a DRC cellular shop in which processing times decrease with operator task repetition. LNQ and EDD are selected as main "where" rules. Then, to examine the impact of intra versus inter-cell assignments, four "where" heuristics are developed by modifying these rules. In the first two rules, LNQ and EDD are applied to machines not currently staffed (LNQ-U and EDD-U) regardless of where the machines are. The third and fourth rules, LNQ-P and EDD-P, allow operators to be transferred outside their primary cell only if there is no remaining job in their primary cell. The combination of two "when" rules and six "where" rules are analyzed for the three levels of learning rates and three levels of staffing levels. The results show in all cases that the EDD heuristic has the advantage in all type of "where" rules. The relative performance of worker assignment rules depends both on the rate at which the operators learn and on the staffing constraints.

2.2.4 Queue Discipline

In most of the DRC studies, the queue discipline (part dispatching rules) has not been the primary interest. However, many of the studies investigated the interaction between several queue discipline and worker assignment rules (Hottenstein and Bowman, 1998). They reported that the use of right "where" rules lead to substantial improvement in the shop performance and this decision is not independent of parts schedules (Hottenstein and Bowman, 1998). Treleven (1989) emphasizes that the choice of part dispatching rules has a significant impact on the shop performance of DRC systems.

A queue discipline is defined by Blackstone et. al. (1982) as the selection of the next job to be processed from a set of jobs awaiting service. The selection of queue disciplines for DRC systems is based on the previous studies in the machine limited systems (Lee, 1997). The queue disciplines in DRC studies are summarized in Table

2.1. The table extends and updates the work of Hottenstein and Bowman (1998) that shows the dispatching rules in DRC systems. They are FISFS (First in System First Served), FIFO (First in First Out), SPT (Shortest Processing Time), EDD (Earliest Due Date), LST (Least Slack Time), CRT (Critical Ratio), and MODD (Modified Due Date).

Table 2.1 Dispatching rules used in DRC systems

Study	**Dispatching Rules**								
	FIFO	**FISFS**	**SPT**	**SLT**	**EDD**	**CRT**	**2Q**	**CMDD**	**MODD**
Nelson (1967)	X	X	X						
Fryer (1973, 1974a, 1975)		X	X						
Fryer (1974b)		X							
Weeks and Fryer (1976)		X	X	X					
Gunther (1979)	X		X						
Gunther (1981)	X		X						
Treleven and Elvers (1985)		X	X	X	X	X			
Elvers and Treleven (1985)		X	X	X	X	X			
Treleven (1987)			X	X					
Treleven (1988)		X	X	X	X				
Park and Bobrowski (1989)						X			
Park and Bobrowski (1993)						X			
Malhotra et.al (1993)					X				
Felan et.al. (1993)			X						
Malhotra and Kher (1994)					X				
Kher and Malhotra (1994)					X				
Morris and Tersine (1994)	X								
Lee (1997)		X	X		X				
Fredendall et. al. (1996)								X	X
Liao and Lin (1998)			X						X
Kher (2000)					X		X		
Suresh and Slomp (2000)	X		X						
Kher and Fry (2001)					X		X		
Kannan and Jensen (2004)			X						
Yue et.al., 2007	X								

Nelson (1967) indicates that assigning workers to a work center with a combination of the LNQ “where” rule and the SPT or FISFS dispatching rules is the most effective in reducing the mean and variance of the flow time. Fryer (1973); Fryer (1975) and Treleven (1987) report that SPT decreases mean flow time, but increases its variance. The results are also confirmed by Gunther (1979) that considers transfer delay times in a DRC shop. Weeks and Fryer (1976) report that the SPT rule yields a better performance than the due-date based slack rules for all performance measures, except for the variance of lateness.

Fredendall et. al. (1994) used two dispatching rules to examine the impact of information usage in the dispatching rules on the system performance. Firstly, the modified operation due date (MODD) is the maximum of operation time plus the current time, or the operation's due date. Secondly, the critical machine due date (CMDD) uses the SPT rule at critical work centers and the EDD rule at non-critical work centers. The results indicate that no significant differences are observed between the MODD and CMDD rules for any performance measures.

Kher and Fry (2001) compared the performance of a two-queue (2Q) and the EDD rules to investigate the impact of dispatching rules in a DRC shop where a near-perfect deliver performance is necessary for vital customers. The 2Q rule includes two types of queues, one for high priority jobs and one for normal priority jobs. This rule requires that workers must process jobs from the high priority queues first. EDD is used to sequence the jobs in both queues. The results of the experiments show that the 2Q rule gives better performance for vital customer orders and a poorer performance for non-vital customers.

Although most of the abovementioned studies report that different dispatching rules perform well in different DRC shop configurations, a general conclusion cannot be obtained about the performance of these rules. The experimental results show that DRC configurations (i.e., transfer delay times, worker efficiencies, etc.) and interaction between worker assignment rules and dispatching rules strongly affect the performance of the dispatching rule used.

Patel et al. (1999) proposed a scheduling approach based on genetic algorithms (GAs) for DRC manufacturing systems. They compared six different dispatching rules according to eight different performance measures. Their methodology determines the best schedule given the DPRs. Its main disadvantage is that the problem size extensively limits the solution; it is time consuming even for small sized problems.

2.2.5 Evaluation Metrics

Many performance measures are used for analyzing DRC manufacturing systems. Most of them are listed in Table 2.2. Although many studies considered more than one performance measure to evaluate scheduling and design of DRC manufacturing, most of them did not consider the aggregation of the performance measures. However, several, and possibly conflicting, criteria might come about in the decision process, which makes it difficult to determine the right criterion. This necessitates the multi-criteria evaluation of alternative rule combinations.

Some researchers developed cost functions to evaluate performances of the investigated scheduling rules for DRC shops. Park and Bobrowski (1989) developed a cost function including inventory holding cost, late penalty and worker transfer cost. Holding costs are proportional to the amount of work completed on a job. Late penalty charges are assessed as a dollar amount per hour for the work content job, and per time period late. Worker transfer costs are charged as a dollar amount per transfer. A similar cost function is used to evaluate order review rules and worker assignment rules by Fredenall et al. (1996).

Yildiz and Tunali (2007) suggested a unit penalty cost function to implement their proposed worker flexibility policy for a CONWIP line. The cost function consists of four components: total machine cost per job produced in the line, total worker cost per job produced in the line, control cost per job, and total WIP carrying cost per job. To determine the optimum level of the design parameters considered, RSM is developed based on this cost function.

Table 2.2 Performance measures

Study	**Performance Measures**														
	WU	NJS	NJSV	MFT	MFTV	MLT	LTV	MT	PLJ	NWT	MQT	QTV	NQT	WIP	S
Allen (1963)	X	X													
Nelson (1967)		X	X	X	X										
Fryer (1973, 1974a, 1974b, 1975)				X	X					X					
Hogg et.al. (1975)	X			X	X						X		X		LBT
Weeks and Fryer (1976)				X	X	X	X		X	X					
Gunther (1989)				X	X					X					PTT
Treleven and Elvers (1985)				X	X				X	X	X	X			
Elvers and Treleven (1985)				X	X				X	X	X	X			
Treleven (1987)						X	X		X		X	X			
Treleven (1988)					X							X			
Bobrowski and Park (1989)				X				X	X						
Felan et.al. (1993)	X							X	X	X				X	
Malhotra et.al. (1993)				X				X	X						DLV
Malhotra and Kher (1994)	X			X				X	X						
Morris and Tersine (1994)				X										X	MU
Fry et.al. (1995)				X				X		X					DLV
Chen (1995)															TR
Liao and Lin						X									
Kher (2000)								X							RMST
Jensen (2000)				X				X							RMST
Felan and Fry (2001)								X	X						DLV
Mossier and Mahmoodi (2002)				X				X	X						NJW
Kannan and Jensen (2004)				X	X			X							
Djassemi (2005)				X										X	MU
Yue et al. (2007)				X											

WU: worker utilization, NJS: Number of jobs in system, NJSV: variance of NJS, MFT: mean flow time, MFTV: variance of MFT, MLT: mean lateness, LTV: variance of MLT, MT: Mean Tardiness, PLJ: percentage of late job, NWT: number of worker transfer, MQT: mean queue time, QTV: variance of MQT, NQT: normalized queue time, WIP: work-in process inventory, S:special, LBT: worker blocking time, PTT: Percentage of time spent to transfer, DLV: direct worker variance, MU: machine utilization, TR: throughput rate, RMST: root mean squared tardiness, NJW: number of job waiting worker transfer

Although all these applications are inherently multi-criteria decision making problems, the literature review reveals that there is no effort on the multi-criteria scheduling of DRC systems. However, in practice, a decision maker aims to find a schedule that meets each criterion or objective of the system at some level. As mentioned before, one of the main aims of this research is to fill this gap in the literature.

All the aforementioned studies have pointed out that the efficiency of the worker assignment rules is highly dependent on the performance criteria of interest and on system state conditions. No single worker assignment rule pair performs well for all performance criteria and the system state conditions. When the operating conditions or selected performance criteria are changed, an immediate response is necessary. Therefore, given the variable performance of worker assignment rules, it would be interesting to change these rules dynamically according to system state changes. This requires a real-time scheduling mechanism in DRC systems. However, studies on real-time scheduling of DRC systems are not common in the literature. To the best of the author's knowledge, there is only one simple work on real-time scheduling of DRC systems. Lee (1997) developed artificial intelligence based adaptive scheduling approaches to real-time scheduling of DRC manufacturing systems. He developed a state-dependent algorithm and compared it with regression metamodeling and neural network based scheduling algorithms. Because of its simplicity, neural network based approaches performed worse than the other approaches, even than the static scheduling approaches. Furthermore, the multi-criteria nature of the problem was not taken into account.

Although studies on real-time scheduling of DRC systems are not common in the literature, various methods have been proposed for machine-only constrained manufacturing systems. These methods will be further discussed in the next section.

2.3 Real-time Scheduling

Scheduling is a decision making process that plays an important role in most manufacturing and service industries (Pinedo and Chao, 1999). Scheduling has been defined as "*the art of assigning resources to tasks in order to insure the termination of these tasks in a reasonable amount of time*" (Dempster, 1981).

Successful management of all processes of a manufacturing firm requires many decisions. Decisions made at higher planning levels may affect the scheduling process directly (Pinedo and Chao, 1999). Figure 2.2 depicts a typical information flow in manufacturing systems. Scheduling requires the integration of many different kinds of data, e.g. process models, relationships between tasks and resources, definition of objectives and performance measures, and the underlying data structures and algorithms that tie them all together (Jones and Rabelo, 1998).

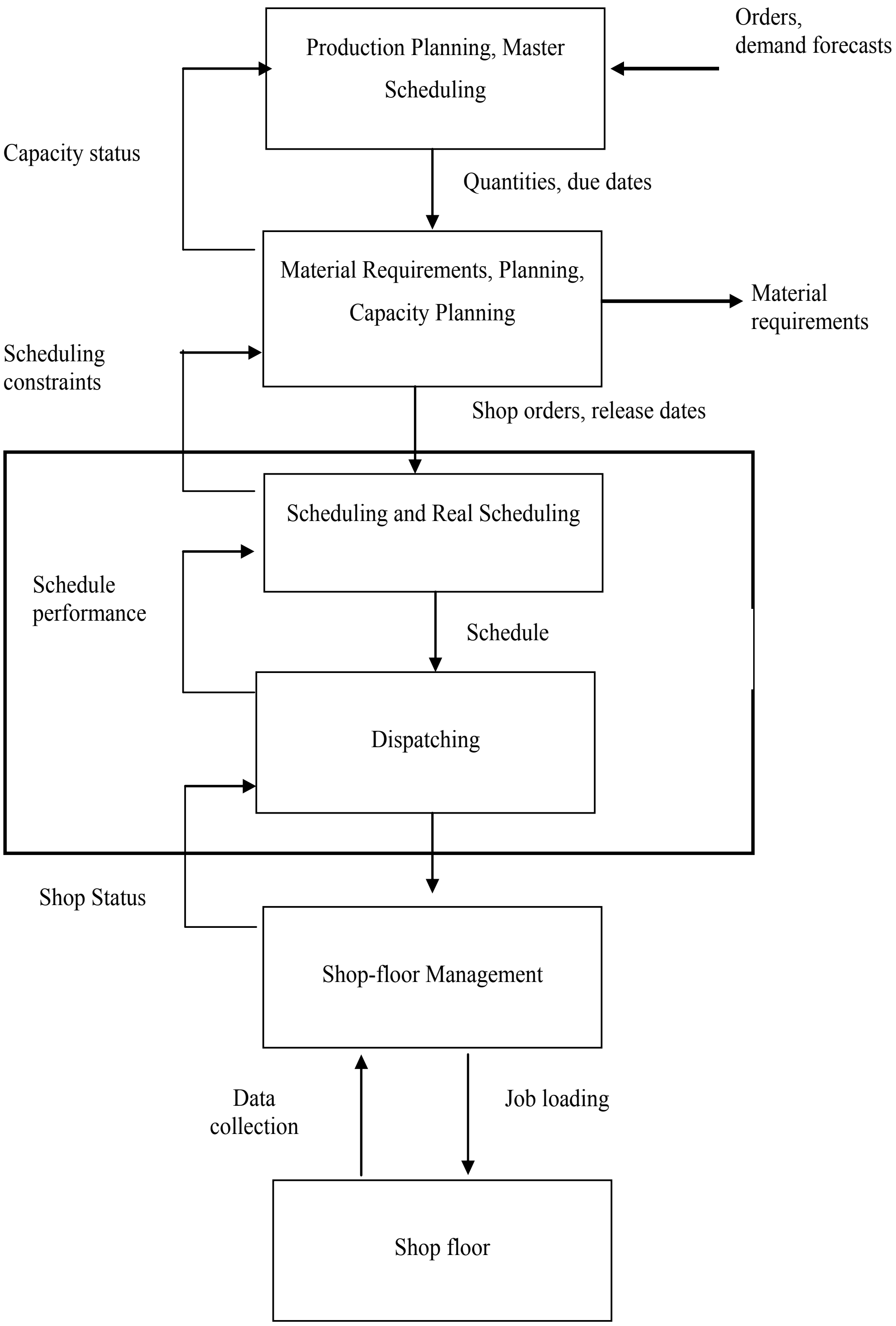

Figure2.2. Information flow diagram in a manufacturing system (Pinedo & Chao, 1999, pp.7)

Graves (1981) and Patel (1997) introduced a functional classification scheme for scheduling problems as follows:

- *Requirements generation*:
    - *Open shop*: All production orders are generated by customer requests and no inventory is stocked (e.g., make to order)
    - *Closed shop*: All customer requests are satisfied from inventory (e.g., make to stock)
- *Processing complexity*: It is concerned with the number of processing steps associated with each production task or item.
    - Single machine, single stage,
    - Parallel machine, single stage,
    - Flow shop, multistage,
    - Job shop, multistage.
- Parameter variability
    - *Deterministic*: All parameters are known fixed.
    - *Stochastic*: All or some parameters are uncertain.
- Scheduling environment (e.g. dynamic or static)
    - *Static*: It is considered if none of the initial data change overtime.
    - *Dynamic*: It is considered if the data change with time.

Job processing has many distinctive characteristics and is often subject to some unusual constraints. Pinedo and Chao (1999) list some of the most common processing characteristics and constraints as follows:

- Precedence constraints
- Routing constraints
- Material handling constraints
- Sequence-dependent setup times and costs
- Preemptions
- Storage-space and waiting-time constraints

Due to the complicated settings of most manufacturing systems, determining good schedules for these systems is difficult. Scheduling is considered to be the most difficult problem in manufacturing because of its NP-completeness (Patel, 1997).

Classical scheduling approaches usually solve the scheduling problem with optimal or suboptimal schedule (Xiang and Lee, 2007). Most of the problems are assumed as deterministic and static (Sabuncuoglu and Kizilişik, 2003). Additionally, the solutions can easily become infeasible in real manufacturing systems since they assume highly unrealistic assumptions. In reality, manufacturing systems are complex, dynamic, and stochastic systems with a wide variety of products, processes, production levels, and unexpected disturbances (Xiang and Lee, 2007). Mostly, it may be possible to formulate these problems, but solving these to optimality may require an enormous amount of computer time (Pinedo and Chao, 1999). Therefore, instead of the optimal solution, maintaining a feasible solution alone can sometimes be the only goal of the scheduling practice (Sabuncuoglu and Kizilisik, 2003).

When a dynamic and stochastic manufacturing environment is encountered in which static scheduling may be impractical, the use of real-time scheduling approaches is required (Xiang and Lee, 2007).

Sabuncuoglu and Hommertzheim (1992) defined real-time scheduling as follows:

"*Real-time scheduling is a short-term decision making process which generates and updates the schedule based on the current status of system and the overall system requirements.*"

Numerous real-time scheduling approaches have been developed for various manufacturing systems, including single machine systems, parallel machine systems, flow shops, job shops, and flexible manufacturing systems. However, as discussed in Section 2.2, the real-time scheduling of DRC systems is not common in the literature. DRC researches can be classified into: (1) testing the performance of several worker assignment rule pairs in terms of several criteria, and (2) designing dynamic worker assignment algorithms.

As discussed before, similar to job DPRs in machine constrained manufacturing systems, it has been indicated in the DRC literature that the efficiency of the worker assignment rules are highly dependent on the performance criteria of interest and on system state conditions. Unfortunately, just as job DPRs, there is no worker assignment rule that is globally better than all the others. When the operating conditions or selected performance criteria are changed, worker assignment rules currently selected can become ineffective with regard to the new conditions. Therefore, real-time control or dynamic selection of worker assignment rules is required to achieve improvement in overall system performance.

Recall that, to cope with these problems, this research proposes three novel multi-criteria real-time scheduling approaches for DRC systems. The two of them, which are based on the selection of traditional rule combinations, use ANN based real-time multi-criteria schedulers, which are activated over successive time periods. On the other hand, the third one uses a fuzzy-based on-line scheduler, which is activated each time a scheduling decision is to be made.

Although various real-time scheduling approaches exist, the literature review in the next section focuses on simulation based, AI based and knowledge based completely reactive (on-line) real-time scheduling approaches.

2.3.1 Real-time Scheduling Approaches

Aytug et al. (2005) classify scheduling approaches with executional uncertainties into three categories based on the problem formulation: completely reactive, robust scheduling and predictive-reactive scheduling approaches.

In completely reactive scheduling, no firm schedule is generated in advance and decisions are made locally in real-time. The on-line dispatching rules that create partial schedules based on local information are frequently used. Other dispatching rule-based approaches that allow the system to select these rules dynamically are also completely reactive approaches. Most of the machine learning based, knowledge based, neural network based and fuzzy logic based approaches in which one schedule is made at a time when it is needed according to the changes in the system conditions are also classified into this category (Aytug et al., 2005).

The robust scheduling approaches focus on creating a schedule which, when implemented, minimizes the effect of disruptions on the primary performance measure of the schedule (Aytug et al., 2005). For example, Wu and Storer (1994), Mehta and Uzsoy (1999) and O'Donovan et al. (1999) developed robust scheduling approaches that generate stable schedules.

In predictive–reactive scheduling, scheduling is presented as a two step process. Firstly, a predictive schedule, which determines the planned start and completion times of operations of the jobs, is generated. Secondly, this schedule is then updated according to the unexpected disruptions (Aytug et al., 2005). For example, Sabuncuoglu and Karabuk (1999) proposed a filtered beam search based scheduling/rescheduling algorithm for a multi-resource FMS environment. The performances of several reactive policies are tested in the presence of machine breakdowns and processing time variations. In another study, Sabuncuoglu and Bayiz (2000) analyzed the effects of various shop floor configurations (the load allocation, system complexity and stochasticity) on the performance of on-line and off-line scheduling methods. They modeled several reactive policies. Results show that the relative performances of scheduling approaches are affected more by the system load while the system size has insignificant impact. Furthermore, they reported that the proposed methods based on the filtered-beam search outperform online dispatching rules when the load across machines are not uniform, and the performance of off-line scheduling method and on-line dispatching mechanisms provides close results when there is considerable uncertainty and variability in the system. Sabuncuoglu and Kizilisik (2003) proposed several reactive scheduling policies (when-to-schedule and how-to-schedule policies) and test their performances under various experimental conditions. The scheduling algorithm used in the rescheduling method is a heuristic based on the filtered beam search algorithm. In addition, the authors also compared online and offline scheduling approaches. In online scheduling, the least work remaining dispatching rule is selected for scheduling. The results indicate that as the frequency of rescheduling increases, the performance of the off-line scheduling algorithm gets better, and the variable time interval method is better than the fixed time interval method. They also reported that dispatching rules are found to be more robust to interruptions than the optimum-seeking off-line scheduling algorithm.

A comprehensive list of robust and reactive scheduling approaches can be found in a recent work of Aytug et al. (2005).

Considering the above classification, the real-time multi-criteria scheduling procedures proposed in this thesis can be considered as a completely reactive scheduling approach. In the next section, completely reactive scheduling approaches are discussed in detail under two sub-sections: simulation-based and AI-based approaches.

2.3.1.1 Simulation-Based Approaches

Simulation-based approaches are generally used to present a comparative analysis of dispatching rules (DPRs) and to determine the best DPR with respect to the current system state. A dispatching rule is a rule that prioritizes all the jobs that are waiting for processing on a machine. The prioritization scheme may take into account of the attributes of the jobs and the machines, as well as the current time (Pinedo and Chao, 1999). Dispatching rules can be very simple or extremely complex (Pierreval and Mebarki, 1997). Although numerous DPRs have been proposed over the years, in different levels of complexity and capability, there is no DPR that is globally better than all the others (Blackstone et al., 1982; Pierreval, 1992; Sabuncuoglu, 1998). Pierreval and Mebarki (1997) state that the efficiency of DPRs depends on the performance criteria employed as well as on the operating conditions of the manufacturing system. Instead of using a single dispatching rule for a long time, changing a dispatching rule over successive short-time periods based on the current system state could improve the performance (Ishii and Talavage, 1991). A tool is then required to help the decision maker select the best rule for each particular state of the system for dynamic scheduling decisions. Due to the difficulty and inflexibility of analytical models, almost all studies employ discrete event simulation to evaluate the performance of DPRs under a specified system state (Ishii and Talavage, 1991).

Simulation is a powerful tool to analyze complex, dynamic and stochastic systems. In this regard, simulation-based adaptive control approaches are commonly used to select the DPR that gives the best performance.

A simulation-based real-time scheduling system is usually composed of four main components (Yoon and Shen, 2006): "*a monitoring system to collect data from the physical shop floor; a simulator to generate simulation models, run the models, and analyze their results; a decision-making system to generate decisions such as schedules and priority rules; and an execution system to control the shop floor*". Generally, a simulation-based real-time scheduling utilizes discrete event simulation to evaluate dispatching rules for a short time period. The rule with the best performance during the time period is then selected, and applied to the physical system. The evaluation/application process is carried on repeatedly, based on the relative short time frame. In the long run, the scheduling of the system consists of the combinations of different dispatching rules in each short time period (Wu and Wysk, 1989).

In simulation based approaches, the scheduling mechanism can be activated by significant operational changes (i.e., event-triggered) or at the end of each time interval, which is constant or non-constant. In the event-triggered (or event-driven) approaches, an initial schedule is generated at the beginning of a period and it is revised when such significant operational changes occur as major breakdowns, minor breakdown, and new part arrivals (Jeong and Kim, 1998).

In the time-interval approaches, a simulation model is usually adopted to represent the manufacturing system. Then the system is periodically simulated to consider the system state changes. At the end of each period, the best DPR is chosen with respect to the selected performance measures. The major motivation behind these approaches is that changing DPRs dynamically performs better than applying the same DPR during the whole simulation run (Wu and Wysk, 1989).

In one of the earliest studies in real-time scheduling literature, Davis and Jones (1988) introduced a simulation-based decision support system for real-time scheduling of flexible manufacturing systems (FMSs) in stochastic environments. The scheduling problem is decomposed into a two-level decision making problem: scheduling and control. Simulation is used to determine the appropriate schedules.

Wu and Wysk (1989) proposed a simulation based real-time scheduling algorithm for FMSs. The algorithm, called multi-pass scheduling algorithm, divides the time horizon into shorter intervals. At the beginning of each interval, the performance of alternative dispatching rules is evaluated with the simulation model, and the rule with the best performance is selected for the next time interval. The results show that the proposed approach gives better performance than a single pass scheduling algorithm which uses a single dispatching rule during the scheduling period.

A number of other authors have followed Wu and Wysk (1989)'s work and extended it in various ways. Although Wu and Wysk (1989) considered constant lengths for scheduling interval, Ishi and Talavage (1991) proposed a transient based approach to define the next scheduling interval for the FMS scheduling. The proposed approach selects the dispatching rules for each time interval dynamically by a multi pass algorithm considering the changes of the system state. In order to eliminate the problem of censored data, they proposed four dispatching rule selection algorithms. Results of the experiments show that multi-pass scheduling algorithms perform better than the single-pass algorithm, and determining the length of scheduling period based on the system transient state makes the performance of the algorithm much more stable than using a constant short time period. In another study, Lee (1989) used a multi-pass real-time scheduling algorithm to maintain the overall performance above a certain level. Different from the above approaches, the next scheduling point is triggered when the performance measures reach pre-specified thresholds.

In another study, Kim and Kim (1994) proposed a multi pass scheduling and control mechanism in which the discrete event simulation was used to evaluate the performances of DPRs and to select the best one with respect to the performance criterion. The real-time control system monitors the shop floor periodically and compares actual and estimated performance values continuously. The scheduling mechanism is triggered when either the difference between the actual and estimated performance values exceeds the preset performance limit, or a major disturbance occurs. Different from previous studies, Ishii and Talavage (1994) used a different rule on each machine in each period. Based on Kim and Kim (1994)'s work, Jeong and Kim (1998) proposed several scheduling strategies for operating the mechanisms by considering two factors that might influence the mechanism, i.e. the type of simulation model used in the mechanism and the time of determining new DPRs.

Kutanoglu and Sabuncuoglu (2001a) proposed iterative simulation-based scheduling mechanisms for manufacturing systems that operate in dynamic and stochastic environments. A multi-pass rule selection algorithm and the lead time iteration method were tested in a job shop with machine failure and processing time variations. The experimental results showed that the multi-pass or iterative algorithm is better than single–pass algorithms on average. In another study, Kutanoglu and Sabuncuoglu (2001b) tested various schedule repair heuristics based on rerouting developed for unexpected machine failures in dynamic job shop environments.

Chan and Chan (2001) and Chan et al. (2003) analyzed dynamic DPRs by a preemptive method in FMSs. Firstly, the decision maker prioritizes the goals in the order of importance. The model is then optimized using one goal at a time. The preemptive method is adopted to allow real-time machine dispatching in an FMS. The operational rules are changed when certain numbers of outputs are produced by the system. The results show that the proposed approach can improve the performance by changing the corresponding DPR at the right time.

Chong et al. (2003) proposed a simulation-based real-time scheduling mechanism to adapt to the prevailing manufacturing conditions. Both offline and online simulations are used in the scheduling mechanism. The offline simulation is used to build reference indices by comparing different scheduling approaches according to the modified mean flow time performances. The online simulation then uses these reference indices to select the best scheduling approach.

Singh et al. (2007) proposed a multi-pass real-time scheduling methodology that considers several DPRs simultaneously for selecting a job for processing. The proposed methodology allows continuously monitoring of the attained values of the performance. It is seen from the results that the performance of the dynamic manufacturing system can be improved by changing DPRs corresponding to the worst performance criteria at the appropriate deterioration in the performance measures.

Results of the studies based on the simulation and DPRs show that the proposed methodologies perform better than fixed (single-pass) scheduling methodologies. However, all these studies need a number of simulation runs before finding the best DPR at each rescheduling point. Therefore, it can be time consuming to use simulation-based real-time scheduling approaches.

Some researchers proposed problem specific heuristics for real-time scheduling of manufacturing systems and analyzed the performance of these heuristics through simulation models (e.g. Yamamoto and Nof 1985; Ishii and Muraki, 1996; Mehta and Uzsoy 1999; O'Donovan et al., 1999; Akturk and Gorgulu, 1999). These heuristics do not guarantee to find an optimal schedule, but have the ability to find reasonably good solutions in a short time (Ouelhadj and Petrovic, 2007).

For example, Sabuncuoglu and Hommertzheim (1992) proposed an online dispatching algorithm for the FMS scheduling. The algorithm schedules the jobs on machine or an automated guided vehicle (AGV) one at a time as the status of the system change. The proposed algorithm was compared with existing scheduling rules under different performance criteria. In general, the dynamic scheduling algorithm provides superior performance than the standard scheduling rules. In another study, Subramaniam et. al. (2000) developed three heuristics for machine selection and tested the performance of these heuristics by simulation. The results of the simulation study indicate that the performance of simple dispatching rules is significantly improved when used with machine selection rules. Tunali (1997) investigated whether employing flexible process plans instead of prefixed ones improves the performance of a job-shop type FMS in terms of mean flow time objective. The manufacturing system considered is subject to unexpected machine breakdowns. The results of simulation experiments indicate that employing a flexible routing approach which enables basing the routing decisions on the most current system status information helps to improve the dynamic adjustability of current schedule.

Extensive discussion for simulation based real-time scheduling can be found in review studies of Vieira et. al., (2003); Yoon and Shen (2006); and Ouelhadj and Petrovic (2007).

2.3.1.2 Artificial Intelligence-Based Approaches

Alternatively, some researchers have paid attention to AI-based real-time scheduling approaches. Their basic motivation is that the selection of the best DPR at each rescheduling point can be performed more quickly through some AI techniques, e.g. neural networks, expert systems, knowledge-based, case based reasoning and fuzzy logic (Shi-jin et al., 2007). AI-based approaches also require some simulation runs of the manufacturing system at the outset to gain expertise about DPRs and the system behavior. This expertise is then used to determine the best DPR for each system state.

2.3.1.2.1 Knowledge-Based and Machine Learning Approaches. Up to date, many researches have developed numerous knowledge-based scheduling approaches (e.g. Alexander, 1985; Bullers et al., 1980; Kempf et al., 1991; Park et al., 1996; Zhang and Chen, 1999). Chandra and Talavage (1991) developed an intelligent part dispatching strategy for FMSs. A decision rule based reasoning algorithm is proposed which takes into account the current state and trends of the system. The performance of the proposed scheduler is compared with those of the DPRs. Simulation based experimental results show that significant improvements can be achieved by selecting dispatching rules via simple reasoning algorithms.

Pierreval (1992) proposed an expert system method which dynamically selects a combination of DPR considering the production objectives. A numerical example is also provided for a simplified flow shop. The results illustrate that the proposed approach is capable of achieving better results than popular DPRs through dynamically altered DPRs. In another study, Pierreval and Mebarki (1997) developed a rule based scheduling strategy based on a dynamic selection of pre-determined DPRs. The proposed strategy selects the DPRs considering the prevailing states of the system in order to meet the primary objective and maintain good results on a secondary objective. The results show that the proposed scheduling strategy improves the mean tardiness and conditional mean tardiness criteria significantly compared to classical DPRs.

Toni et al. (1996) developed a production scheduler based on a rule based experts system for solving the lot production scheduling problems. The proposed scheduler provides superior performance over single pass DPRs approach. However, it has the disadvantage of high computational time and requires the complete monitoring storing houses and work center backlogs.

Kunnathar et al. (2004) proposed a rule based expert system for dynamic scheduling of job shops. It is compared with other classical DPRs strategies. Results show that the proposed approach gives good results in terms of mean flow time, mean tardiness and percentage of tardy job objectives.

Shnits and Sinreich (2006) developed a two-stage multi-criteria methodology for FMSs. The first stage deals with the selection of a dominant decision criterion and a relevant scheduling rule set through a rule-based algorithm. In the second stage, the best scheduling rule, which is expected to advance the selected criteria more than others, is selected through a look ahead multi-pass simulation. The proposed control methodology is compared to a selected group of scheduling policies using data envelopment analysis. The results show that the proposed approach provides superior results within reasonable computational time.

Inductive learning (e.g. Shaw et al., 1992; Piramuthu et al, 1994; Piramuthu et al., 2000; Priore et al., 2006) and reinforcement learning (e.g. Kim and Lee, 1996; Zomaya et al., 1998; Agarwal et al., 2006) are adaptive knowledge-based dynamic scheduling systems. For example, Piramuthu et. al. (2000) proposed an adaptive scheduler for dynamic manufacturing systems. The rule selection logic is performed through the knowledge base generated by an inductive learning algorithm using a set of training examples. In the proposed knowledge based system, a genetic algorithm is also used to generate a knowledge base for sequencing applications. The major drawback of these systems is that solving complex problems is a difficult task because definitions of parameters and states are more complicated.

2.3.1.2.2 Artificial Neural Network Based Approaches. Because of their flexibility and adaptability properties, many researches developed real-time scheduling methodologies based on artificial neural networks (ANNs) to schedule complex manufacturing systems (Arzi and Iaroslavitz, 1999; Chen, Huang, and Centeno, 1999; Chen and Muraki, 1997; Li, Chen, and Lin, 2003). Generally, ANNs are used for two main purposes in the real-time scheduling literature. Firstly, in most of the studies, ANNs are used for meta-modeling purposes to determine the performance of alternative schedules in each rescheduling point. Secondly, the scheduling is conducted through an ANN model. It is time consuming to obtain optimum schedule through the ANN and can be infeasible for large size and complex problems. Therefore, the use of ANNs for function approximation, pattern recognition, and clustering is more powerful than for optimization of stochastic and dynamic manufacturing systems.

Sim et al. (1994) developed an expert neural network, which integrates an expert system and a neural network, for dynamic scheduling of the job shop problem. The performance of the ANN is improved via the expert system developed by allowing the sub-networks to be trained separately. Each of the sub-networks corresponds to an activation environment represented by an arrival rate of jobs and the scheduling criterion. Results of the experiments illustrate that the proposed approach improves the performance of the ANN.

Cho and Wysk (1993) developed a robust adaptive scheduler to support the intelligent work center controller. A BPNN was developed to generate several part dispatching strategies based on the workstation status. The generated strategies are then evaluated via the multi pass simulator and the best one which maximizes the system efficiency is selected. The results show that the scheduler provides a suitable support for scheduling of work centers. Son and Souza (1997) and Sun and Yih (1996) developed simulation and ANN based decision support systems for scheduling of work cells similar to the work of Wu and Wysk (1993).

In another study, Geneste and Garbot (1997) developed two approaches, fuzzy inference system and BPNN. The experimental results show that the fuzzy inference system does not provide significant improvements. The NN model gives the weight of each candidate DPR with respect to the objectives of the workshop manager and characteristics of the work shop. The model gives a better solution than the fuzzy inference.

Above studies use ANN models to rank appropriate scheduling rules. Different from the abovementioned approaches, Arzi and Iaroslavitz (1999) proposed an ANN based production control system for a flexible manufacturing cell. The proposed control system used the multi layer ANN to predict an FMS's performance. The scheduling rule with the best predicted performance measure value is selected for the next scheduling period at each rescheduling point. The proposed approach is compared with a decision tree based production control system and single pass scheduling approach. Results show that the proposed control system performed significantly better than other approaches compared.

Priroe et al. (2006) proposed three different types of machine learning algorithms for dynamic scheduling of FMSs. They are case based reasoning, C.45 inductive learning and BPNN. The BPNN approach is similar to the one in Arzi and Iaroslavitz (1999). Simulation results indicate that proposed approaches provide significant improvements over existing DPRs.

Multi layer BPNNs are used to develop decision support systems for real-time scheduling of manufacturing systems in the above studies. Different from these studies, Min et al. (1998) utilized competitive neural networks with Kohonen learning rule for real-time scheduling of FMSs. The developed NN model is used to classify the candidate DPRs that have similar overall performance. The proposed approach combined the competitive ANN and search algorithm to meet the multiple objectives given by the FMS operator. The competitive network generates the next decision rules based on the current decision rules, a current system status and performance measure. The simulation results indicate that the FMS scheduler is able to satisfy multiple objectives given by the operator. In their later work, Min and Yih (2003) proposed the same multi-objective scheduler to select dispatching rules for both machines and automated material handling systems, and to obtain the desired performance measures at the end of short production intervals for a semiconductor wafer fabrication system.

Another approach for real-time scheduling is a hybrid approach that integrates many AI techniques. Rabelo et al. (1993) developed a scheme which integrates modular ANNs, parallel Monte-Carlo simulation, genetic algorithms and machine learning for scheduling of FMSs. Holter et al. (1995) developed an intelligent manufacturing controller which integrates neural networks and genetic algorithms for the single machine problem. Kim et al (1998) developed a multiple objective FMS scheduler that integrates inductive learning, competitive neural networks and simulation. Although the hybrid approaches improve the scheduler performance, the computational effort and time are major drawbacks of such approaches, especially in the real-time scheduling of complex and large size manufacturing systems.

Detailed discussion of ANN based scheduling approaches can be found in Sabuncuoglu (1998) and Akyol and Bayhan (2007).

In recent years, agent based approaches to dynamic manufacturing scheduling have gained increasing attention (Shen, 2002; Xiang and Lee, 2007). There is a substantial evidence that multi-agent systems are one of the most promising approaches in building complex, robust, and cost-effective next-generation manufacturing scheduling systems because of their autonomous, distributed and dynamic nature, and robustness against failures (Parunak, 1996, 2000; Shen et al., 2001; Brennan and Norrie, 2001; Xiang and Lee, 2007). Recently, Xiang and Lee (2007) developed an efficient agent-based dynamic scheduling based on the ant colony intelligence for real-world manufacturing systems.

2.3.1.2.3 Scheduling Through the Fuzzy Approach. Fuzzy set theory-based scheduling models have been developed in modeling and solving different scheduling problems in mainly different ways. The following lists some of the scheduling problems solved through the fuzzy approach:

- Such uncertain parameters as processing times and due dates are modeled by *fuzzy numbers* to yield their fuzzy counterparts, i.e. fuzzy processing times and due dates. In such problems, the solution is obtained through fuzzy arithmetic operations (Petrovic et al., 2007).

- Fuzzy inference engines, i.e., *fuzzy rules*, are used to build aggregated dispatching rules so that multiple performance measures can be taken into account simultaneously (Srinoi, 2006).

- *Fuzzy sets* have been used to represent flexible constraints, such as release dates or due dates (Petrovic et al., 2007).

- *Fuzzy logic* is used to select only the most appropriate dispatching rule from several candidates (Srinoi, 2006).

- *Fuzzy decision* concept (Zadeh, 1970; Yager, 1978) is used to combine a set of heuristic rules in a single fuzzy dispatching criterion. The routing alternative to be selected or the part to be processed next is determined through the fuzzy dispatching criterion developed.

The use of fuzzy sets to represent imprecise nature of parameters or flexible constraints is beyond the scope of this thesis. The interested reader can refer to the works of Guiffrida and Nagi (1998), and Chan and Chan (2004), which review the application of fuzzy set theory in solving scheduling problems. Therefore, this review focuses on the use of fuzzy sets in multi-criteria and dynamic scheduling problems.

Some researchers introduce fuzzy-logic based multi-criteria decision making methods to rank the most suitable dispatching rule or the most satisfactory schedules based on a decision maker's preferences. Kazeroni et al. (1997) evaluate different combinations of dispatching rules and machine selection rules by using a fuzzy multi-criteria decision making technique for an FMS. The alternative combinations are evaluated based on six performance measures: net profit, lead time, makespan, machine utilization, delay in input buffer, and WIP in input buffer. To obtain the performances of dispatching and machine selection rule combinations, a simulation model is run for each combination. To determine how an alternative satisfies an objective, a membership function is developed for each performance measure. Then the priority of each alternative is determined using fuzzy decision concept of Yager (1978). The weights of performance measure are determined via analytical hierarchy process (AHP). Finally, the alternative which has the highest priority is selected. Chan et al. (2002) also use the same methodology to evaluate the different combinations of dispatching rules and machine selection rules. However, in this study, they use a different multi-criteria decision making method to select the scheduling rules, such as simple additive weighting, max-max, and max-min.

Petroni and Rizzi (2002) present a fuzzy logic based group decision making tool to rank flow shop dispatching rules under multiple performance criteria. In this study, five alternative dispatching rules are evaluated by three decision makers in terms of three different performance measures through linguistic variables, such as worst, poor, fair, good and best. The relative weights of the performance measures are also determined by decision makers by linguistically assessing the importance of the performance measures. Finally, the fuzzy suitability index for each dispatching rule is obtained by means of a weighted average of fuzzified rating assigned by the decision makers. In order to rank the alternatives, fuzzy suitability indexes are defuzzified by Yager's formula (1981).

Lee et al. (2002) use some linguistic values to evaluate each criterion and to represent its relative weight for the schedules of a multi-criteria environment. The performance of a given schedule is determined by the fuzzy suitability index calculated by fuzzy arithmetic. Because of the combinatory property of the scheduling problem, a heuristic approach, the tabu search, is involved to find the most satisfactory schedule. It should be noted that while the abovementioned methods use fuzzy logic to rank dynamic dispatching rule pairs, this study aims to find a static schedule under multiple criteria.

As mentioned before, some researchers apply fuzzy rule-based approaches to schedule manufacturing systems, which are continuously changing, under multiple performance criteria. Various forms of fuzzy rule-based approaches are developed to assist different scheduling problems. Some of them are used to determine priority of the parts waiting to be processed, while the others are used to select the most appropriate dispatching rule set based on the changing states.

Hintz and Zimmermann (1989) use fuzzy logic to control the releasing of parts into the systems and the scheduling of parts and tools in FMSs by aggregating dispatching rules. Results show that the proposed approach provides a good compromise solution of the three conflicting objectives.

Grabot and Geneste (1994) combine several dispatching rules using fuzzy logic so as to obtain a compromise solution between job lateness, tardiness, and flow time performance measures. A number of fuzzy rules are developed to build aggregated dispatching rules. The results show that combining dispatching rules provides promising results, instead of using traditional rules that are only able to consider one criterion at a time. Custodio et al. (1994) propose a fuzzy decision system to select part routes, to sequence the parts in the queue and to control the production rate.

Noumann and Gu (1997) proposed a fuzzy dispatching method in which the fuzzy rule base includes different scheduling aspects such as due dates and inventory levels as well as control aspects such as buffer levels and part process plans. There are two performance measures of interest; minimizing late parts and minimizing buffer levels. The proposed methodology contains an optimization mechanism for the weights. The results of this study indicate that the fuzzy dispatching method gives an improvement over certain existing dispatching rules.

Yu et al. (1999) developed a multi-criteria FMS scheduling approach based on fuzzy inference systems. In the proposed approach, a fuzzy inference system is used to determine the current preference levels of the objectives considering changes of the production environment. A multi-criteria scheduling decision is then performed, using the partitioned combination of the preference levels. The results of this study demonstrate the applicability of the proposed approach.

Tedford and Lowe (1999) present a scheduling system for flexible manufacturing systems which incorporates an adaptive fuzzy logic system. Task index and priority index for each task when moving from one stage to another and a resource index of each machine at the end of each week are determined using fuzzy rules. The tasks are then backward scheduled to the selected machine considering these indexes. The results indicate that the proposed system performs better than traditional dispatching rules.

Subramaniam et al. (2000) developed a fuzzy scheduling method that selects the appropriate dispatching rules from a list of candidate rules based on the prevailing conditions in the job shop. The selection of the dispatching rules is performed by a fuzzy inference system that evaluates the appropriateness of the rules considering relative work length, relative work remaining and relative work remaining in the next machine queue performance criteria. The results show that the fuzzy scheduler provides better performance than common dispatching rules.

Lee et al. (2001) present a fuzzy adaptive scheduling method for an FMS part dispatching problem. An automated knowledge acquisition system is also developed to obtain effective scheduling rules for the FMS. A number of samples of representative state vectors are used in the knowledge acquisition phase. Distributed fuzzy sets are then employed in calculating the suitability index of the rules for the selected state vectors. Finally, the most appropriate rule is applied to the system. Simulation results show that the proposed method produces productive and robust schedules than common dispatching rules.

Chan et al. (2002 and 2003) describe a real-time fuzzy expert system to determine routes of parts and to select the part to be processed next in an FMS. The authors use fuzzy logic in two different ways. In the first case, following weighted additive approach; different heuristic rules about route selection are combined into a single fuzzy priority rule. The weights of the rules are determined by the AHP. Then the route with the highest priority is selected for the part to be routed. In the second case, the part to be processed next is determined using a fuzzy inference system that combines shortest imminent operation time and slack per remaining number of operation rules. The proposed approach is compared with a number of combinations of traditional dispatching rules and route selection rules. The results of this study show that the proposed approach is a promising alternative.

Fanti et al. (1998) used the Yager's weighted max-min approach to determine the priority of the jobs waiting to be processed. The proposed approach combines the SPT, EDD and LNQ rules to obtain a single fuzzy priority. The authors show that the weights of the rules strongly affect the performance of the proposed approach. Therefore, a genetic algorithm based search procedure is also proposed to obtain the best weight combination. The numerical experiments demonstrate the effectiveness of the proposed approach.

Canbolat and Gundogar (2004) proposed a fuzzy logic-based scheduling system for job shops which combines the SPT, CR and next machine's load rules to determine fuzzy priority of the job to be processed next. Fuzzy priority values of the jobs are calculated through a fuzzy inference system. The job with the highest priority is selected as the part to be processed next. The performance of the proposed approach is compared with those of traditional dispatching rules via simulation. The results indicate that the proposed approach provides significant improvements on mean flow time, mean tardiness, work in process and throughput simultaneously.

Bilkay et al. (2004) proposed a two-stage fuzzy logic based algorithm for the job shop scheduling. The first stage deals with assigning priorities to part types to be processed considering the batch size, due date, total processing time and tool slots needed. The fuzzy priorities of the job types are determined using a Sugeno type fuzzy inference system. In the second stage, operation-machine allocation and scheduling is performed using another fuzzy inference system. A re-scheduling algorithm for machine failure is also proposed. The results of experiments show that the proposed approach improves the system efficiency.

Another fuzzy logic based approach that selects machines and assigns jobs to the selected machines is developed for FMSs by Srinoi et al. (2006). In order to perform scheduling, a fuzzy inference system is developed with four fuzzy input variables: machine allocated processing time, machine priority, due date priority and setup time priority, and one output fuzzy variable; the job priority. The proposed approach is compared with some other methods reported in the literature in terms of average machine utilization, meeting due dates, setup times, work in process and mean flow times. The results of the experiments show that the proposed approach gives better performance in most performance measures.

Caprihan et al. (2006) developed a fuzzy logic based dispatching strategy to determine routes of jobs dynamically for an FMS. In the design of the proposed strategy, a fuzzy rule base is designed by combining two known dispatching rules: WINQ and NNIQ. Different from other studies in the literature, it is assumed that information delays exist in the FMS considered. Although these delays impact system performance adversely, the results show that the proposed approach performs better than WINQ and NNIQ rules to cope with the information delays.

Petrovic et al. (2006) present a fuzzy logic based decision support system for the parallel machine scheduling/rescheduling problem. A predictive schedule that can absorb uncertain disruptions is generated in the first step. In the proposed approach, two types of decisions are also made by Sugeno type fuzzy inference engines: (i) when to schedule; (ii) which rescheduling method to use. The results show that the predictive schedule is effective, and the fuzzy inference engines perform well in rescheduling.

2.4 Gaps in the Literature and the Motivation of the Proposed Research

As evidenced by the current research on DRC literature, the significance of worker scheduling on shop floor performance is widely accepted. Overall, there exist two viewpoints in the DRC literature:

- When to transfer workers between work centers, and the next work centers they are transferred to are important scheduling decisions as well as job dispatching. Interactions between several dispatching and worker assignment rules are also important.

- There is a strong need for a systematic approach to scheduling of DRC systems, especially for dynamically identifying appropriate “when” and “where” rules based on current shop floor conditions.

A synthesis of the literature review presented reveals that there are five important and emerging issues in the current DRC literature, which leads to the several research questions related to the gaps in the literature:

i. Dynamic selection of worker assignment rules: There are numerous studies that propose different worker assignment rules, analyze their performance and select the best one via simulation according to the performance criterion selected. Almost all of the papers surveyed stated that worker assignment rules have a significant bearing on the performance of a DRC system. In such environments, poor decision making becomes more severe. The literature also pointed out that, similar to job DPRs in machine-only constrained manufacturing systems, efficiency of worker assignment rules highly depends on the performance criteria of interest and on the system conditions. However, just as job DPRs, there is no worker assignment rule globally better than all the others. When the operating conditions or the performance criteria are changed, the worker assignment rules currently selected can become ineffective with regard to the new conditions. Therefore, dynamic selection of worker assignment rules is required to improve overall system performance. However, to the best of the author’s knowledge, only one study has been devoted on how to dynamically select the worker assignment rules based on the changing states. This fact leads to following research question:

1) How can we develop effective real-time control systems which can help the shop manager determine the appropriate worker assignment rule set based on current system states?

ii. Multi-criteria nature of the DRC scheduling problem: The literature review reveals that numerous researchers have paid considerable attention to evaluating different dispatching rule and worker assignment rule combinations in DRC systems.

Although all these applications are inherently multi-criteria decision making problems, the literature review reveals that there is no sufficient effort on multi-criteria scheduling of DRC systems. However, several, and possibly conflicting, criteria might come about in the decision process, which makes it difficult to determine the right criterion. In other words, the decision maker aims to find a schedule that meets each criterion or objective of the system at some level. This fact leads to following research questions:

2) How can we extent the proposed real-time scheduling methodology so that it can deal with multiple criteria?
3) How such multi-criteria aggregation schemes as PROMETHEE and FIS can be used in multi-criteria scheduling of DRC systems?

iii. Artificial intelligence in DRC scheduling: It is clear from the literature review that most researches on DRC scheduling are based on discrete event simulation. Although, in recent years, numerous AI techniques have been successfully applied to other scheduling problems, little research has been devoted to AI techniques, such as ANN and inductive learning, for DRC scheduling. Consequently, the research questions are:

4) How can ANNs be used in modeling DRC manufacturing systems?
5) How can they help decision makers improve DRC system performance?

iv. The use of traditional worker assignment rules: Recall that this research proposes three multi-criteria real-time scheduling methodologies for DRC manufacturing systems. The first two methodologies focus on the dynamic selection of appropriate set of dispatching rules (DPRs), worker assignment rules and routing decisions of jobs with regard to multiple performance criteria. Although the proposed approaches, which change the scheduling rules according to state changes and multiple performance measures, achieve better results than each one of the competing rule set, their performances are subject to the performance of the dispatching rule sets. To cope with these drawbacks, various approaches based on fuzzy logic have been presented for machine only constrained systems. Most of them deal with the scheduling problem of FMS type production systems and focus on part dispatching and routing selection. Furthermore, to the best of the author's knowledge, there is no effort on the use of fuzzy sets in DRC scheduling. A fuzzy-based scheduling approach has not yet been proposed for DRC manufacturing systems. Considering this fact and the gaps in the literature, the related research questions are:

6) How can we develop a fuzzy-based real-time scheduling system for DRC systems?
7) How can the traditional "where" rules that consider only one criterion at a time be combined using fuzzy arithmetic?
8) How can be traditional "when" rules improved through fuzzy reasoning?

Besides the DRC literature, this chapter also provided a review on the real-time scheduling literature. In the light of this review, the following important and emerging issues in the current real-time scheduling literature should be addressed:

v. Multi-criteria real-time scheduling. In the related literature, many single-performance measures have been studied. Although some of the proposed approaches are able to cope with the bi-criteria scheduling problem, little research has been devoted on the use of multi-criteria decision making techniques in real-time scheduling approaches. In recent years, a well known multi-criteria decision making technique, PROMETHEE, have been utilized in a variety of real-life decision making problems. However, to the best of the author's knowledge, PROMETHEE has not yet been applied in scheduling problems. These facts raise the same research question as:

9) How can we develop a PROMETHEE based real-time scheduling approach in DRC systems?

vi. Fuzzy real-time control approaches. The fuzzy real-time approaches in the literature include a number of variables that directly affect the performance of these approaches, e.g. the weights and membership functions. Although some of them involve optimization algorithms to optimize these parameters, to the best of the author's knowledge, none of them use an adaptive control scheme to update these parameters during the scheduling period in order to achieve a decision maker's changing aspiration levels and to adapt to the current shop conditions. Considering this fact and the gap in the literature, the last research question of interest is:

10) How can we extend the proposed fuzzy real-time scheduling approach so that it can also satisfy a decision maker's changing preferences or maintain the current performance considering the prevailing shop conditions?

CHAPTER THREE
ARTIFICIAL INTELLIGENCE

3.1 Introduction

The growth in competition in advanced manufacturing industry, and the additional management challenges it brings, has motivated both practitioner and academic interest on the development of powerful techniques and technologies that can help to improve lead time performance, flexibility and responsiveness of companies. In today's highly competitive, global operating environment, it is impossible to achieve these capabilities without intelligent manufacturing systems which provide real-time control of manufacturing processes. One of the features of intelligent systems is that they have real-time built-in capability to communicate with system's environment, perceive changes and adapt to these changes (Monfared and Yang, 2005).

In the past decade, increasing competitive pressure, the rapid pace of technological change and the recent trend on responsive manufacturing philosophy are motivating the firms to focus on artificial intelligence applications in manufacturing. Artificial intelligence (AI) is the generic name given to field of computer science dedicated to development of programs that attempt to replicate human intelligence (Fonseca and Navaresse, 2002). AI-based techniques have already being used in intelligent manufacturing for more than twenty years.

In the literature, many definitions of AI exit. Some definitions of AI are listed below (Jang, et al., 1996):

- "*AI is the study of agents that exist in an environment, and perceive and act.*" (Russell and Norving, 1995)

- *"AI is the art of making computers do smart things."* (Waldrop, 1987)

- *"AI is programming style, where programs operate on data according to rules in order to accomplish goals."* (Taylor, 1988)

- *"AI is the activity providing such machines as computers with the ability to display behavior that would be regarded as intelligent if it were observed in humans."* (McLeod, 1979)

Artificial neural networks (ANNs) and fuzzy logic (FL) are parts of the AI techniques that have gained an important role in solving problems with extreme difficulty or unknown analytical solutions (Fonseca and Navaresse, 2002). Lin and Lee (1996) define FL and ANNs as follows:

"*FL is based on the way of the brain deals with inexact information, while ANNs are modeled after the physical structure of the brain.*"

They also listed the similarities and differences between FL and ANNs (Lin and Lee, 1996):

- Both of them are numerical model-free estimators and dynamical systems,
- They share the common ability to improve the intelligence of systems working in uncertain, imprecise, and noisy environments,
- Both ANNs and FL have been shown to have capability of modeling complex nonlinear processes to arbitrary degrees of accuracy,
- While fuzzy systems combine fuzzy sets with fuzzy rules to produce overall complex nonlinear behavior, ANNs are trainable dynamical systems whose learning, noise-tolerance and generalization abilities grow out their connectionist structures, their dynamics and their distributed data representation.

Over the years, many AI techniques have been developed for scheduling of manufacturing systems. Among them, ANNs and FL play important roles.

As mentioned in Chapter 1, the aim of this dissertation is to develop novel real-time scheduling methodologies for DRC manufacturing systems. These methodologies include simulation, artificial neural networks, fuzzy sets and fuzzy inference systems. Therefore, this chapter is devoted to explain them to build the proposed methodologies in this research. A general overview of how ANNs and fuzzy sets are used in solving scheduling problems and what makes them appropriate tools for solving DRC scheduling problems are also given in this chapter.

This chapter is further organized as follows. Section 3.2 is devoted to explain artificial neural networks. Section 3.3 presents brief explanation of fuzzy sets and fuzzy inference systems.

3.2 Brief Overview of ANNs

Artificial neural networks (ANNs) are simplified mathematical models of theorized mind and brain (Sabuncuoglu, 1998). In its most general form, an ANN can model the way in which the brain performs a particular function. ANNs simulate neurons interconnected in a similar manner as the human brain’s neurons (Fonseca et. al., 2003).

In the pioneering work on neurocomputing, McCulloch and Pitts (1943) presented the fist mathematical model of a single biological neuron. After McCulloch and Pitts (1943)’s works, many studies have been presented to show the capabilities of neural networks. Since ANNs can successfully understand complex relationships between the input and output variables that are difficult or impossible to analytically relate, ANNs are preferred in many real-world problems, such as pattern matching and classification, function approximation, optimization, vector quantization, and data clustering (Lin & Lee, 1996; Potvin & Smith, 2003). The popularity of ANNs has been influenced by the numerous features offered by ANNs. These features can be identified as (Lee, 1997):

- Approximate nonlinear functions.
- Little process understanding of the system required.
- Ability to continually learn and adapt.
- Robust (fault tolerant model).
- Rapid computation.

On the other hand, the main disadvantage is the lack of self-explanation (Metaxiotis and Psarras, 2003). Due to the high degree of interconnections among the neurons in a network, it will also require a considerable amount of time for training in the network (Sim et.al., 1994).

During the late 1980s, the research on neural networks in manufacturing grew fast. Increasing competitive pressure, the rapid pace of technological change and the recent trend on just-in-time (JIT) manufacturing philosophy motivate firms to be more and more flexible in product design, process planning, scheduling and process control. It is clear that this may be achieved by building intelligent systems that can adapt to changes in their environment (Huang and Zhang, 1994). Today, ANNs is one of the most emerging research areas in AI to achieve these objectives. Different types of ANNs have been developed and applied in almost all area in manufacturing. Since this study presents ANN based scheduling approaches, a general overview of how ANNs are used in solving scheduling problems and what makes them appropriate tools for solving these problems are given in the following subsections.

3.2.1 Basic characteristics and classification of ANN models

The fundamental concept of ANNs is the structure of the information processing system. Basic components of these networks are the neurons connected to other neurons by means of connective links, each with associated weight. Every neuron applies an input, activation and an output function to its net input (sum of weighted input signals) to calculate its output. The combination of different functions determines the neuron model (Corsten and May, 1996). After receiving a proper training, ANNs are capable of achieving desired response to new inputs (Fonseca and

Navaresse, 2002). There are three basic elements of an ANN model, which is illustrated in Figure 3.1 (Haykin, 1999):

- *"A set of connecting links or synapses, each characteristic by a weight of its own. Specially, an input signal j connected to neuron k is multiplied by the synaptic weight* w_{kj}*,*
- *An adder, which sums the input signals weighted by the respective synapses of the neuron, and*
- *An activation function, which limits the permissible amplitude range of the output signal some finite value. It defines the output of the neuron in terms of the induced local field, which is formed by the linear combiner output* u_k*, and the bias* b_k*. This externally applied bias is used in the training of the network.*"

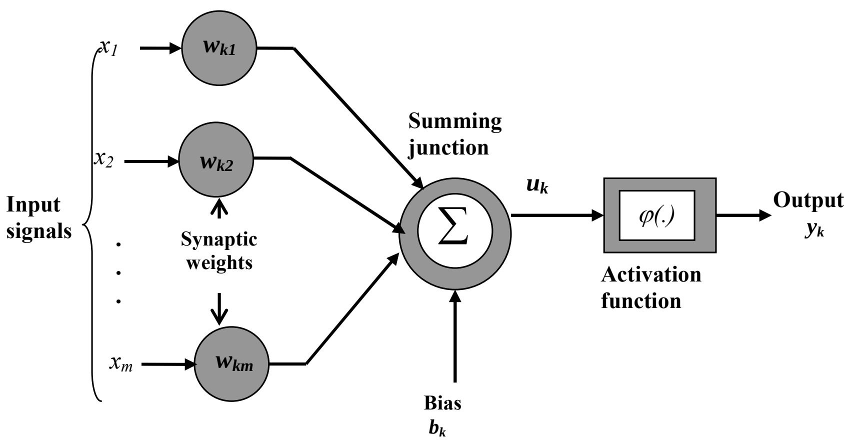

Figure 3.1 Non-linear model of a neuron (Haykin, 1999)

The activation function, denoted by $\varphi(\cdot)$, defines the output of an activation value of a neuron through its net input (Lin and Lee, 1996). There are many different types of activation functions. Selection of the activation function depends on the particular problem considered (Ham and Kostanic, 2000). To explain these functions is beyond the scope of this thesis. A comprehensive explanation can be found in Haykin (1994).

Different classification schemes can be presented for ANNs. For example, Ham and Kostanic (2000) indicated that neural networks can be classified according to how they learn or type of training that is required, and the various applications they perform, those that use activation functions versus basis functions, whether they are recurrent or non-recurrent, and the type of training inputs.

Haykin (1994) stated that ANNs may be classified according to network architectures. Since ANNs have a large number of highly interconnected processing elements that usually operate in parallel and are configured in regular architectures, an ANN can be specified by the structure that organizes these processing elements and the connection geometry among them, such as single-layer and multi-layer networks (Lin and Lee, 1996). Figure 3.2 illustrates two different network structure types.

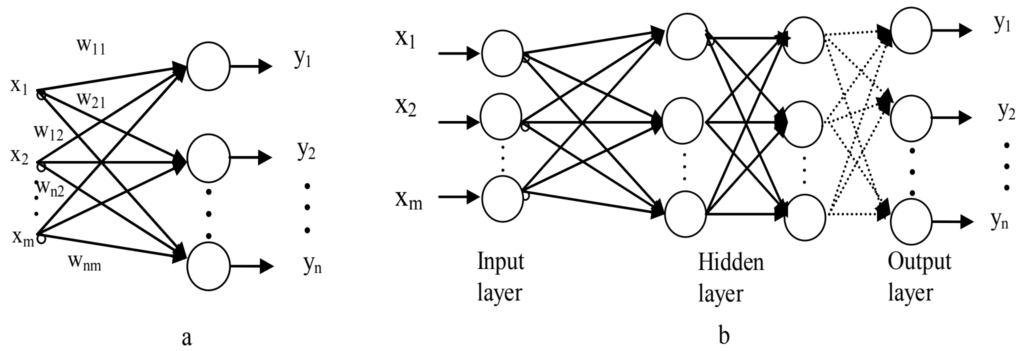

Figure 3.2 a) Single layer feedforward network b) Multi layer feedforward network (Lin and Lee, 1996, p.211)

Since no processing element output is an input to a node in the same layer or in a preceding layer, this type of networks are feedforward networks. The single layer and multi layer networks are feedforward networks (Lin and Lee, 1996). The other type of NNs is recurrent networks. It distinguishes itself from a feedforward neural network in that it has at least one feedback loop (Haykin, 1994). One of the consequences of these connections is that dynamical behaviors can be produced with recurrent networks (Lin and Lee, 1996).

The other important component in identifying an ANN is the learning rules. A learning rule is concerned with updating the connecting weights in an ANN. In general, learning rules are classified into three categories: supervised learning, unsupervised learning, and reinforcement learning (Haykin, 1994).

The developments of new neural network architectures have motivated the researchers to focus on the ANN applications on the scheduling and combinatorial optimization problems. These studies can be classified according to various classification factors such as processing complexity and scheduling criteria (Sabuncuoglu, 1996). Sabuncuoglu (1996) classified neural network types used in scheduling problems as follows:

- Multi-layer perceptrons,
- Hopfield network and other optimizing networks,
- Competitive networks,

While Hopfield networks are used for solving combinatorial optimization problems, competitive networks are used for clustering data in manufacturing applications. Multi layered, feedforward, non-linear network models are commonly referred to as multilayer perceptrons (MLPs) (Fonseca et al., 2003).

In the scheduling literature, the backpropagation based multi-layer network (BPNN) models are the most popular neural network models because of their ability to learn more complex mappings and strong mathematical foundation. Recall from Chapter 1 that this research presents three real-time scheduling approaches which include BPNN models. Therefore, in the next section, a detailed explanation of the backpropagation learning algorithm is given.

3.2.2 Backpropagation ANN models

A supervised learning neural network basically approximates the values of k dependent output variables as a function of n independent input variables, on the basis of samples of the system behavior. It can be seen as an extended version of a multi-variable non-linear regression (Arzi and Iaroslavitz, 1999). BPNN, which is first introduced by Werbos (Werbos, 1974), is most widely used learning algorithm in neural networks. After the work of Werbos (1974), some other researchers have rediscovered this method several times, such as Parker (1982), LeCun (1985) and Rumelhart et al (1986).

BPNNs have several advantages (Cho and Wysk, 1993): (i) They have an approximate answering capability even if the input data are quite noisy and incomplete. (ii) They can easily model complex and nonlinear relationships between inputs and outputs. (iii) Their response times are fast. (iv) Once they are trained, they yield satisfactory results even in the case of large scaling problem.

The backpropagation algorithm is based on a “Least Mean Squares Approach” (Haykin, 1994). The training algorithm tries to minimize the error function by an iterative gradient algorithm. The error backpropagation process consists of two phases through the different layers of the network (Priore, et al, 2006): a forward pass and a backward pass. Haykin (1994) explains the basic steps of the BPNN learning as follows:

The error signal at the output neuron k at iteration n is calculated by Equation (3.1).

$$e_k(n) = d_k(n) - y_k(n) \tag{3.1}$$

The value of squared error (SE_k) for neuron k is defined by Equation 3.2.

$$SE_k(n) = \frac{1}{2} e_k^2(n) \tag{3.2}$$

The sum of squared errors of the network can be defined by Equation (3.3).

$$\xi(n) = \frac{1}{2}\sum_{k \in C} e_k^2(n) \tag{3.3}$$

C in Equation 3.3 includes all neurons in the output layer of the network.

Let N denote the total number of patterns contained in the training set. The average squared error is obtained by summing $\xi(n)$ over n and then normalizing it with respect to N as in Equation 3.4.

$$\xi_{av} = \frac{1}{N}\sum_{n=1}^{N} \xi(n) \tag{3.4}$$

The weight adjustments are made appropriate to the respective errors computed for each pattern presented to the network. The net internal activity level $v_k(n)$ produced at the input of the nonlinearity associated with neuron k is calculated by Equation (3.5).

$$v_k(n) = \sum_{i=0}^{p} w_{ki}(n) y_k(n) \tag{3.5}$$

where p is the total number of inputs applied to neuron k. The synaptic weight $w_{k0}(n)$ equals the threshold ϕ_k applied to neuron k. Hence the function signal $y_k(n)$ appearing at the output of neuron k at iteration n is defined by Equation (3.6).

$$y_k(n) = \quad \varphi_{\mathrm{k}}(v_k(n)) \tag{3.6}$$

Similar to the LMS algorithm, the backpropagation algorithm applies a correction $\Delta w_{ki}(n)$ to the synaptic weight $w_{ki}(n)$, which is proportional to the instantaneous gradient calculated by equation (3.7).

$$\frac{\partial \xi(n)}{\partial w_{ki}(n)} = \frac{\partial \xi(n)}{\partial e_k(n)} \frac{\partial e_k(n)}{\partial y_k(n)} \frac{\partial y_k(n)}{\partial v_k(n)} \frac{\partial v_k(n)}{\partial w_{ki}(n)} \tag{3.7}$$

Hence, the use of Equation (3.7) yields

$$\frac{\partial \xi_k(n)}{\partial w_{ki}(n)} = -e_k(n)\varphi_k^{'}(v_k(n))y_k(n) \tag{3.8}$$

The correction $\Delta w_{ki}(n)$ applied to $w_{ki}(n)$ is defined by the delta rule as follows

$$\Delta w_{ki}(n) = -\eta \frac{\partial \xi_k(n)}{\partial w_{ki}(n)} \tag{3.9}$$

where η is the rate of the learning parameter. Accordingly, the use of Equations (3.8) and (3.9) provides $\Delta w_{ki}(n) = -\eta\delta_k(n)y_k(n)$, where the local gradient $\delta_k(n)$ is itself defined by

$$\delta_k(n) = -\frac{\partial \xi_k(n)}{\partial e_k(n)} \frac{\partial e_k(n)}{\partial y_k(n)} \frac{\partial y_k(n)}{\partial v_k(n)} = e_k(n)\varphi_k^{'}(v_k(n)) \tag{3.10}$$

The computation of δ for each neuron necessitates knowledge of the derivative of the activation function $\varphi(\cdot)$ associated with that neuron. It is clear that the activation function must be continuous to take its derivative. The sigmoid function is one of the most commonly used continuously differentiable nonlinear activation functions in MLPs. With respect to this activation function, $\varphi_k(n)$ is calculated by:

$$v_k(n) = \frac{1}{1+\exp(-v_k(n))}, \qquad -\infty < v_k(n) < \infty \tag{3.11}$$

The steps of the training algorithm are then given in Table 3.1.

Table 3.1 Backpropagation learning algorithms (Lin and Lee, 1996)

Backpropagation learning algorithms
Step 1. Choose η, α ∈ [0,1], $\xi_{\max}$ (maximum tolerable error) Initialize the weights to small random variables.
Step2. Apply the *n*th input pattern to the input layer. $y_k(n) = x_i(n)$ for all *i* where $y_k(n)$ is output of neuron *k*.
Step 3. Propagate the signal forward through the network using $y_k(n)$
Step4. Compute error value and error signals $e_k(n)$ for the output layer
Step5: Propagate the errors backward to update the weights and compute error signals for the preceding layers. Compute the δ 's of the network by proceeding backward, layer by layer. $\delta_k^{(L)}(n) = e_k^{(L)}(n) y_k(n)[1 - y_k(n)]$ for neuron *k* in output layer *L* $\delta_k^{(l)}(n) = y_k^{(l)}(n)[1 - y_k(n)] \sum_j \delta_j^{(l+1)}(n) w_{jk}^{l+1}(n)$ for neuron *k* in hidden layer *l*
Update the synaptic weights of the network in layer *l* according to delta rule $w_{ki}^{(l)}(n+1) = w_{ki}^{l}(n) + \alpha[w_{ki}^{l}(n) - w_{ki}^{l}(n-1)] + \eta \delta_k^{(l)} y_i^{(l-1)}(n)$
Step6 Check whether the whole set of training data has been cycled once. If k<p, then k=k+1and go to step2; otherwise, go to step7.
Step7. Check the error is acceptable If $E<E_{\max}$., then terminate the training process and output the final weights; otherwise, ξ_{av} =0 and *n*=1, and initiate the new training epoch by going to step 2.

3.3 Fuzzy Logic

Besides ANNs, another way of realistically modeling a complex system is the use of fuzzy sets, which allow some degree of uncertainty or “fuzziness” in its description. Fuzzy sets, introduced by Zadeh (Zadeh, 1965), are a generalization of conventional set theory. Bezdek (1993) gives a simple definition as “*a mathematical way to represent vagueness in everyday life*”. Fuzzy set theory was firstly used for decision making by Belman and Zadeh (1970). Up to date, numerous fuzzy methods have been developed to solve different real-world problems. Different production scheduling problems have been solved using fuzzy logic based approaches. As mentioned in Chapter 2 in detail, numerous researchers have reported the potential of fuzzy logic based scheduling approaches in representing complex systems (Petrovic and Duenas, 2006), and in allowing simple knowledge representations of scheduling principles through fuzzy IF-THEN rules (Ioannidis and Tsourvelouidis, 2006).

The main objective of this section is to review basic concepts of fuzzy set theory (FST) and fuzzy inference, which will be used in the proposed methodologies.

The basic definitions of fuzzy sets and fuzzy inference are given briefly in the following sections.

3.3.1 Fuzzy sets

In general, a fuzzy set is defined as follows (Sakawa, 1993, p.7):

"Let X denotes a universal set. Then a fuzzy set F in X is defined as a set of ordered pairs $F = \{(x, \mu_F(x)) \mid x \in X\}$*, where* $\mu_F(x)$ *is called the membership function for the fuzzy set F.* $\mu_F(x)$ *represents the grade of membership of x in F. Thus, the nearer the value of* $\mu_F(x)$ *to unity is, the higher the grade of membership of x in F."*

A fuzzy set *F* is expressed as follows (Sakawa, 1993):

- When *X* is a finite set whose elements are $x_1, x_2, \ldots, x_n$,

$$F = \{(x_1, \mu_F(x_1)), (x_2, \mu_F(x_2), \ldots., (x_n, \mu_F(x_n))\} \tag{3.12}$$

- When *X* is infinite,

$$F = \int_X \mu_F(x) / x \tag{3.13}$$

Where "$\int$"denote the set-theoretic "or".

Since the definition of fuzzy sets is completely different from those of classical set theory, basic definitions about fuzzy sets should be given for better understanding (Zimmerman, 1996; Terano et al., 1992):

- *"The support of a fuzzy set F, S(F), is the crisp set of all x∈X such that* $\mu_F(x) > 0$.

- *A fuzzy set with a membership function that has a grade of 1 is called normal. In other words, A is called "normal" if and only if* $\max_{x \in X} \mu_F(x) = 1$.
- *A fuzzy set F is convex if*

  $\mu_F(\lambda x_1 + (1-\lambda)x_2) \geq \min\{\mu_F(x_1), \mu_F(x_2)\}, x_1, x_2 \in X, \lambda \in [0,1]$
- *The crisp set of elements that belong to the fuzzy set F at least to the degree* α *is called the* α*-level set:*

  $F_\alpha = \{x \in X \mid \mu_F(x) \geq \alpha\}$

  $F_\alpha = \{x \in X \mid \mu_F(x) > \alpha\}$ *is called strong* α*-level set or strong* α*-cut".*

  Examples of an α - level set are illustrated in Figure 3.3.

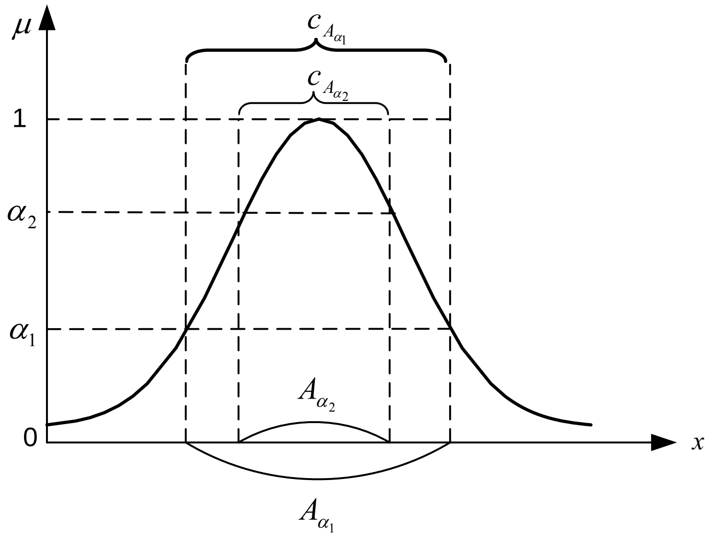

Figure 3.3 Examples of α - level sets (Sakawa, 1993, p. 15)

3.3.1.1 Basic Operations in Fuzzy Set Theory

As known, the basic operations in classical set theory are those of intersection, union and complement. Fuzzy sets have also similar operations and provide a number of functions for aggregating two or more fuzzy sets or fuzzy relations; however these operations are defined using the membership functions. Consider two fuzzy sets *A* and *B* with membership functions $\mu_A(x)$ and $\mu_B(x)$ respectively. These two fuzzy sets can be combined in different ways as follows (Sakawa, 1993; Zimmerman, 1996):

- *Intersection*: The intersection of two fuzzy sets *A* and *B* is defined by the membership function $\mu_C(x)$ of the intersection $C = A \cap B$ as follows:

  $\mu_C(x) = \min\{\mu_A(x), \mu_B(x)\}, \quad x \in X$,
- *Union*: The union of two fuzzy sets *A* and *B* is defined by the membership function $\mu_D(x)$ of the union $D = A \cup B$ as follows:

  $\mu_D(x) = \max\{\mu_A(x), \mu_B(x)\}, \quad x \in X$,
- *Complementation*: The membership function of the complement of a normalized fuzzy set *A*, denoted by $\overline{A}$, is defined as follows:

  $\mu_{\overline{A}}(x) = 1 - \mu_A(x), \qquad x \in X$.

3.3.1.2 Fuzzy Numbers and Algebraic Operations

A fuzzy number is a quantity whose value is imprecise. Fuzzy numbers are used to depict the real-world using imprecise numerical information. A fuzzy number can be expressed in some membership function forms. *L-R* type fuzzy numbers are introduced by Dubois and Prade (1978) as follows (Sakawa, 1993, p.26):

"A fuzzy number M is said to be an L-R fuzzy number if

$$\mu_M(x) = \begin{cases} L\left(\dfrac{m-x}{\alpha}\right) & x \le m, \ \alpha > 0 \\ R\left(\dfrac{x-m}{\beta}\right) & x \ge m, \ \beta > 0 \end{cases} \tag{3.14}$$

where m is the mean value of M and α *and* β *are left and right spreads, respectively, and a function L(.) is a left shape function satisfying*

(1) L(x)=L(-x)

(2) L(0)=1

(3) L(x) is nonincreasing on [0,∞*)."*

Symbolically, M is denoted by $(m,\alpha,\beta)_{LR}$. It is obvious that the different functions can be chosen for $L(x)$, however the linear function is the most widely used one. A triangular linear fuzzy number can be expressed as $A=(m,\alpha,\beta)$. If $l=m-\alpha$ and $u=m+\beta$, the membership function of positive triangular fuzzy number A is defined as:

$$\mu_A(x)=\begin{cases}\dfrac{x-l}{m-l} & l<x\le m\\[2ex] \dfrac{u-x}{u-m} & m<x\le u\\[2ex] 0 & \text{otherwise}\end{cases} \tag{3.15}$$

where $l>0$.

Figure 3.4 illustrates a triangular membership function.

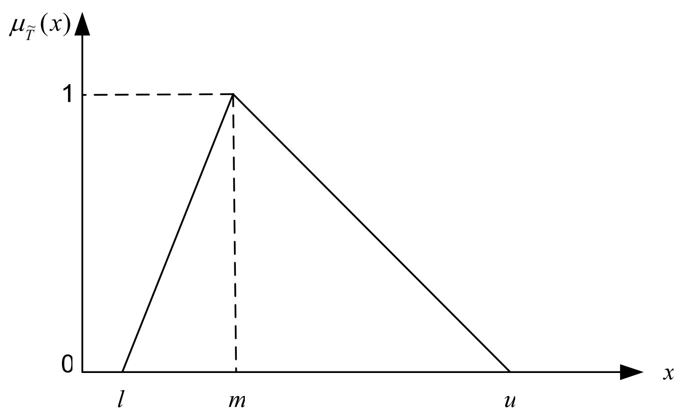

Figure 3.4 A triangular fuzzy number

Since the characteristics of a fuzzy number are different from crisp numbers, the algebraic operations with fuzzy numbers are different from classical operations, and much more difficult compared with the algebraic operations of crisp numbers.

Consider two L-R type fuzzy numbers M= $(m,\alpha,\beta)_{LR}$ and N= $(n,\gamma,\delta)_{LR}$. Dubois and Prade (1978) define the basic operations as follows (Zimmerman, 1996):

- $(m,\alpha,\beta)_{LR} \oplus (n,\gamma,\delta)_{LR} = (m+n,\ \alpha+\gamma,\ \beta+\delta)_{LR}$
- $-(m,\alpha,\beta)_{LR}=(-m,\beta,\alpha)_{LR}$
- $(m,\alpha,\beta)_{LR} \Theta (n,\gamma,\delta)_{LR} = (m-n,\ \alpha+\delta,\ \beta+\gamma)_{LR}$
- If M<0 and N>0, then

  $(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} \cong (mn,\ m\gamma+n\alpha,\ m\delta+n\beta)_{LR}$

  If M<0 and N>0, then

  $(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} \cong (mn,\ n\alpha-m\delta+,\ n\beta- m\gamma)_{RL}$

  If M<0 and N<0, then

  $(m,\alpha,\beta)_{LR} \otimes (n,\gamma,\delta)_{LR} \cong (mn,- n\beta- m\delta,\ -n\alpha- m\gamma)_{RL}$

3.3.1.3 Fuzzy Sets in Decision Making

As stated before, most real-world problems are inherently a multiple criteria decision making problem. However, these problems generally occur in a somewhat uncertain environment. The performance of alternatives, constraints of the problem and goals of decision makers may not be known precisely. In such cases, classical decision making tools become insufficient to model, analyze and solve these problems (Araz, 2007).

Belman and Zadeh (1970) indicated that much of the decision making in the real world takes place in an environment in which the goals, the constraints, and the consequences of possible actions are not known precisely. Then, they firstly introduced fuzzy goals, fuzzy constraints and fuzzy decision concepts (Sakawa, 1993). Assume in a decision making problem that there are k fuzzy goals $G_1,..,G_k$ represented by their membership functions $\mu_{G_1}(x),...,\mu_{G_k}(x)$, and m fuzzy constraints $C_1,..,C_m$ represented by their membership functions $\mu_{C_1}(x),...,\mu_{C_m}(x)$. Belman and Zadeh (1970) defined fuzzy decision D and its membership function as follows:

$$\left.\begin{aligned} &D = G_1 \cap \ldots \cap G_k \cap C_1 \cap \ldots \cap C_m \\ &\mu_D(x) = \min(\mu_{G_1}(x), \ldots, \mu_{G_k}(x), \mu_{C_1}(x), \ldots, \mu_{C_m}(x)) \end{aligned}\right\} \qquad (3.16)$$

The maximizing decision is then defined as (Sakawa, 1993):

$$\underset{x \in X}{\text{maximize}}\, \mu_D(x) = \underset{x \in X}{\text{maximize}} \;\; \min(\mu_{G_1}(x), \ldots, \mu_{G_k}(x), \mu_{C_1}(x), \ldots, \mu_{C_m}(x)) \qquad (3.17)$$

The concepts of fuzzy goal, fuzzy constraint and fuzzy decision have already been used for many types of decision problems. As discussed in Chapter 2, some researchers have paid more attention to develop scheduling methods that use fuzzy set theory. Some of them use membership functions to define fuzzy goals for routing selection problems (Chan et al. 2002; 2003), while the others select the most suitable dispatching rule based on linguistic fuzzy multi-criteria evaluation (Kazeroni et al., 2002; Petroni and Rizzi, 2002). Besides, a lot of research efforts have been directed to use FIS for scheduling problems. Therefore, FIS is explained in the next section in detail.

3.3.2 Fuzzy Inference System

A fuzzy inference system (FIS) is a popular computer framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. Because of its strong theoretical background and ease of use, it has already been applied to numerous decision making problems such as automatic control, data classification, decision analysis, expert systems, time series prediction, robotics, and pattern recognition (Jang et al., 1997).

In the FIS, the solution of a problem comes from the 'expert experience' of a human operator in the design of the system. Generally, a decision maker describes the nonlinear input-output relationships through an IF-THEN structure which includes linguistic fuzzy variables, membership functions, fuzzy rules, implication processes and decomposition (Lin and Lee, 1996). The most important elements of the IF-THEN structure are fuzzy rules which can be defined as follows (Zadeh, 1977):

If *(antecedent)* then *(consequent)*

The calculus of fuzzy IF-THEN rules is quite simple; all rules are evaluated in parallel, which is one of the more important characteristics of fuzzy inference systems (Yu et al., 1999).

The typical architecture of a FIS is comprised of three conceptual components (Jang et al., 1997):

- a rule base, which contains a selection of fuzzy rules,
- a database, which defines the membership functions used in the fuzzy rules,
- a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion.

The inputs of a basic fuzzy inference system can be either fuzzy or crisp. After all rules have been defined, the reasoning process starts with the computation of all the rule-consequence pairs. Then the consequences are aggregated into one fuzzy set describing the possible actions (Zimmermann, 1996). The outputs are almost always fuzzy sets. When it is necessary to have a crisp output, defuzzification of the fuzzy output is needed. A fuzzy inference system with a crisp output is shown in Figure 3.5 (Jang et al., 1997).

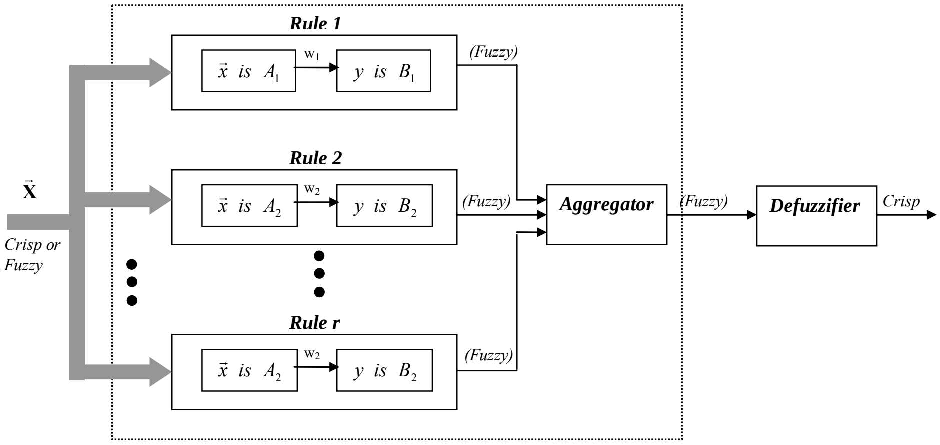

Figure 3.5 Block diagram for a fuzzy inference system (Jang et.al., 1997, p.74)

The most frequently used FISs are Mamdani (1975) and Sugeno (Sugeno and Yasukawa, 1993) type FISs. These two types of inference systems vary somewhat in the way outputs are determined (Matlab Toolbox, 2007). In Mamdani type inference, the outputs are expected to be defined by fuzzy sets with their corresponding characteristic membership functions. The latter method requires that the membership functions of the output variable be only equal to a linear function or a constant. The following sub-sections are devoted to explain both types of inference systems.

3.3.2.1 Mamdani Fuzzy Models

The Mamdani fuzzy inference system (Mamdani and Assilian, 1975) is one of the first control systems that use fuzzy sets, and the most commonly used fuzzy methodology. Figure 3.6 illustrates how a two-rule Mamdani fuzzy inference system derives the overall output z when subjected to two crisp inputs x and y (Jang et al., 1997).

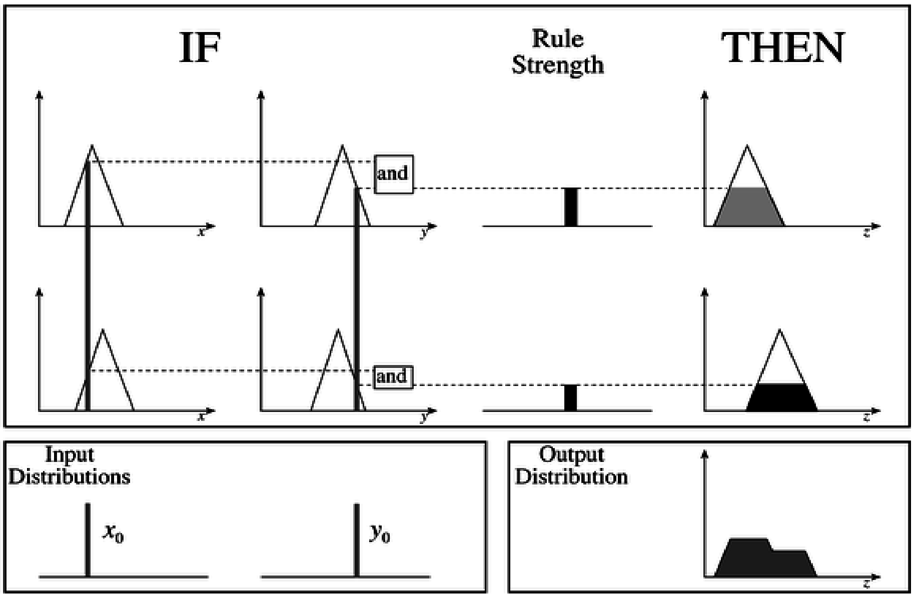

Figure 3.6 Diagramatic representation of Mamdani fuzzy inference system (Lin and Lee, 1996, p.155)

The definition of linguistic variables and rules are the main design steps when implementing a Mamdani FIS. FIS rules are characterized by a collection of fuzzy IF-THEN rules in which the antecedents and consequents involve linguistic variables. The fuzzy rules describe the input-output relation of the system. The form of the FIS rules in the case of two-input-single-output systems is (Lin and Lee, 1996):

$$R_i\text{: IF } x \text{ is } A_i\text{, AND } y \text{ is } B_i\text{, THEN } z = C_i \quad i=1,2,\ldots,n \tag{3.18}$$

where $x,\ldots,y$ and z are linguistic variables representing the process state variables and the control variable, respectively, and A_i, B_i and C_i are the linguistic values of the linguistic variables $x,\ldots,y$ and z in the universes of discourse $U,\ldots,V$ and W, respectively.

In order to derive conclusions from a set of fuzzy if-then rules, the first step is to compute the degrees of membership of input values in the rule antecedes. Employing the minimum operator, the firing strength of rule R is:

$$\alpha_{R_i} = \min\left\{ \mu_{Ai}(x^{input}), \mu_{Bi}(y^{input}) \right\} \tag{3.19}$$

This concept enables one to obtain the validity of the rule consequences. It is assumed that rules with a low degree of membership in the antecedent also have little validity and therefore cut off the consequence of fuzzy sets at the height of the antecedent degree of membership (Zimmerman, 1996). Formally,

$$\mu_{C_i}^{consequence}(z) = \min\left\{ \alpha_{R_i}, \mu_{C_i}(z) \right\} \tag{3.20}$$

Fuzzy output distribution can now be derived by aggregating the consequences of all of the fuzzy rules using the maximum operator as follows:

$$\mu^{consequence}(z) = \max_{i=1,..,n}\left\{ \mu_{C_i}^{consequnce}(z) \right\} \tag{3.21}$$

It is important to note that Mamdani's method takes into account all rules in a single stage and that no changing occurs. Thus the inference process in fuzzy control is much simpler than in most expert systems (Zimmerman, 1996). After the aggregation process, it is desired to come up with a single crisp output from a FIS using a defuzzification strategy. Explanations of the most popular defuzzification strategies can be found in the work of Jang et al. (1996).

As mentioned before, Mamdani type inference has received much attention from the researchers who work on scheduling of manufacturing systems. Most of them use this type of inference engines to determine the states of the manufacturing system (Chan et al., 2003), select the most appropriate dispatching rule based on the conditions prevailing in the job shop (Subramaniam et al., 2000) or determine job priorities in real-time (Bilkay et al., 2004).

3.3.2.2 Sugeno Fuzzy Models

The Sugeno fuzzy model was proposed by Takagi, Sugeno and Kang (Takagi and Sugeno, 1985; Sugeno and Kang, 1988) in effort to develop a systematic approach to generating fuzzy rules from a given input-output data set (Jang, et al., 1996). As mentioned before, different from Mamdani type inference, it requires that the membership functions of the output variable are only equal to a linear function or a constant.

A Sugeno inference system can be represented as follows:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = f(x\ ,\ y) \tag{3.22}$$

where A and B are fuzzy sets in the antecedent, while $z = f\,(x,\ y)$ is a crisp function in the consequent (Jang, *et al*., 1996). The output is computed with the help of degrees of membership that are evaluated exactly as in the Mamdani controller.

$$\mu^{Sugeno} = \frac{\sum_R \alpha_R . f_R(x_1, x_2, ..., x_n)}{\sum_R \alpha_R} \tag{3.23}$$

Figure 3.9 shows the fuzzy reasoning procedure for the Sugeno fuzzy model.

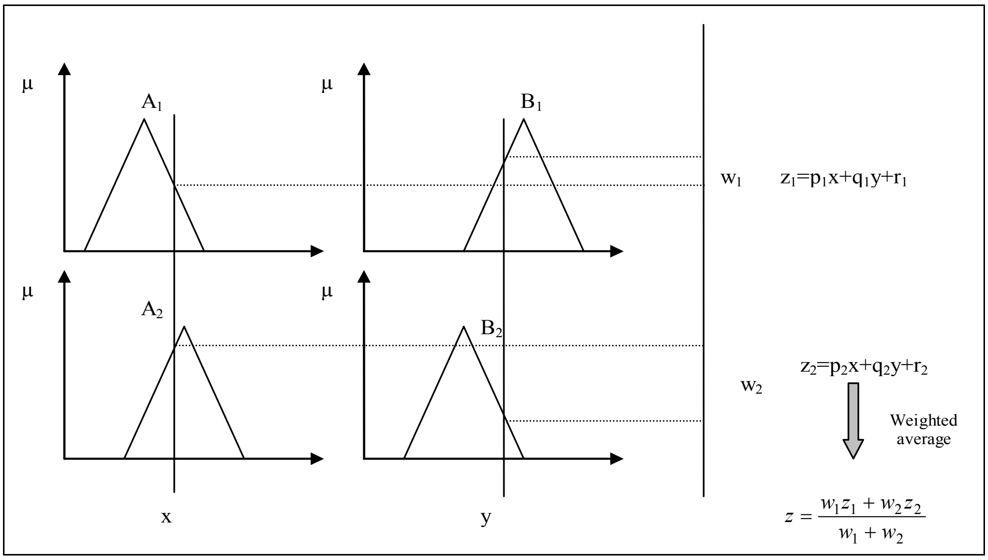

Figure 3.9 Diagramatic representation of Sugeno fuzzy inference system (Jang, *et.al*., 1996, p.81)

Because it is a more compact and computationally efficient representation than a Mamdani system, the Sugeno system lends itself to the use of adaptive techniques for constructing fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system best models the data (Matlab Toolbox, 2007). As compared to Mamdani type systems, the use of Sugeno type inference systems is not common in the scheduling literature.

3.4 Summary

In this chapter, we gave a brief overview of the fundamentals of ANNs and Fuzzy set theory. Decision making in a fuzzy environment was also discussed. BPNN and fuzzy inference, which will be used throughout the remainder of this thesis, were explained in detail.

In the next chapters, the proposed real-time DRC scheduling approaches are introduced.

CHAPTER FOUR
A NOVEL MULTI-CRITERIA REAL-TIME SCHEDULING APPROACH FOR DRC SYSTEMS THROUGH ANN AND FIS

4.1 Introduction

As emphasized in Chapter 2, with increasing importance of responsive manufacturing philosophy and effective scheduling decisions on the performance of shop floor, many firms are forced to adopt real-time scheduling methodologies. The literature review in Chapter 2 also reveals that there is a strong need for employing adaptive control-based mechanisms to determine scheduling rules dynamically to respond to changing manufacturing settings in Dual Resource Constrained (DRC) manufacturing systems. This research proposes three different real-time scheduling methodologies in this respect. The first two mainly deal with the dynamic selection of appropriate set of dispatching rules (DPRs), worker assignment rules and routing decisions of jobs with regard to multiple performance criteria. The third one uses a fuzzy priority-based control scheme to perform the dynamic scheduling of jobs, workers and routes rather than traditional DPRs, worker assignment rules and specific routing decisions.

This chapter introduces the first methodology. More specifically, the first methodology schedules machines and operators through DPRs and worker assignment rules, respectively. Candidate DPRs and worker assignment rules are selected dynamically based on changing manufacturing states. The proposed methodology consists of three modules; simulation, Artificial Neural Networks (ANNs), and a Fuzzy Inference System (FIS). The multi-criteria nature of the dynamic scheduling problem is also handled by the FIS.

As discussed in Chapter 2, although a number of methods have been proposed for dynamic scheduling problems (for DRC systems), most of them do not take into account the multi-criteria side of the problem. Therefore, the proposed methodology is centered on developing a new multi-criteria adaptive control scheme based on neural networks and fuzzy inference for DRC systems.

This chapter is organized as follows. Section 4.2 introduces the proposed real-time scheduling methodology. Its advantages are also discussed via simulation experiments in this section. Section 4.3 elaborates the experimental studies. The results are discussed in Section 4.4. Finally, concluding remarks are given in section 4.5.

4.2 A multi-criteria adaptive control scheme based on neural networks and fuzzy inference for DRC systems

The proposed dynamic scheduling methodology, called MCDRC-FIS, schedules parts and operators through DPRs, routing rules and worker assignment rules. Candidate DPRs, routing rules and worker assignment rules are selected dynamically based on the changing states. This methodology alters not only part DPRs, routing rules and worker assignment rules but also the multi-criteria performance of the system in real time, which affects the selection of the appropriate scheduling rules. The methodology also provides a mechanism that is an interface with the shop floor monitoring and controlling the states, and actual performance measures of the manufacturing system. The basic structure of the methodology is given in Figure 4.1.

It is assumed that the DRC system is operated for a pre-determined long time interval. The decisions about DPRs, routing rules and worker assignment rules to be applied should be made for short production intervals and updated at the beginning of each interval (decision point).

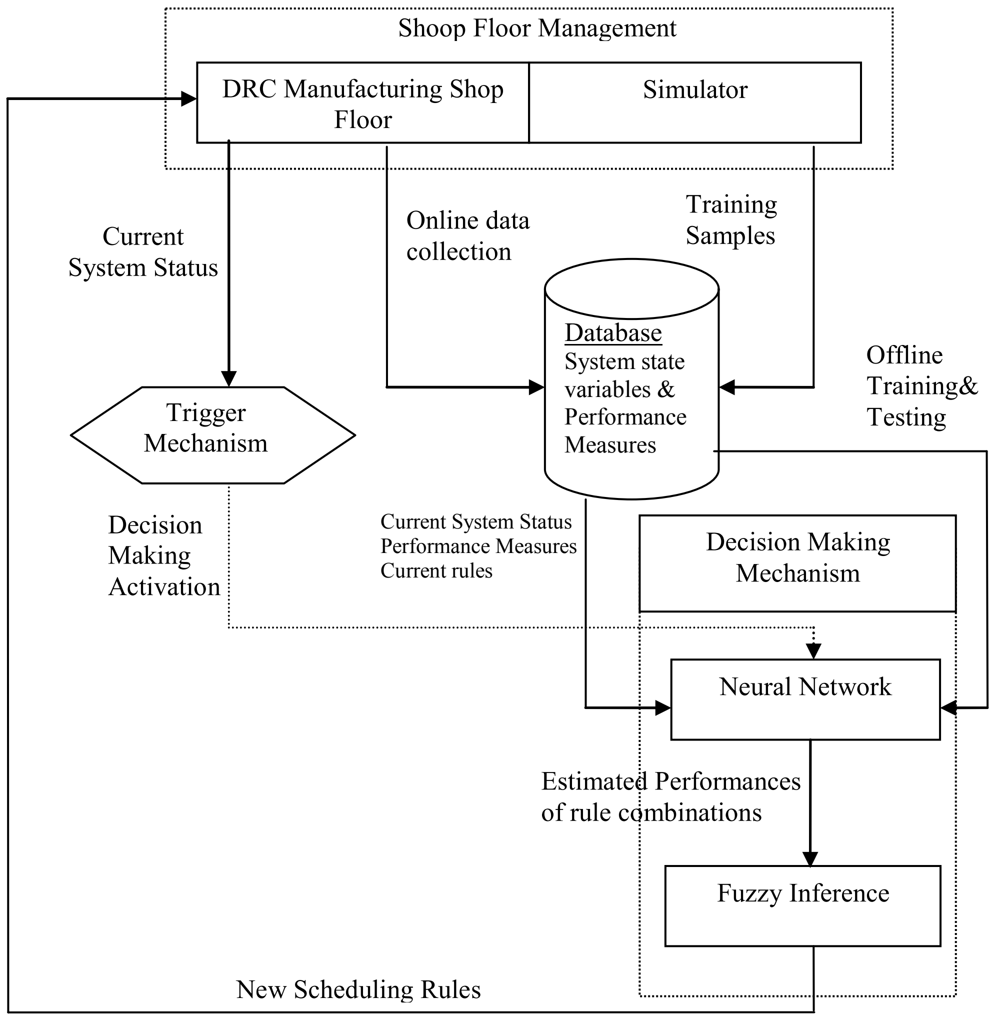

Figure 4.1 MCDRC-FIS architecture

The MCDRC-FIS methodology consists of three modules; shop floor management, ANNs, and a FIS. The shop floor management module is responsible for applying required scheduling rules, and monitoring the system states and performance measures of the system. This module also includes a simulation module that generates a sample data to train and test ANNs. The sample data is made up of different combinations of decision variables (rule combinations) and system states. At the beginning of a scheduling period, ANNs are then used to estimate performances of candidate DPR, routing rule and worker assignment rule combinations for short production intervals based on system states. In other words, ANNs play the role of a look-ahead simulation model that produces the performances of all rule combinations during the next scheduling period. In order to perform multi-criteria evaluation of alternative rule combinations, the FIS aggregates the performance values of the rule combinations generated by ANNs to yield an overall performance. The rule combination which will be used during the next production interval (scheduling period) is then determined based on this overall performance.

The multi-criteria nature of the dynamic scheduling problem is also handled by the FIS. In machine-only constrained systems, most of the dynamic scheduling approaches consider optimization of a single manufacturing performance criterion, and in general use dispatching rules because they can be altered easily to adapt to changing manufacturing conditions. However, several, and possibly conflicting, criteria might come about in the decision process, which makes it difficult to determine the right criterion. These rules are not effective enough in such a multi-criteria decision making environment. In this case, a scheduling system should prioritize these criteria, and determine an overall criterion based on this prioritization. In other words, the decision maker aims to find a schedule that satisfies all criteria or objectives simultaneously.

4.2.1 The Simulator

The simulator is used to create necessary data for training and testing ANNs. To do this, an experimental design is conducted for various system states and combinations of DPRs, routing rules and worker assignment rules. This study has developed a parametric simulator to easily model various DRC manufacturing configurations and create their schedules. Figure 4.2 shows the input and output data of the simulator. The input data are automatically read from a database to create a simulation model. The system is then simulated with respect to these experiment points. Training samples for ANNs are gathered from these simulation runs. This phase is carried out offline at the beginning of the scheduling. However, it is clear that in case of major system changes (in cases of major machine breakdowns, adding new machines, part types and routes or processing time changes), a new simulation should be performed. Accordingly, new training samples should be created.

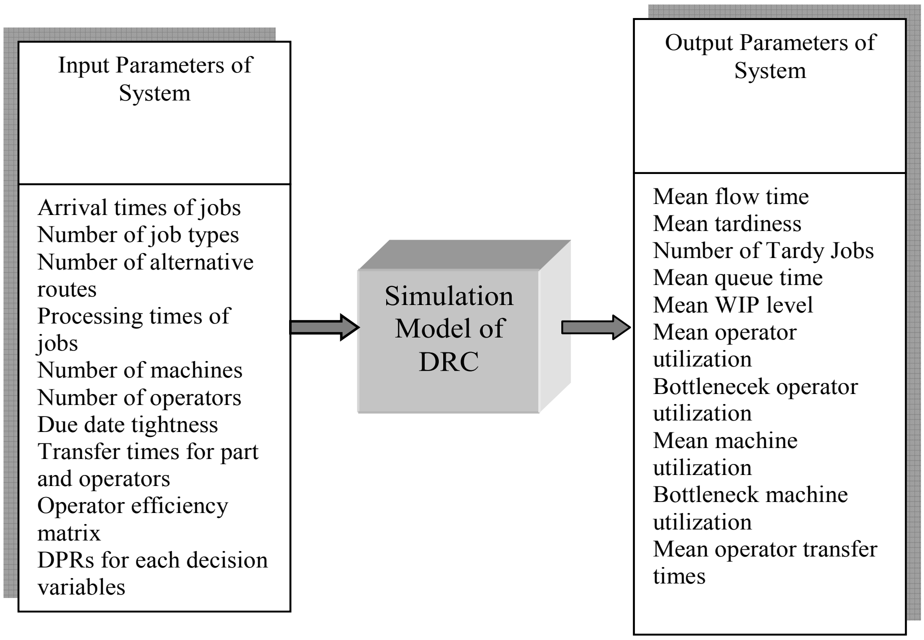

Figure 4.2 Input and output data for the simulation model

The basic steps of the simulator module are summarized in Figure 4.3.

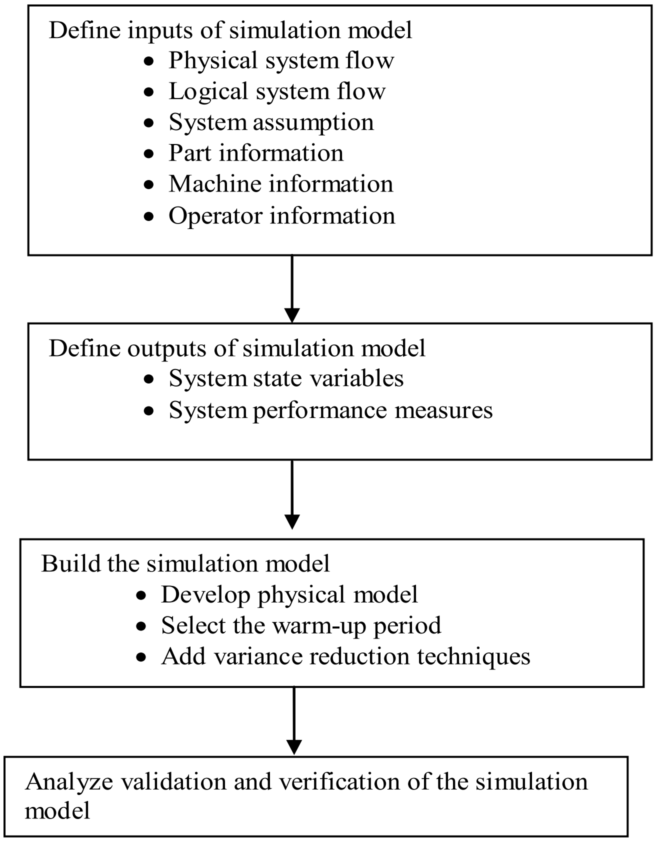

Figure 4.3 Basic steps of developing simulator

4.2.2 ANNs

ANN models are used as meta-models. A meta-model is a mathematical approximation of a simulation model that represents the relationship between inputs and outputs of the system. The meta-modeling approach is helpful when the simulation becomes very large and costly.

In general, regression analysis has been combined with simulation for building meta-models (Law and Kelton, 1991). However, regression meta-models have some drawbacks: it is limited to approximate a subset of the simulation domain, sensitive to deviations from statistical model assumptions, and it is possible to select incorrect functional form during the analysis (Fonseca et al., 2003). On the other hand, some researchers have stated that meta-modeling through Artificial Neural Network (ANN) models may overcome these disadvantages of traditional regression approaches (Fonseca et al., 2003; Kilmer et al., 1997).

In this research, ANNs are used to estimate the performance measures at each decision point; obtained by applying alternative DPR, routing rule and worker assignment rule sets in the consecutive scheduling period. The proposed methodology utilizes backpropagation Neural Networks (BPNNs), which are well known pattern classifiers and function approximators (Lippman, 1987; Freeman and Sakapura, 1991; Priore *et al*., 2006).

The backpropagation algorithm is derived from a "Least Mean Squares Approach". The parameters of learning rate, momentum rate and activation function strongly affect the performance of ANNs, and there are not common methods to determine them. Generally, they are determined with trial and error. Some optimization techniques like genetic algorithms (GAs) can also be used. Yet these lengthen the solution time. MCDRC-FIS uses a GA solver embedded in the ANN tool to determine the learning rate and the number of neurons in the hidden layer, while the other parameters are determined with the trial and error basis.

As mentioned above, the training samples are gathered from the simulation runs. A training sample consists of the relevant inputs, such as system parameters (e.g. due date tightness factor), system state variables (e.g. Average Queue Length), current system performance measures (e.g. mean flow time), the scheduling rule combination applied in the previous production interval, and the next scheduling rule combination to be applied. The sample has one output, i.e. the performance value, obtained by applying the next scheduling rule combination. If more than one performance measure exists, an ANN model is constructed for each of them. The information about the inputs should be collected at the beginning in the scheduling period, while the outputs should be measured at the end of the period. The basic steps of developing ANN models are summarized in Figure 4.4.

Although the training samples are obtained by simulation in the experiments, it is possible to get them from the actual data. Arzi and Iaroslavitz (1999) state that the performance of ANNs can be improved by gathering the actual samples continuously and retraining the ANNs periodically, while considering all the gathered samples. It is clear the proposed approach allows such a retraining phase.

Since ANN models are trained and tested offline, the methods employing them can make decisions quickly. Hence, MCDRC-FIS has the advantage of a rapid response. At each decision point (the beginning of each scheduling period), the system parameters, system state variables, current system performance measures, the scheduling rule combination applied in the previous production interval, and the alternative scheduling rule combination to be applied in the next interval are fed to the ANNs related to the performance measures of interest. The performance measures of alternative rule combinations, obtained by applying the scheduling rule combinations, are estimated through the trained ANNs. Since the multiple performance criteria exist, the scheduling rule combination with the best compromised solution is then selected through the FIS module.

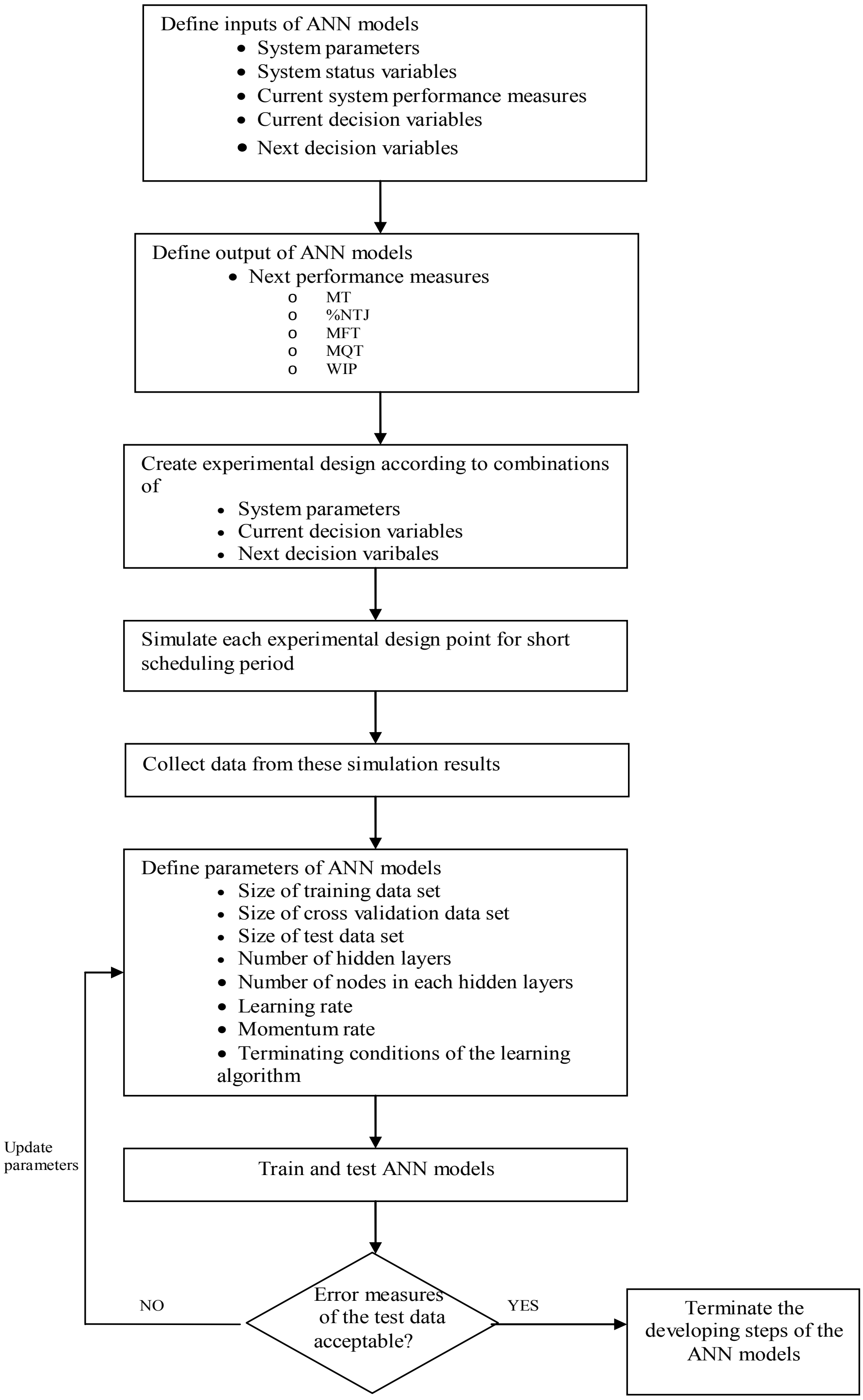

Figure 4.4 Basic steps of developing ANN models

4.2.3 The Fuzzy Inference System

In many real-life scheduling problems, it is often desirable to achieve a compromise solution according to a number of different criteria. Such multi-criteria scheduling problems generally have been solved by either evaluating each objective separately or employing some overall cost functions. However, evaluation of each objective separately does not yield satisfactory results, and it is difficult to determine the costs in practice. The decision maker also aims to satisfy each objective at some level, and evaluate all the performance measures simultaneously. An aggregation function is therefore needed to obtain a compromise solution. In this respect, while the ANN models nonlinear relationships between system parameters and performance measures, a fuzzy inference system aggregates these performance measures to perform the aggregation of all the objectives.

A Mamdani type FIS (Mamdani and Assilian, 1975) is used because of its ability in representing nonlinear systems. The methodology defines membership functions for each performance measure using linguistic variables such as “mean tardiness is LOW”, “mean tardiness is MEDIUM” and “mean tardiness is HIGH”. The inputs of the system are the values of performance measures of a specific rule combination. The output is a score of the selected rule combination which is used to evaluate alternatives. The membership for the output is also defined using five linguistic variables: VERYLOW, LOW, MEDIUM, HIGH and VERYHIGH.

Recall that MCDRC-FIS periodically reviews the system status and, at each scheduling point, the performances of all alternative rule combinations that include DPR, alternative route and worker assignment rules are determined via ANN models. At this point, the FIS is run for all alternative rule combinations by feeding inputs into the FIS to obtain a score for each rule combination. The alternative with the highest score is then selected as the new scheduling rule combinations. The new rule combination that includes DPR, routing rule and worker assignment rule is utilized until the next scheduling point.

4.2.4 Determining the Length of Scheduling Period

As discussed above, the decision about when a new scheduling rule combination should be applied (determining the next scheduling point) is related to the length of the production intervals (scheduling periods). The length of the scheduling periods can be fixed or variable. MCDRC-FIS can be applied in both cases.

In the fixed length scheduling period case, the performance of the manufacturing system is periodically monitored to respond to system changes. At each scheduling point, the performances of all alternative rule combinations that include DPR, routing rule and worker assignment rule are determined via ANN models. Then, the FIS is used to evaluate the alternatives and select the best one.

In the variable length scheduling period case, an initial schedule is generated at the beginning of a period, and then the performance measures of the manufacturing system are monitored continuously and compared with some thresholds set by the decision maker. When the current values of the performance measures exceed the threshold values, the rescheduling mechanism is triggered (similar to the one in Lee (1989)). At each rescheduling point, MCDRC-FIS is employed to determine the next scheduling rule set.

A hypothetical case problem is given in the next section to elaborate the methodology.

4.3 Experimental Studies

The experimental studies are classified into three groups:

1. Comparison of the proposed scheduling approach with other scheduling approaches in different variation levels,
2. Investigation of the effects of the length of the scheduling period on the performance of MCDRC-FIS

3. Comparison of the fixed length scheduling period and variable length scheduling period.

The first group of the experimental studies compares the performance of MCDRC-FIS with fixed, random and multi-pass scheduling approaches. The effects of the variation levels of the manufacturing system considered are also investigated via the first experiments. During these experiments, it is assumed that the next scheduling point is determined periodically. Since the length of the scheduling period affects the performance of real-time scheduling approaches, the second group involves evaluating the effects of the length of the scheduling period on the performance of MCDRC-FIS. As discussed earlier, MCDRC-FIS can be applied in fixed and variable length scheduling period cases. Therefore, the third group of the experiments compares the two monitoring approaches.

4.3.1 The Manufacturing System

The hypothetical DRC manufacturing system consists of 24 departments. There are identical parallel machines in some departments. The total number of machines and workers is 31 and 15, respectively. Ten different part types are processed through flexible routings. The mean of processing time of jobs on each machine, alternative routes of each part types and the distance matrix for the departments are given in Appendix A. Other definitions are as follows.

p_{ij} is processing time of job i on machine j for i = 1, 2,…, 10; j = 1, 2,…, 31.

v_i is the number of operations for job i

d_i is due date of job i

t_i is arrival time of job i

S_{ij} is starting time of job i on machine j

IB_j is input buffer of machine j

OB_j is output buffer of machine j

Q_{ij} is entering time of job i on IB_j

K is due date allowance factor

C_i is completion time of job i

n is total number of jobs produced in the system

m is total number of machines in the system

o is total number of operators

The main assumptions are:

- The inter-arrival times for jobs are generated from the exponential distribution with a changing mean value in the scheduling period, i.e. the underlying process is non-stationary.
- Transfer times for operators and parts between workstations are 0.75 min/unit distance.
- The set-up times is considered as 20% of processing time.
- Machine breakdowns are not considered.
- Workers are homogeneous.
- Workers are full cross-trained.
- Due dates of arriving jobs are calculated from the TWK method (Baker, 1984) through Equation (4.1):

$$d_i = t_i + (K \times \sum_{j=1}^{v_i} p_{ij}) \tag{4.1}$$

- Preemption of jobs is not allowed.
- When a job arrives at an empty work centre, the operator is selected in a cyclic manner from available workers.

The scheduling process is carried out by the shop manager who selects the worker assignment rules and dispatching rules in addition to the job routes. In other words, there are four decisions to be made. The first two are related to the “when” and “where” worker assignment rules to determine when to transfer a worker from a work center to another, and which work centre a worker to be transferred to, respectively. The selection of parts by machines is related to the part scheduling rules, also called DPRs. Due to the routing flexibility, the selection of machines by parts should also be considered. These variables and rules are given in Table 4.1 (a), and their definitions in Table 4.1 (b).

Table 4.1 (a) Decision variables and associated rules

Decision Variable	**Associated Rules**
When rules	*Centralized Rule*: A worker is eligible for transfer each time a current job is completed, even if the queue in the current work center contains more jobs *Decentralized Rule*: A worker is eligible for transfer only when idle
Where rules	The worker is transferred to the work center: • with the most jobs in queue (*LNQ*) • containing the job with the longest waiting time in queue (*LWT*) • containing the job with the shortest processing time and traveling time (*MSPT*) • containing the job with the earliest due date (*EDDS*)
Machine selection by parts	*SNQ*: Fewest waiting jobs for the machine *SFT*: Shortest flow time at an operation *LAUF*: Lowest average utilization first
Part selection by machines	*FIFO*: First in first out *SPT*: Shortest Processing Time *EDD*: Earliest due date *SRPT*: Shortest remaining processing times. *CRT*: Critical Ratio (Ratio-selects the job that has the lowest ratio of due date minus current date to total estimated remaining processing time. *MST*: Minimum Slack Time *CR/SPT*: (CRT2) Critical ratio/shortest processing time

Table 4.1 (b) Definitions of the rules

DPRs	*Definition*
First in First Out (FIFO)	$pr_j = \min_{i \in I}(Q_{ij})$
Shortest Processing Time (SPT)	$pr_j = \min_{i \in I}(p_{ij})$
Earliest Due Date (EDD)	$pr_j = \min_{i \in I}(d_i)$
Shortest Remaining Processing Time (SPR)	$pr_j = \min_{i \in I}\left((\sum_{j=1}^{m} p_{ij}) - fpr_i \right)$
Critical Ratio (CRT)	$pr_j = \min_{i \in I}\left(\frac{(d_i - tnow) - (\sum_{j=1}^{m} p_{ij}) - fpr)}{d_i - tnow} \right)$
Minimum Slack Time (MS)	$pr_j = \min_{i \in I}(d_i - tnow)$
Critical ratio/ processing time (CR/SPT)	$pr_j = \min_{i \in I}\left(\frac{CRT_i}{p_{ij}} \right)$

As discussed earlier, the efficiency of the abovementioned rules highly depends on the performance criteria of interest and on the system states. Five performance measures are considered to evaluate the performance of the proposed methodology:

- Mean Tardiness (MT): $MT = \frac{\sum_{i=1}^{n} \max\left(0, C_i - d_i\right)}{n}$ (4.2)

- Percentage of tardy job (%NTJ): $\%NTJ = \frac{NTJ}{n} \times 100$ (4.3)

where $NTJ = \sum_{i=1}^{n}((C_i - d_i) > 0) \times 1 + ((C_i - d_i) \leq 0) \times 0)$ (4.4)

- Mean Flow Time (MFT): $MFT = \frac{\sum_{i=1}^{n}(C_i - t_i)}{n}$ (4.5)

- Mean Queue Time (MQT): $MQT = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m}(S_{ij} - Q_{ij})}{n \times m}$ (4.6)

- Work in Process (WIP) in the system at the any time.

4.3.2 Experimental Design

As discussed above, the proposed real-time scheduling approach consists of three main models: simulation, ANN and FIS. To execute the proposed methodology online, the simulation and ANN models must be first developed offline. In this phase, after inputs and appropriate parameters of the models are determined, the models are constructed according to the specification of the case problem considered. In the following subsections, the model development phases are given in detail.

4.3.2.1 Data Collection

A simulation model in ARENA 3.0 was constructed to represent the real shop floor in the experiments; and used to monitor the system, and to train and test the neural network models. The simulation model was validated by controlling some input-output relation for the case problem.

The manufacturing system is monitored for 60.000 minutes with a warm-up period of 15.000 minutes. The variance reduction technique of common random numbers (Pegden et al., 1990) is used for synchronization of random numbers so that the alternative rule combinations are compared under similar conditions. 20 replications are run to estimate the performance measures.

The training and testing data required for the ANNs are obtained by simulation runs by randomly changing scheduling rule combination every production interval. In order to comprehensively represent the relationship between system state variables, selected rule combinations and performance measures, 1300 design points, which consist of the combination of some system state variables and rule combinations, are randomly selected. In the design points, the combination of current and next scheduling rule sets is randomly changed at each scheduling point. The length of each scheduling period is set to 5000 minutes. For each combination of the rules, input-output pairs are collected from the simulation model for short scheduling periods. The 1300 data set obtained from the simulation runs are used to train and test the ANNs.

4.3.2.2 Training and Testing ANN models

The performance of a metamodel depends on the selection of the inputs of ANN models to estimate the output of the system. Therefore, the effects of the candidate inputs on the ANN metamodel performance should be analyzed. Firstly, three system parameters are selected to analyze their effects on the performance measures. *K* is related to due date tightness, which is called the allowance factor and used in Equation 3.1 to determine the due date of each arriving job. The second one is the mean time between arrival times of jobs (*A*). The third one is the number of part types in the system (*N*). Many studies showed that these parameters have significant impact on the system performance (Kim and Jeong, 1998; Schintz *et al*, 2006). Their levels are given in Table 4.2.

Table 4.2 The different levels of system parameters

Decision Variables (Factors)	Definition	Level
K	Due date allowance factor	1-2-3-4-5-6-7-8
A	Arrival rate	4-5-6
N	Number of part types in system	6-7-8-9-10

Using the data generated from a full factorial experimental design, involving 120 experimental simulation runs, ANOVA (analysis of variance) is employed to determine whether varying levels of factors or their interactions affect the process. They are summarized in Tables 4.3-4.7. As can be seen from the tables, these results indicate that the main effects of *K*, *A* and *N* have a significant impact on all performance measures. The two-way interaction effects between these parameters are also important for each performance measure, except for %NTJ. However, none of the performance measures are affected by the three-way interactions.

Table 4.3 Full Factorial Analysis of *K*, *A*, *N* for MT

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	2432558	2432558	810853	19,05	0,000
2-Way Interactions	3	1660059	1660059	553353	13,00	0,000
3-Way Interactions	1	181	181	181	0,00	0,948
Residual Error	152	6470516	6470516	42569		
Total	159	10563314				

Table 4.4 Full Factorial Analysis of *K*, *A*, *N* for %NTJ

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	1148123856	1148123856	382707952	107.60	0.000
2-Way Interactions	3	11238194	11238194	3746065	1.05	0.371
3-Way Interactions	1	1051533	1051533	1051533	0.30	0.587
Residual Error	152	540610342	540610342	3556647		
Total	159	1701023925				

Table 4.5 Full Factorial Analysis of *K*, *A*, *N* for MFT

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	2597079	2597079	865693	19.81	0.000
2-Way Interactions	3	1663432	1663432	554477	12.69	0.000
3-Way Interactions	1	95	95	95	0.00	0.963
Residual Error	152	6641916	6641916	43697		
Total	159	10902522				

Table 4.6 Full Factorial Analysis of *K*, *A*, *N* for MQT

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	112894	112894	37631.5	20.01	0.000
2-Way Interactions	3	72630	72630	24209.9	12.88	0.000
3-Way Interactions	1	4	4	3.9	0.00	0.964
Residual Error	152	285815	285815	1880.4		
Total	159	471343				

Table 4.7 Full Factorial Analysis of *K*, *A*, *N* for WIP

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	156489	156489	52163.0	21.13	0.000
2-Way Interactions	3	94939	94939	31646.2	12.82	0.000
3-Way Interactions	1	6	6	5.8	0.00	0.961
Residual Error	152	375184	375184	2468.3		
Total	159	626618				

To show the effects of the parameters on the system performances in detail, some design points are selected and the values of the performance measures are plotted against the factor levels of the parameters. In these figures, all the values of the performance measures are normalized according to the first experiment value. The design points of *A*= 4.5 and *N* = 9 are selected to show the effects of the values of *K* on the system performances. The results of these design points are illustrated in Figure 4.5. As can be seen from the figure, the increase in *K* improves the tardiness based performance measures such as MT and %NTJ. For the other performance measures, when *K* is 1, the minimum value of the performance measures is achieved. It can also be concluded from this figure that a reasonable range of the values of *K* is in between 1 and 7. However, when the value of *K* is higher than 7, there is no considerable impact on the performance measures. Consequently, this suggests that parameter *K* has a considerable effect on the system performance and should be selected as one of the inputs of the ANN models.

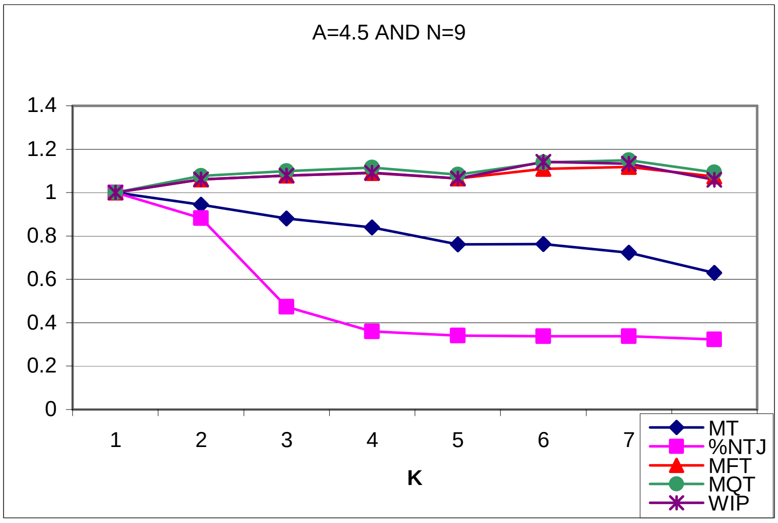

Figure 4.5 Effects of *K* on the system performance

In order to investigate the effects of parameter *A* on the system performances, similar experiments should also be conducted. In this case, the value of *K* is set to 4 and *N* to 9. As can be seen in Figure 4.6, when *A* increases, all performance measures decrease. It is clear that when the number of the job arrivals increases (if *A* decreases), the bottleneck situations occur more frequently. It causes deterioration in the system performances. The results of the experiment also show that a reasonable range of the values of *A* is in between 4.5 and 6. Consequently, parameter *A* is selected as the second input of the ANN models.

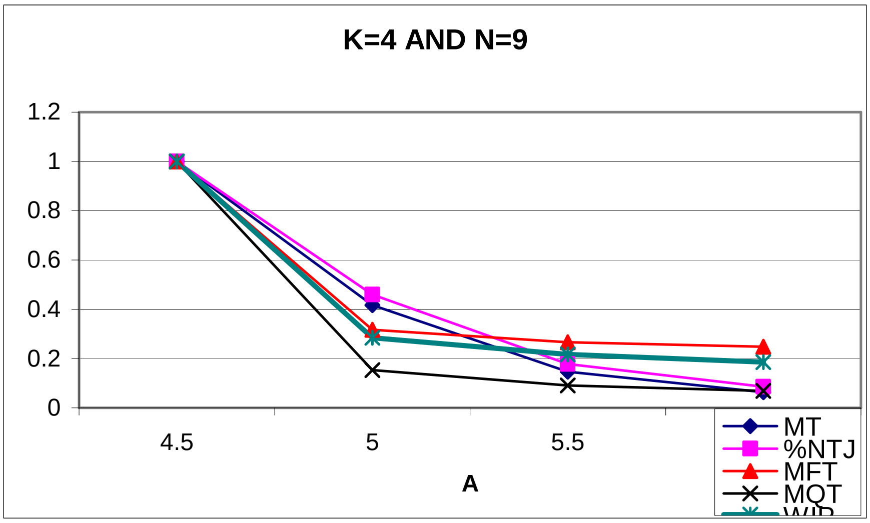

Figure 4.6 Effects of *A* on the system performance

Finally, the effects of the number of part types in the system, *N*, on the performance is investigated. The case of *K*=4 and *A*=4.5 are analyzed for this experiment. As can be seen in Figure 4.7, small changes in *N* affect the performance of the system. Consequently, *N* is selected as the third input parameter of the ANN models.

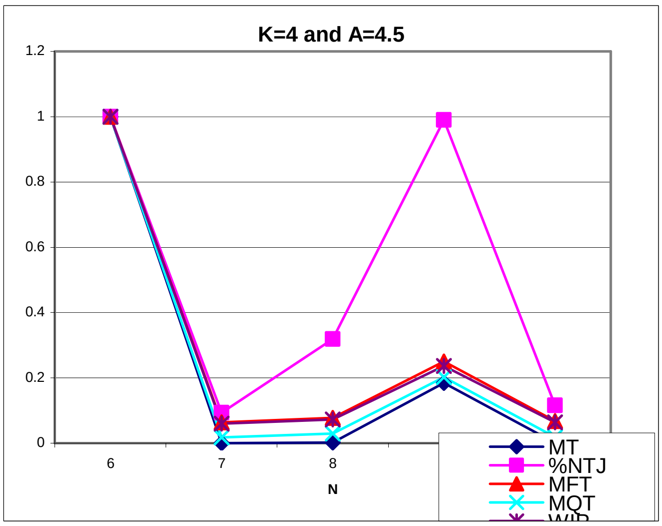

Figure 4.7 Effects of *N* on the system performance

As mentioned above, besides the system parameters *K*, *A* and *N*, some system state variables including system status variables and current system performance measures are also considered as the inputs of ANNs based meta-model for each performance measure. The system state variables considered are given in Table 4.8.

Table 4.8 System state variables

System state variables	Definition
MMU	Mean Machine Utilization
MOUTI	Mean Operator Utilization
MXOUTI	Bottleneck Operator Utilization
AQL	Average Queue Length
MOT	Mean Operator Transfer Time
CMT	Current Mean Tardiness
CNTJ	Current Percentage of Tardy Jobs
CMFT	Current Mean Flow Time
CMQT	Current Mean Queue Time
CWIP	Current Work-in-Process Inventory

To determine whether levels or values of the system state variables listed in Table 4.8, and the system parameters listed in Table 4.9, including *K*, *A*, and *N*, affect the performance measures, their effects on the system performance are analyzed with ANOVA through the 1300 data set gathered from the simulation module.

Table 4.9 System parameters

System parameters	Definition
v11	Current when rule
v12	Current where rule
v13	Current part dispatching rule
v14	Current alternative route selection rule
v21	Next when rule
v22	Next where rule
v23	Next part dispatching rule
v24	Next alternative route selection rule
K	Current due date tightness factor
A	Current mean arrival time
N	Current number of part type in the system

It is observed from ANOVA results that all factors considered in the analysis have significant impact on the performance measures. Therefore, both the system parameters and the system state variables are considered as the inputs of the ANN based metamodeling to estimate the performance measures. The outputs are the performance measures considered.

In order to build an ANN model for each performance measure, the same 1300 data set is used, 1000 and 130 of which are selected for training and cross validation of the ANN models, respectively. NeuroSolutions 4.0 software is used to develop the ANN models. The backpropagation learning algorithm is used for the training. When the number of learning epochs is greater than 20.000 or the mean square error is less than 0.0001, the learning process stops. The remaining 170 data set is used for the testing.

Validity of a neural network depends on several design parameters, e.g. the number of hidden layers, the number of nodes in each hidden layer, the transfer function type, the learning rate, and momentum rate. In general, these design parameters are determined by trial and error (Savsar and Choueiki, 2000). In this study, only the number of the nodes in the hidden layer is determined through the genetic algorithm solver of NeuroSolutions 4. Some error measures, e.g. mean error (ME), mean absolute error (MAE), mean squared error (MSE), root MSE (RMSE), and percentage error (%error), are calculated for the validity of the neural network. Figure 4.8 depicts its topology. The test and design parameters of the trained ANN models are given in Table 4.10.

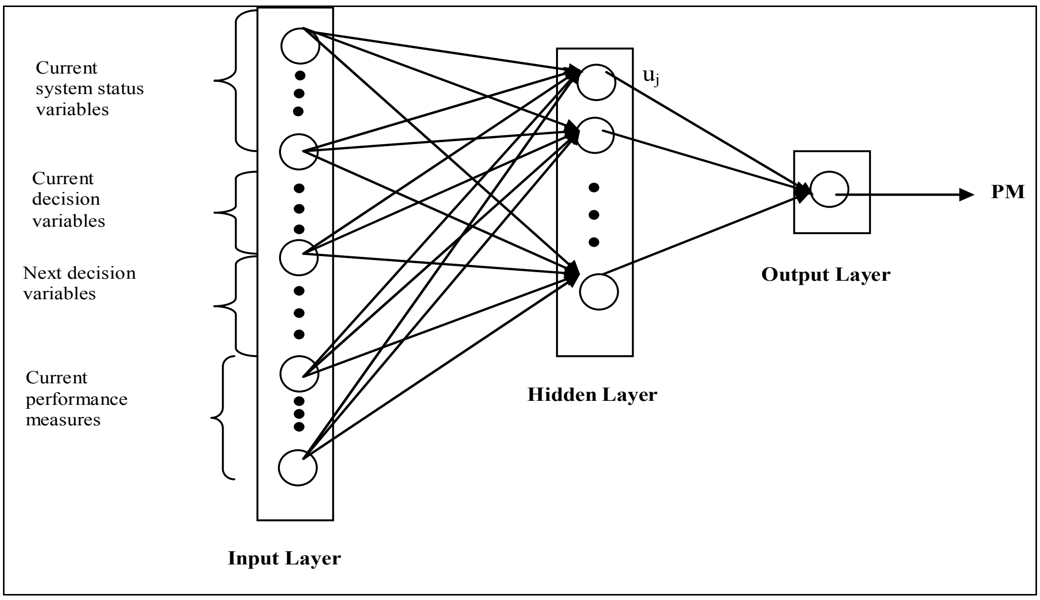

Figure 4.8 The structure of the ANN models developed

Table 4.10 Design parameters and test results for NN models

PM	# of HL	# of neuron in HL1	# of neuron in HL2	# of neuron in HL3	ME	MAE	MSE	RMSE	% Error
MT	2	19	24	-	0.0047	0.0162	0.0020	0.0446	1.2996
NTJ	3	1	1	1	0.0204	0.0647	0.0114	0.1070	0.1641
MFT	2	20	19	-	0.0085	0.0216	0.0033	0.0578	2.4418
MQT	1	23	-	-	0.0064	0.0197	0.0029	0.0534	1.7071
WIP	2	24	19	-	0.0077	0.0166	0.0004	0.0210	0.7966

The results show that the ANN models provide accurate estimates for all performance measures. As discussed earlier, the scheduling of the DRC system is performed through the appropriate selection of the aforementioned DPRs, worker assignment rules and routes of the jobs. Therefore, any combination of scheduling rules should identify the time of worker transfers (determined by the when rule), the department to which the worker is transferred (where rule), the sequence of jobs in each department (DPRs) and the route of each job type. The trained ANN models are used at each rescheduling point to estimate the performance measures of each alternative rule combination, i.e. a rule set.

4.3.2.3 The FIS Model

Once the performance measure values, obtained by applying each scheduling rule combination (or rule sets), are determined through ANN models in terms of each performance measure, the FIS model should be constructed to aggregate the performance measures of each alternative rule combination and to rank the alternative combinations.

As mentioned in Chapter 3, there are five steps in a fuzzy inference system (Yu et.al., 1999):

Step 1: *fuzzification of the input variables and output variables*. Since there are five performance measures considered, the selection of DPRs, the routes of the job type and worker assignment rules depend on five fuzzy factors (variables); MT, NTJ, MFT, MQT and WIP. They are the input variables to determine the scheduling rule combination. The output variable is the score of each alternative which is used to evaluate alternative rule combinations. Firstly, the membership functions must be defined for each input and output. The more the number of the membership functions to partition the region, the more the number of the rules needed (Canbolat and Gungor, 2003). While three membership functions (or linguistic variables) are defined for the inputs, the output (score) is represented by five membership functions (or linguistic variables). The type of the membership functions defined is triangular as shown in Figure 4.9.

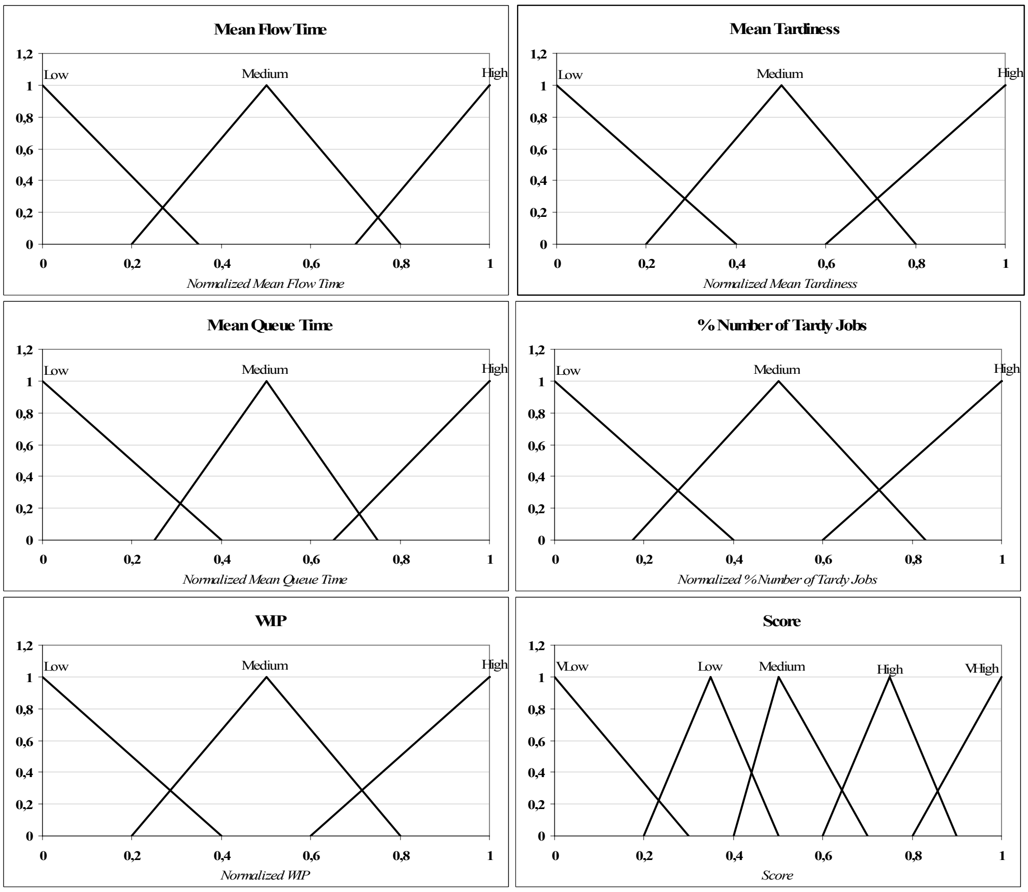

Figure 4.9 Membership functions of the inputs and the output

Step 2: application of the fuzzy operators (AND or OR): In this case problem, the AND operator is used to define the input and output relation.

Step 3: implication from the antecedent to the consequent: The rules which define relationships between the inputs and the output are developed by the decision maker.

Since each of MT, NTJ, MFT, MQ and WIP has three states, the total number of the rules is 243. Table 4.11 is a sample of these rules.

Table 4.11 FIS rules

Rule Definition
Rule1. **If** MT is **LOW** and %NTJ is **LOW** and MFT is **LOW** and MQ is **LOW** and WIP is **LOW** then **fuzzy priority** is **VERY HIGH**.
Rule2. If MT is **LOW** and %NTJ is **LOW** and MFT is **MEDIUM** and MQ is **LOW** and WIP is **LOW** then fuzzy priority is **HIGH**.
……………………………………………………………………………………….
Rule243. If MT is **HIGH** and %NTJ is **HIGH** and MFT is **HIGH** and MQ is **HIGH** and WIP is **HIGH** then fuzzy priority is **VERY LOW**.

Step 4: aggregation of the consequences across the rules. As discussed in Section 3.3.2.1, the maximum operator is used for the aggregation of the consequences.

Step 5: defuzzification. In this study, the centroid method is used for the defuzzification of the variables.

To show the effectiveness of the FIS model developed, the results of the scheduling rule combination selected by the FIS model are compared with those of five different alternatives. The alternatives are selected by minimizing only one performance measure at a time, e.g., minimum MT, and minimum %NTJ. Figure 4.10 indicates that there is no alternative scheduling rule combination better than the other alternative solutions for all performance measures. Different solution alternatives have superior performances for different objectives. However, in real-life cases, the decision maker wants to reach a compromise solution instead of maximizing (or minimizing) only one objective at a time. It can be seen from the figure that the FIS models are efficient and flexible to achieve a compromise solution for more than one objective at a time.

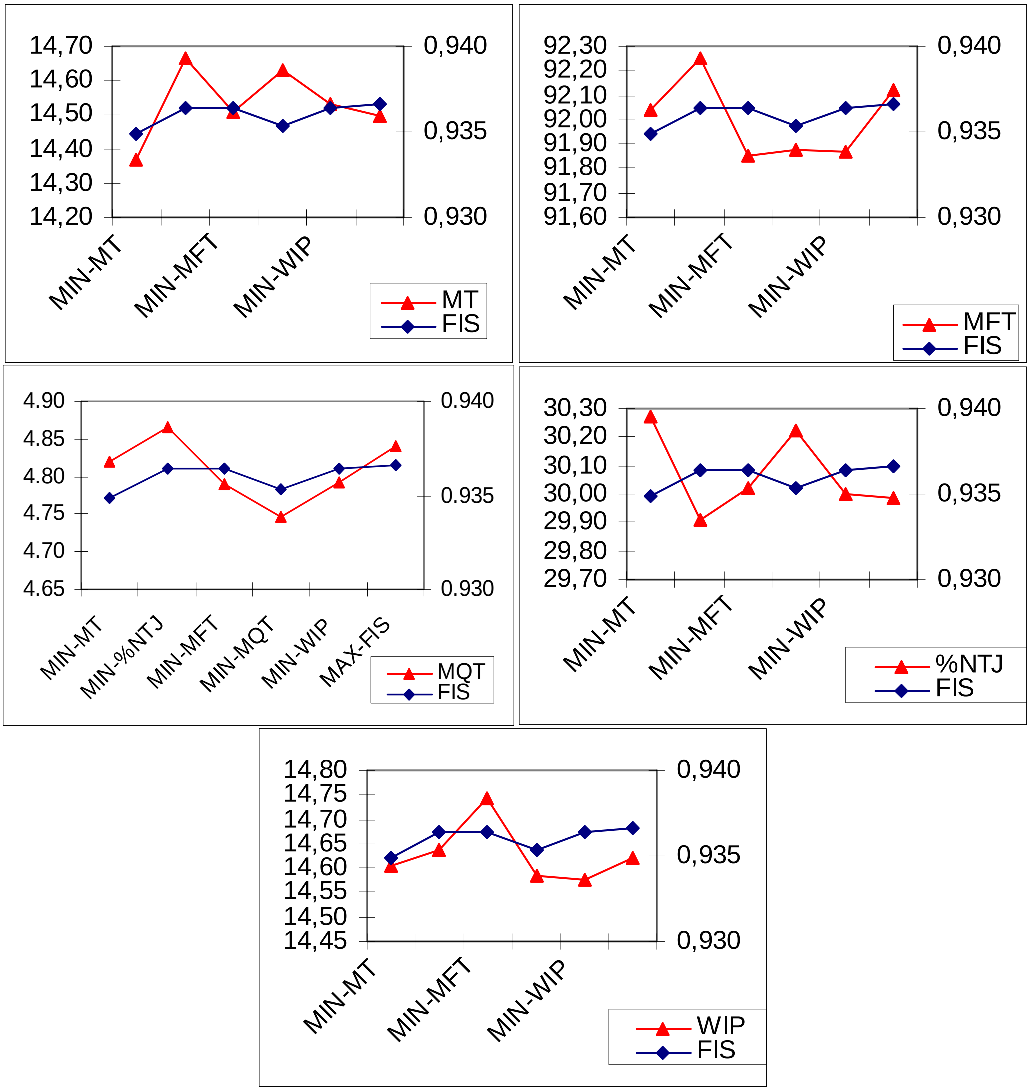

Figure 4.10 The comparison of FIS and other single-objective approaches

Recall that MCDRC-FIS reviews the system status periodically and changes the scheduling rule combination at each scheduling point, and the performance measures of all alternative rule combinations are determined via ANN models. At this point, the FIS is applied to all alternative solutions by feeding five inputs into the fuzzy inference system to obtain a score for each alternative rule combination. The alternative with the highest priority is selected for the next scheduling period. The new rule combination that includes job DPR, worker assignment rule and routing rule is then utilized till the next scheduling point.

4.4 Results and Discussions

In this section, the performance of MCDRC-FIS is evaluated through the experiments classified into these three groups. The evaluations are in section 4.4.1, 4.4.2, and 4.4.3, respectively.

In the first group, the performance is evaluated by comparing the approach with the fixed, multi-pass (MULTIFIS) and random (RND) scheduling algorithms.

The fixed scheduling selects a combination of decision variables (scheduling rule combination) according to the performance of the simulation results at the beginning of the planning period. The random scheduling algorithm selects a scheduling rule for each decision variable randomly in each short time interval. The performance of MCDRC-FIS is compared with those of the two scheduling mechanisms.

The multi-pass scheduling algorithm, e.g. see Wu and Wysk (1989), Kim and Kim (1994), selects a combination of decision variables in each short scheduling interval. Each candidate scheduling rule combination is evaluated at each rescheduling point under the same manufacturing conditions. The appropriate scheduling rule combination is selected with respect to the results of a series of discrete event simulations (Kim and Kim, 1994). Since the computer time needed for the experiments can become overwhelming in the multi-pass algorithm, only five simulation replications are run to collect the data. Theoretically, more replications may be needed. However, the response time is more important for the real time scheduling methodologies. Due to the large number of replications for highly dynamic systems, hence high computation time, it would be time consuming at each decision point and the mechanism may not be used for the real-time scheduling purpose (Jeong and Kim, 1998). This is the main disadvantage of the multi-pass scheduling approaches.

In order to compare all these approaches with MCDRC-FIS, each alternative method is integrated with the FIS model to select the appropriate scheduling rule combination according to the decision maker's preferences.

4.4.1 Comparison of MCDRC-FIS with other Scheduling Approaches for Different Variation Levels

In order to show the efficiency of MCDRC-FIS under different system variation (VR) levels, the scheduling approaches above are used in the DRC manufacturing system. Three problem sets are generated by altering system parameters *K*, *A*, *N* according to some distributions, shown in Table 4.12, during the planning period. Parameter change time also depends on another distribution called PCT. A parameter variation level is the variance of the parameter obtained from the simulation results, given in Table 4.13.

Table 4.12 Test problems

System parameters	Test Problems		
	Low variation (L)	Medium variation (M)	High variation (H)
K	uniform(1, 4)	uniform(1, 6)	expo(3)
A	uniform(4.5, 6)	uniform(4.5, 8)	uniform(4.5, 8)
N	uniform(8, 10)	uniform(7, 10)	uniform(6, 10)
PCT	uniform(1500, 3000)	uniform(1000, 2000)	expo(1500)
Processing time distribution	uniform(p_{ij}, $0.8p_{ij}$)	normal(p_{ij}, $0.25p_{ij}$)	normal(p_{ij}, $0.25p_{ij}$)

In this experiment, the length of the scheduling period (production interval) (*p*) is fixed and set to 5000 min. To determine the fixed scheduling rule, all alternative decision rule combinations are evaluated through simulation at the beginning of the scheduling. All alternatives are evaluated by the FIS model developed and the best rule combination with the highest score is selected to be compared with the other methods. The rule combination of 2343 (v1=2 (decentralized), v2=3 (MSPT), v3=4 (SRPT), v4=3 (LAUF)) is selected as the fixed scheduling rule to be employed, which is also the initial scheduling rule combination for all other methods. A rule combination is coded in such a way that the elements of the code represent the "when rule", "where rule", "part dispatching rule" and "alternative route selection rule", respectively. The value of each decision variable in the combination is equal to the rank of the variable in Table 4.1 (a).

Table 4.13 Variance of the system parameters

	Test Problems		
System parameters	Low variation (L)	Medium variation (M)	High variation (H)
Variance of *K*	2.025974	2.308561	3.94459
Variance of *A*	0.881834	0.910354	1.297221
Variance of NT	1.58825	1.627376	1.671291
Variance of PCT	85977.4	217026.2	2399304

The simulation results are shown in Table 4.14. Mean improvement percentages are given for each method at each decision point. An improvement percentage is $((PM_{Sk})- PM_{ik})/ PM_{ik})100$, where PM_{ik} is the value of the kth performance measure for method i (i =1, 2, 3, and k =1, 2…5) and PM_{Sk} is the value of the kth performance measure for the fixed scheduling. In the table, there are nine decision points for each method (every scheduling period of 5000 minutes). Each row represents percentage improvements of the performance measures derived from the methods with respect to the fixed scheduling rule combination at each decision point. The computation times of the methods are given in the last column of Table 4.14. The changes of the performance measures during the scheduling period are also shown in Figure 4.11.

Table 4.14 % improvement with respect to the fixed scheduling for VR=L and p=5000

Method	v1	v2	v3	v4	%improvement according to fixed scheduling rule 2343					CPU
					MT	%NTJ	MFT	MQT	WIP	(min)
MULTIFIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00	204
	2	2	7	3	15.38	5.03	24.04	12.73	3.12	110
	2	1	6	3	14.13	3.89	18.13	3.14	12.77	102
	2	4	3	3	14.56	8.34	18.12	3.23	15.00	117
	2	2	1	3	13.44	9.85	17.82	12.79	0.61	180
	2	1	7	3	17.26	6.24	17.06	16.46	0.36	93
	1	2	6	3	29.57	11.74	22.62	19.79	8.36	93
	2	3	7	3	23.28	14.67	28.26	36.77	16.71	98
	1	4	7	3	37.89	15.20	45.61	56.41	42.59	97
MCDRC-FIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00	204
	2	2	6	1	21.42	3.40	26.55	19.72	12.24	3
	2	2	7	1	31.70	2.07	26.28	19.68	23.15	3
	2	3	4	1	37.30	8.07	28.60	24.59	26.87	3
	2	2	6	1	43.29	9.60	31.70	38.22	19.02	3
	2	1	4	1	47.83	10.06	32.20	42.77	18.37	3
	2	1	7	3	53.65	11.53	35.42	49.61	23.80	3
	1	2	4	1	37.36	7.60	33.76	44.24	22.69	3
	2	2	7	1	47.12	7.85	48.79	60.61	46.88	3
RND	2	3	4	3	0.00	0.00	0.00	0.00	0.00	204
	2	2	5	1	23.77	4.14	27.67	21.42	10.90	2
	1	2	7	2	-94.47	-15.82	-36.07	-140.91	-66.84	2
	2	1	7	1	-183.44	-17.97	-76.82	-206.83	-93.92	2
	2	1	3	2	-188.79	-20.60	-86.15	-174.14	-128.30	2
	2	4	3	1	-175.09	-19.07	-82.73	-161.25	-118.09	2
	2	1	3	3	-114.63	-13.56	-57.23	-104.24	-86.39	2
	2	2	4	3	-122.92	-7.24	-38.71	-73.01	-60.88	2
	2	4	6	3	-69.31	-4.68	-0.15	-12.00	-4.79	2

It can be seen from the table that the strategies, except for the RND scheduling, that select a new scheduling rule combination during the scheduling period yield considerably better performance than the fixed scheduling. It is expected that the MULTIFIS methodology provides a better improvement than neural network based MCDRC-FIS methodology. The reason is that while MULTIFIS evaluates each alternative scheduling rule combination according to simulation results at each decision points, MCDRC-FIS evaluates each alternative scheduling rule combination according to the estimated values derived from the neural network models.

Although the system states are changed dynamically, MULTIFIS and MCDRC-FIS perform well for each performance measure. At the end of the scheduling period, the MFT is reduced by 37.89% through MULTIFIS and by 47.12% through MCDRC-FIS. Similarly, the MT is reduced by 15.20% and 7.85%, %NTJ is reduced by 45.61% and 48.79%, MQT is reduced by 56.41% and 60.61%, WIP is reduced by 42.59% and 46.89%. Although MULTIFIS requires more computational times, the results show that MCDRC-FIS gives better or closer solutions relative to MULTIFIS within short computation times. The main reason is that the ANN models developed provide a powerful tool to explain the relationship between decision variables and performance measures in spite of complex structure of the DRC manufacturing system. The results also show that MCDRC-FIS has the advantage of immediate response to changes in the system states.

In order to emphasize the need for such a real time scheduling approach, the comparison between RND and fixed scheduling approaches would be interesting. As can be also seen in Figure 4.11, the RND yields the worst performance in all performance measures. Although the RND updates the schedule at each rescheduling point, it does not consider the state changes and does not provide any improvement in the final results. This result supports the claim that real time adaptive scheduling approaches, which alter the scheduling rules according to state changes, are needed in practice.

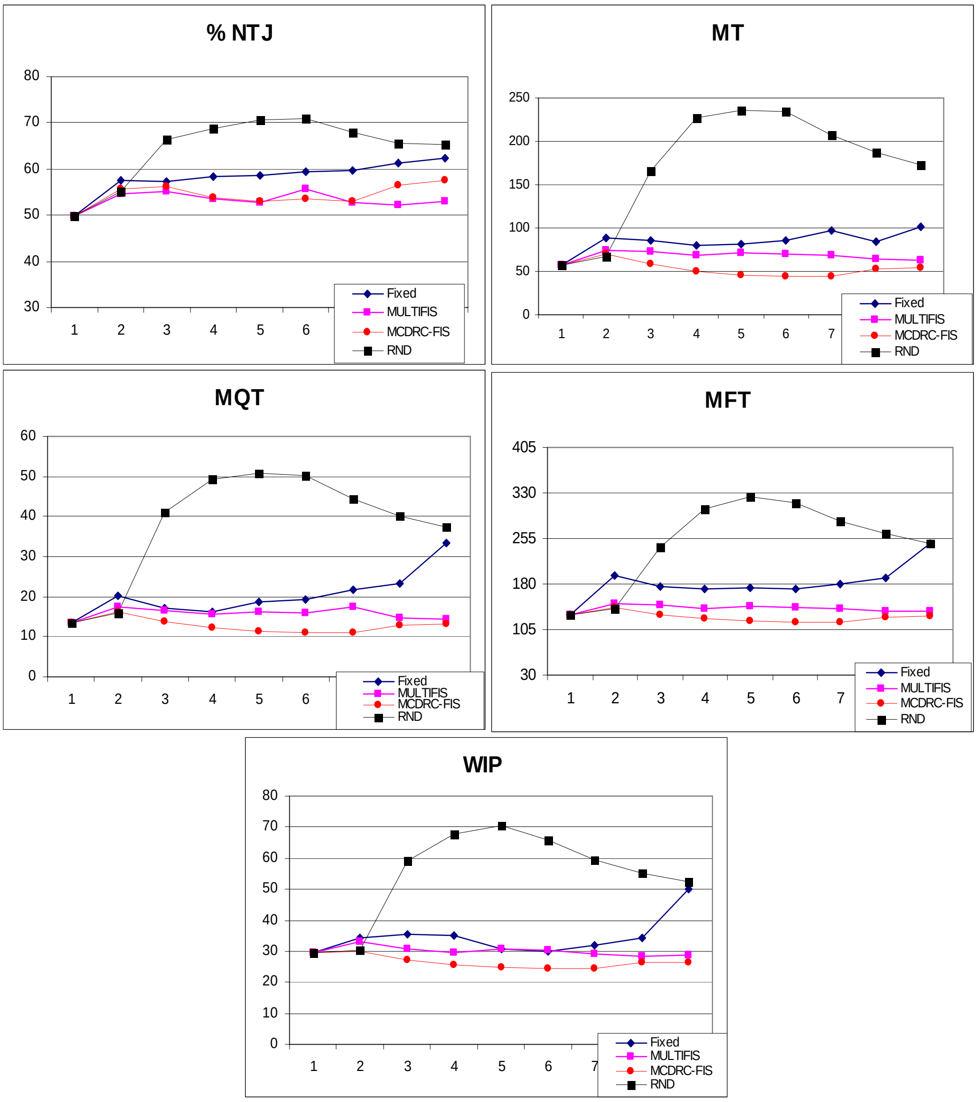

Figure 4.11 Simulation results for VR=L and p=5000

The performances of the scheduling methods under medium and high variation levels are shown in Table 4.15 and 4.16, and in Figure 4.12 and 4.13.

Table 4.15 % improvement relative to the fixed scheduling for VR=M and p=5000

Method	v1	v2	v3	v4	% difference fixed scheduling rule 2343				
					MT	%NTJ	MFT	MQT	WIP
MULTIFIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	4	2	3	19.53	0.91	11.05	35.96	18.72
	2	3	2	1	28.35	12.42	11.81	36.34	19.43
	2	4	6	1	38.23	9.86	13.07	38.91	20.45
	2	4	2	3	34.89	15.01	13.23	38.92	20.46
	1	1	4	3	32.02	14.40	12.57	38.07	19.95
	2	1	4	3	28.46	16.48	12.29	37.43	19.65
	1	4	7	3	26.54	18.53	11.94	36.75	19.33
	2	3	2	1	15.02	24.70	12.10	9.59	19.63
MCDRC-FIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	2	7	1	30.98	-1.71	12.24	37.19	20.13
	2	1	7	3	33.03	8.27	11.85	36.51	19.43
	2	1	4	1	39.48	6.70	12.64	37.84	20.01
	2	2	6	3	29.73	11.76	11.10	34.95	18.83
	1	2	4	1	31.79	11.90	11.62	35.07	19.41
	2	2	4	1	31.47	14.65	12.21	36.32	19.67
	1	2	7	1	31.14	16.63	12.15	35.93	19.54
	2	1	7	3	17.95	22.82	11.89	7.54	19.41
RND	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	1	3	5	1	-25.73	-0.23	7.08	36.19	19.67
	2	1	5	3	1.88	-0.66	1.80	35.00	18.87
	2	2	7	1	-44.99	-10.41	2.90	36.89	19.89
	1	3	6	2	-27.94	0.76	-4.88	8.55	-2.21
	2	4	7	2	-61.57	-9.51	-6.15	-8.74	-24.36
	2	3	5	2	3.58	-10.14	0.16	9.70	-38.20
	2	2	4	1	8.85	-5.54	-8.96	-23.58	-33.58
	2	3	2	2	-12.27	0.47	0.63	-92.90	-34.15

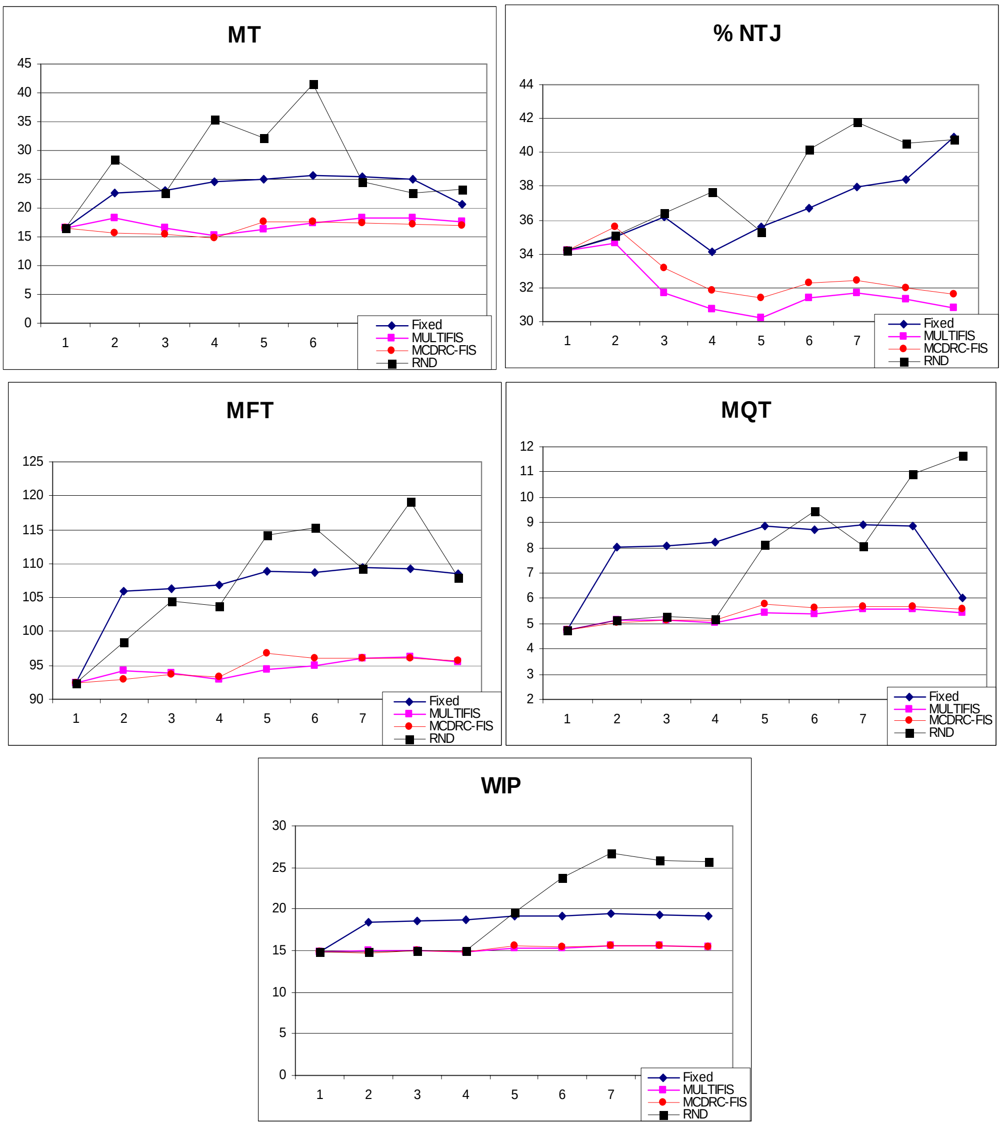

Figure 4.12 Simulation results for VR=M and p=5000

Table 4.16 % improvement relative to the fixed scheduling for VR= H and p=5000

Method	v1	v2	v3	v4	% difference fixed scheduling rule 2343				
					MT	%NTJ	MFT	MQT	WIP
MULTIFIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	4	2	3	-5.79	2.90	-3.83	-35.28	-0.85
	2	3	2	1	-2.15	2.76	-2.88	-16.80	-1.13
	1	4	6	1	-30.99	-1.51	-23.17	-74.29	-26.02
	2	4	2	3	-57.03	-1.66	-39.53	-108.91	-49.48
	2	1	4	3	-76.17	-1.38	-51.22	-153.30	-63.89
	1	1	4	3	-102.98	-1.67	-65.97	-197.43	-87.72
	2	4	7	3	-123.72	-1.90	-78.80	-260.30	-115.92
	2	3	2	1	-195.88	-2.41	-78.40	-270.27	-140.78
MCDRC-FIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	2	7	1	16.95	4.18	8.93	6.99	11.97
	2	1	7	3	23.28	3.99	12.84	19.72	16.31
	2	1	4	1	28.21	4.25	16.25	24.84	16.25
	2	2	6	3	26.68	4.21	15.14	22.81	16.56
	2	2	4	1	28.66	4.02	16.42	24.26	18.54
	1	2	4	1	28.32	3.81	15.99	24.72	19.40
	2	2	7	1	32.63	3.97	18.74	29.49	18.77
	1	1	7	3	30.29	3.87	17.20	26.61	17.47
RND	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	3	5	1	-62.12	-1.47	-37.49	-137.01	-40.23
	2	1	5	3	-83.60	-2.46	-55.63	-140.09	-67.93
	2	2	7	1	-86.43	-0.92	-57.42	-141.98	-59.34
	2	3	6	2	-80.78	-1.18	-54.03	-131.46	-60.93
	2	4	7	2	-100.53	-2.28	-66.44	-155.00	-75.27
	2	3	5	2	-124.09	-2.45	-78.89	-192.93	-80.88
	2	2	4	1	-115.25	-2.00	-74.03	-172.53	-75.47
	2	3	2	2	-114.26	-3.48	-73.17	-165.55	-77.90

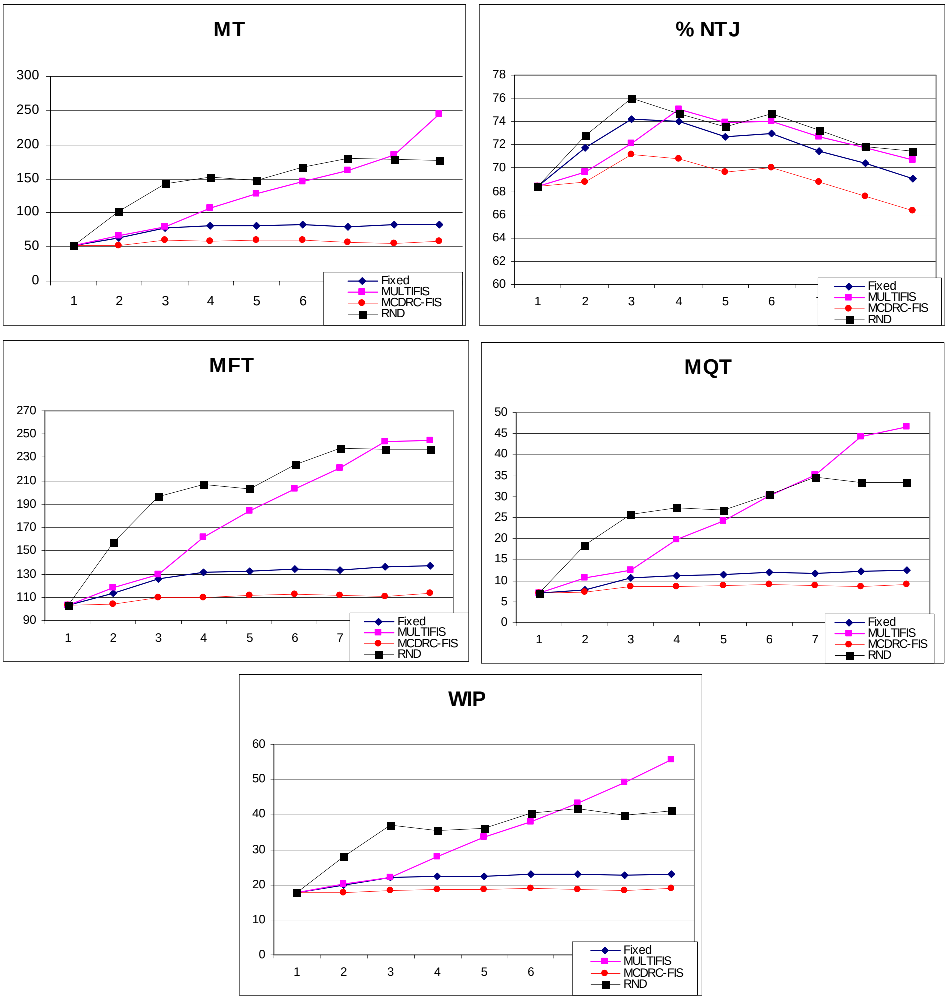

Figure 4.13 Simulation results for VR=H and p=5000

MULTIFIS and MCDRC-FIS outperform fixed scheduling in the medium variation level. However, MCDRC-FIS responds faster than MULTIFIS. On the other hand, MULTIFIS yields the worse performance than fixed and MCDRC-FIS in the high level variation. The basic reason is that the number of simulation replications, five, is not sufficient to represent the dynamic nature of the manufacturing system under high variation level. Therefore, the simulation experiments at each decision point need more replications for more valid results. However, it should be remembered again that it may not be efficient to apply such a time consuming approach in practice.

To show the two-factor effects (the variation of the decision variables and the method applied for scheduling), ANOVA tables for only two performance measures are generated and given in Table 4.17. Different variation levels and scheduling approaches may give different performances in all performance measures. Additionally, interaction effects between variation levels of the system and selected scheduling methods are also important.

Table 4.17 Analysis of variance for the effects of the variation level and methods

Analysis of Variance for MFT					
Source	DF	SS	MS	F	P
VR	2	29714	14857	36,82	0,000
MTH	2	10894	5447	13,50	0,000
Interaction	4	16751	4188	10,38	0,000
Error	72	29056	404		
Total	80	86415			
Analysis of Variance for %NTJ					
Source	DF	SS	MS	F	P
VR	2	18831,54	9415,77	2105,25	0,000
MTH	2	170,37	85,18	19,05	0,000
Interaction	4	83,76	20,94	4,68	0,002
Error	72	322,02	4,47		
Total	80	19407,69			

To show statistically the differences between the methods considered in terms of all performance measures, Least Significant Difference (LSD) (Montgomery, 2001) test is employed and the results are given in Table 4.18 for MT only. The results of statistical comparisons of the methods for other performance measures are also analyzed. The test results show that real time controlled scheduling approaches outperformed the fixed scheduling approach for all variation levels of the manufacturing system. In the low variation level, the differences between MULTIFIS and MCDRC-FIS are not statistically significant at the 95% confidence level. However, when the variation increases, the performance differences between the methods become significant. In the high variation level, MCDRC-FIS outperforms the others. The reason is that the simulation model is run with low replication numbers in MULTIFIS. Hence, the results derived from the simulation do not reflect the variation of the system. The overall results show that the proposed methodology, MCDRC-FIS, significantly improves the performance under different variation levels.

Table 4.18 Results of paired-t test for MT

VR	Method	95 % CI FOR MEAN DIFFERENCE	t-value	p-value
L	Fixed-MULTIFIS	(4.11; 29.20)	4.45	0.002
L	Fixed-MCDRC-FIS	(13.94; 49.05)	6.02	0.000
L	MULTIFIS-MCDRC-FIS	(4.75; 24.93)	1.62	0.145
M	Fixed-MULTIFIS	(4.584; 9.066)	10.22	0.000
M	Fixed-MCDRC-FIS	(5.629; 9.162)	14.05	0.000
M	MULTIFIS-MCDRC-FIS	(-0.613; 1.755)	1.62	0.145
H	Fixed-MULTIFIS	(-117.7; 9.4)	-2.86	0.021
H	Fixed-MCDRC-FIS	(9.50; 28.77)	6.67	0.000
H	MULTIFIS-MCDRC-FIS	(4.9; 141.7)	3.6	0.007

4.4.2 Effects of the Length of the Scheduling Period

In this section, the effects of the length of scheduling periods (production intervals) on the performance of MCDRC-FIS are investigated. The different levels of fixed-time periods are analyzed under medium variation level. Three levels of period length are selected as 2500, 5000, and 15000. The results are given in Table 4.19.

As seen from Table 4.19, the length of the scheduling period is an important factor for the performance of MCDRC-FIS. The shortest time interval (p=2500) gives the worst results. This means that more frequent scheduling negatively affects the performance. The too-long monitoring period (p=15000) gives a worse solution than the medium time period. The results of the experiments show that the medium time period (p=5000) gives better results than short and long time periods. The choice of the appropriate time period can also be determined via some parameter optimization techniques.

Table 4.19 Comparison of different fixed time periods (p=period)

Alternative		Decision Variables				Performance Measures				
		v1	v2	v3	v4	MT	%NTJ	MFT	MQT	WIP
P=5000	MCDRC-FIS	2	3	4	3	16.46	34.18	92.38	4.73	14.78
		2	2	7	1	15.60	35.58	92.92	5.03	14.74
		2	1	7	3	15.38	33.17	93.71	5.14	14.94
		2	1	4	1	14.81	31.83	93.39	5.12	14.93
		2	2	6	3	17.62	31.39	96.73	5.77	15.57
		2	2	4	1	17.53	32.32	96.06	5.65	15.43
		2	2	4	1	17.43	32.41	96.12	5.69	15.58
		2	2	7	1	17.14	32.02	96.04	5.67	15.52
		2	1	7	3	17.02	31.59	95.69	5.58	15.43
P=2500	MCDRC-FIS	2	3	4	3	16.43	28.82	93.83	4.81	14.85
		2	2	7	1	15.49	35.28	92.06	4.79	14.63
		2	1	7	3	16.24	34.45	94.46	5.31	15.01
		2	3	4	2	27.09	40.07	106.59	7.83	18.34
		2	2	7	1	40.88	39.72	123.15	10.87	19.84
		2	1	7	3	36.45	37.83	117.98	9.88	18.90
		2	1	4	1	32.83	35.76	114.20	9.17	18.28
		2	2	4	3	30.97	35.27	111.86	8.69	17.92
		2	1	4	1	29.41	34.56	110.31	8.39	17.73
		2	1	7	3	28.97	34.11	110.00	8.32	17.65
		2	2	4	1	27.63	34.33	108.15	7.98	17.34
		2	2	4	3	26.96	34.48	106.97	7.74	17.25
		2	2	4	3	26.82	34.96	106.42	7.63	17.18
		2	1	6	3	26.32	34.42	106.28	7.60	17.24
		2	1	6	3	26.13	34.24	105.80	7.50	17.14
		2	1	4	1	25.40	33.56	105.31	7.41	17.04
		2	2	6	3	24.99	33.28	104.68	7.28	16.92
		2	1	6	3	24.53	32.87	104.10	7.17	16.82
p=15000	MCDRC-FIS	2	3	4	3	18.84	32.16	96.65	5.63	15.45
		2	2	7	1	17.49	32.30	96.04	5.63	15.41
		2	2	6	3	18.96	33.43	97.48	5.68	15.58

4.4.3 Comparison of the Fixed Length Scheduling Period and Variable Length Scheduling Period

In this section, the experiments focus on the comparison of the fixed and variable length scheduling periods by means of the proposed scheduling approach. As mentioned before, in the variable length scheduling period case, the performance measures are monitored continuously and compared with some thresholds. The thresholds are determined a priori by the decision maker to control the system according to his/her preferences. When the current values of the performance measures exceed the threshold values, the rescheduling mechanism is triggered. The comparison is performed only for the medium variation level. At each scheduling point, MCDRC-FIS is employed to determine the next scheduling rule set. The results are given in Table 4.20.

Table 4.20 Results of MCDRC-FIS for variable length scheduling periods

Decision Variables					Performance Measures				
					MT	%NTJ	MFT	MQT	WIP
				Thresholds	18	35	94	6	15
v1	v2	v3	v4	Time Points					
2	3	4	3	16000	16.46	35.18	92.38	4.73	14.78
2	2	7	1	23000	18.12	32.94	95.20	5.38	15.36
2	1	7	3	27000	18.11	34.20	96.56	5.68	15.47
2	1	4	1	32000	17.23	33.02	95.45	5.48	15.23
2	1	7	3	41000	16.88	31.11	96.03	5.67	15.42
2	2	4	1	47000	17.38	32.56	96.01	5.63	15.43
2	2	4	3	60000	15.34	30.07	92.76	5.08	13.81

Figure 4.14 compares the performance of MCDRC-FIS with fixed length scheduling periods with the performance of MCDRC-FIS with variable length scheduling period in terms of all performance measures at each scheduling point of the latter approach.

The results show that MCDRC-FIS with variable length scheduling periods yields a better result than applying a fixed-time periodic review approach. It is also obvious that MCDRC-FIS with variable length scheduling periods is more responsive than the fixed-time periodic review with respect to system state changes.

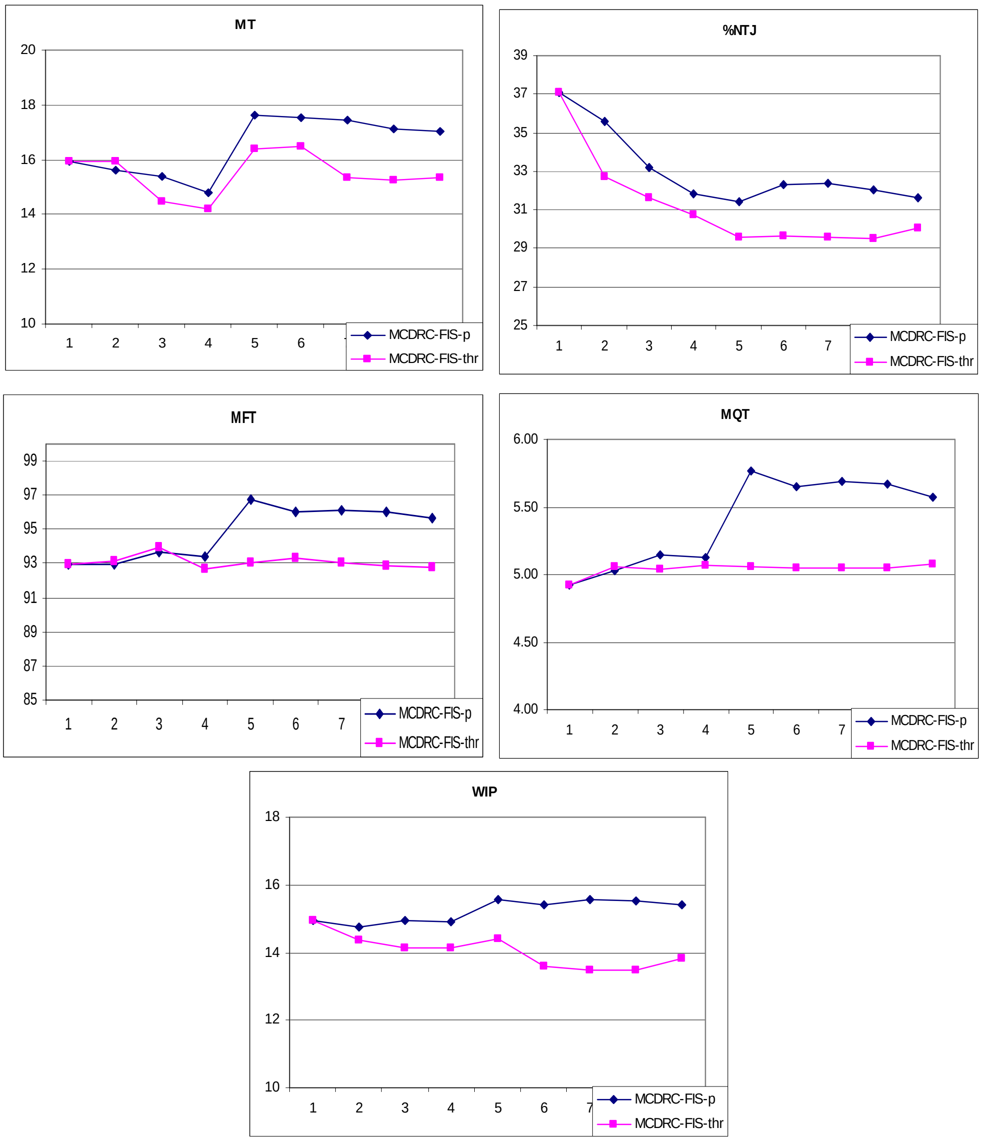

Figure 4.14 Comparisons of fixed period and continuous review approach

4.5 Summary

In this chapter, a multi-criteria scheduling methodology for real-time scheduling for DRC manufacturing systems is proposed. This methodology, called MCDRC-FIS, integrated simulation, ANN and FIS approaches to determine the appropriate scheduling rule combinations to satisfy all objectives set by a decision maker. It was compared with fixed and adaptive scheduling approaches. In general, MCDRC-FIS improves the performance significantly with respect to fixed scheduling approaches.

MCDRC-FIS was also compared with MULTIFIS, fixed and RND approaches for different levels of system variation. The results showed that MCDRC-FIS provides good solutions for all variation levels within short response times.

In order to determine how frequently MCDRC-FIS should be used to update the scheduling rule set, a comparison of its performance under different fixed time periods is employed to determine the appropriate fixed time interval. Although the medium time interval gives the best results in the experiments, the length of the monitoring period is related to the system status and the criteria of interest. Therefore, a reasonable number of experiments should be performed to determine the right length of the scheduling periods. Finally, MCDRC-FIS with fixed length scheduling period is compared with variable length scheduling period-based MCDRC-FIS. The results of this set of experiments indicate that MCDRC-FIS with variable length scheduling periods is more sensitive to respond to the system state changes.

As discussed before, multi-criteria scheduling problems generally need a process of the aggregation of multiple criteria. In the multi-criteria decision making literature, some researchers used outranking relations to form the aggregation models. In the next chapter, a novel real time scheduling approach is proposed which uses a well known outranking approach, PROMETHEE, for aggregation purposes.

CHAPTER FIVE
AN OUTRANKING-BASED MULTI-CRITERIA REAL-TIME SCHEDULING APPROACH FOR DRC SYSTEMS

5.1 Introduction

The first methodology, MCDRC-FIS introduced in Chapter 4, mainly deal with the dynamic selection of the set of dispatching rules (DPRs), worker assignment rules and routing decisions to yield a schedule considering multiple performance criteria, in which its multi-criteria feature is handled by a fuzzy inference. However, the performance of the fuzzy inference is subject to that of a human expert, although it successfully aggregates multiple objectives through linguistic variables. Furthermore, if the number of the inputs and of the membership functions to partition the region increases, the number of the rules needed also increases. In such cases, it may be difficult to determine the right rule, and would be helpful to use a more specific multi-criteria decision approach, e.g. PROMETHEE, to overcome these problems.

This PROMETHEE based DRC scheduler also operates similar to MCDRC-FIS, and incorporates a simulation model and a BPNN besides PROMETHEE.

As discussed in earlier chapters, although a number of methods have been proposed for the dynamic scheduling problem, one of their major shortcomings is that most of them do not consider the multi-criteria evaluation of alternative schedules. Furthermore, multi-criteria decision aid methods that evaluate the alternatives according to multiple, generally conflicting, criteria have not been extensively studied in the scheduling literature. Although there are numerous MCDM methods with different properties, e.g. AHP, multi-attribute utility theory, and TOPSIS, this research uses a well-known outranking method, PROMETHEE, introduced by Brans, et al., (1986), because it is the most suitable one for scheduling problems. It was one of the early MCDA outranking methods. It was designed for ranking alternatives from the best to the worst. Although it was applied in a large variety of real-world decision making problems, to the best of the author's knowledge, PROMETHEE has not been applied in any scheduling problems; machine-only or dual resource constrained.

The reason to use PROMETHEE in this research is fivefold (Dulmin and Minnino, 2003): (i) it is able to deal with both qualitative and quantitative variables (nine-point linguistic scale must be used in AHP), (ii) it is able to manage compensatory effects and understand relations between criteria (linear weighting techniques such as cost functions and AHP are fully compensatory), (iii) it is able to deal with imprecise data through indifference and preference thresholds, (iv) once the parameters are defined at the beginning of a planning horizon, it can evaluate the alternatives automatically without the help of a decision maker (AHP requires a decision maker's guide in each evaluation), (v) it is easy to understand and quick to apply in real-time.

The rest of the chapter is organized as follows. In section 5.2, a brief description of PROMETHEE is given. Section 5.3 is devoted to explain the proposed methodology. Section 5.4 presents an illustrative example. Conclusions are given in section 5.5.

5.2 PROMETHEE

5.2.1 Multi-criteria decision making (MCDM)

A decision problem with more than one conflicting objective makes the solution more difficult. Multi-criteria decision making (MCDM) methods address such problems and the aggregation of their objectives (Araz, 2007).

Zimmermann (1994) classified the MCDM into two categories: multi-objective decision making (MODM) and multi-attribute decision making (MADM). Doumpos and Zopounidis (2002) furthered this classification based on the variable type, discrete and continuous, as in Figure 5.1.

MADM methods describe the alternatives under multiple attributes and generally rank a set of predefined alternative from the best to the worst. Analytical hierarchy process (AHP), multi-attribute utility theory (MAUT) and outranking methods are the most known MADM methods (Doumpos and Zopounidis, 2002).

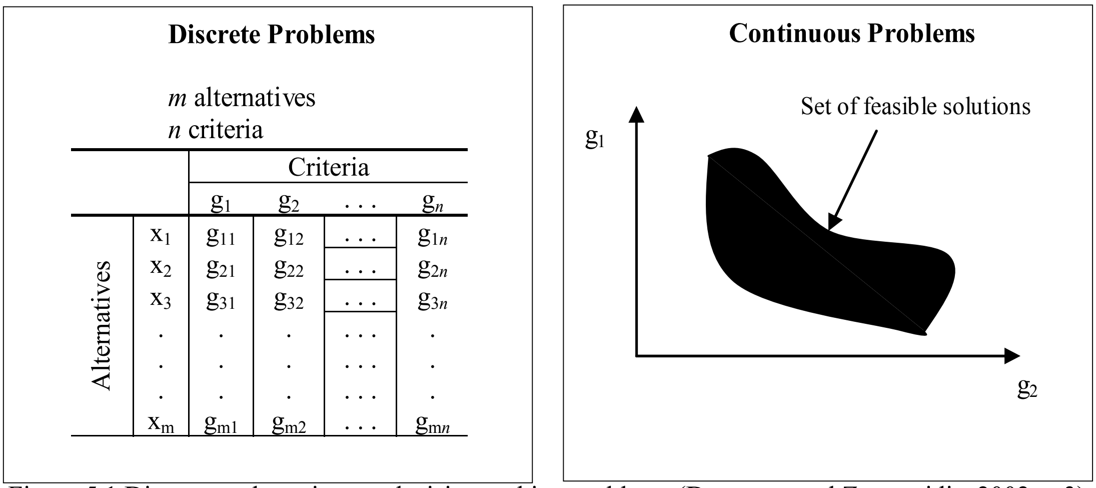

Figure 5.1 Discrete and continuous decision making problems (Doumpos and Zopounidis, 2002, p.3)

Outranking methods determine whether an alternative is preferred over another one. The basic principle of outranking is that alternative *a* will be preferred over *b* if *a* performs better than *b* on a majority of criteria, and there is no criterion such that *b* is strongly better than *a* (Le Teno and Mareschal, 1998).

The other known MADM methods, MAUT and AHP, are fully compensatory. It means that a poor performance of an alternative on a criterion can be compensated by a good performance on another criterion. In contrast to MAUT, AHP or other weighting techniques, outranking methods are only partially compensatory (Dulmin and Mininno, 2003). In outranking methods, it is not necessarily true that the gain on one criterion compensates the lost on another (Geldermann et al., 2000).

Families of ELECTRE and PROMETHEE are the most known and commonly used outranking methods. To the best of the author’s knowledge, outranking methods have not yet been applied to scheduling problems. In the proposed methodology, PROMETHEE is used to evaluate alternative scheduling rule combinations, which consist of a set of DPR, worker assignment rule and routing rule, in each scheduling point. The next section gives a brief overview of the PROMETHEE methodology.

5.2.2 PROMETHEE: Preference Ranking Organisation METHod for Enrichment Evaluations

PROMETHEE (Brans and Vincke, 1985; Brans et al., 1986) is originally developed to select the best alternative among multiple alternatives or to rank the alternatives from the best to the worst. Up to date, several extensions have been proposed to deal with different decision making problems, such as PROMETHEE III, IV, V and PROMSORT (Araz, 2007). Since it is quite simple in conception and application compared to other methods for multi-criteria analysis (Goumas and Lygreou, 2003), a considerable research effort has been directed to use PROMETHEE based methods to solve real-life multi-criteria decision making problems.

Let $A = \{a_1, ..., a_i\}$ denote a set of alternatives and $g_j(a_i)$ represent the value of alternative a_i on criterion g_j (j=1,2,...,J). PROMETHEE ranks the alternatives based on pairwise comparisons. In order to compare two alternatives a_i and a_k, the difference of their values on each criterion is firstly determined: $d_j(a_i, a_k) = g_j(a_i) - g_j(a_k)$. For each pair of actions, a preference function $F_j(a_i,a_k)$ that represents preference level of a_i over a_k on criterion j can be defined as follows,

$$\left.\begin{array}{ll} F_j(a_i, a_k) = 0 & \text{if } d_j(a_i, a_k) \le q_j \\ F_j(a_i, a_k) = 1 & \text{if } d_j(a_i, a_k) \ge p_j \\ 0 < F_j(a_i, a_k) < 1 & \text{iff } q_j < d_j(a_i, a_k) < p_j \end{array}\right\} \tag{5.1}$$

If the difference $d_j(a_i, a_k)$ is smaller than a predefined indifference threshold q_j, it means that two alternatives are indifferent on criterion j. Contrarily, if the difference $d_j(a_i, a_k)$ is larger than a predefined preference threshold p_j, it means that alternative a_i is strictly preferred over alternative a_k on criterion j. Otherwise, alternative a_i has some preference over alternative a_k on criterion j determined through a preference function. Six different types of preference functions shown in Figure 5.2 have been suggested (Brans and Vincke, 1985). Since the alternatives are evaluated on more than one criterion, the preferences should be aggregated using the weights w_j assigned to each criterion as follows:

$$\Pi(a_i, a_k) = \sum w_j F_j(a_i, a_k) \tag{5.2}$$

The quantification of how an alternative a_i outranks all the remaining alternatives is represented by a leaving flow given in Equation 5.3. In the same manner, an entering flow is determined to show how alternative a_i is outranked by all the remaining alternatives as in Equation 5.4.

$$\phi^{+}(a) = \frac{1}{n-1}\sum_{x \in A} \Pi(a, x) \quad \textit{leaving flow} \tag{5.3}$$

$$\phi^{-}(a) = \frac{1}{n-1}\sum_{x \in A} \Pi(x, a) \quad \textit{entering flow} \tag{5.4}$$

In PROMETHEE I, alternative a_i is preferred to alternative a_k, a_i P a_k, if the following conditions are hold:

$$a_i \text{ P } a_k \text{ if: } \varphi^{+}(a_i) \geq \varphi^{+}(a_k) \text{ and } \varphi^{-}(a_i) \leq \varphi^{-}(a_k). \tag{5.5}$$

In the indifference situation (a_i I a_k), there is no reason to say that any alternative is preferred to the other because two alternatives a_i and a_k have the same leaving and entering flows.

$$a_i \text{ I } a_k \text{ if: } \varphi^{+}(a_i) = \varphi^{+}(a_k) \text{ and } \varphi^{-}(a_i) = \varphi^{-}(a_k). \tag{5.6}$$

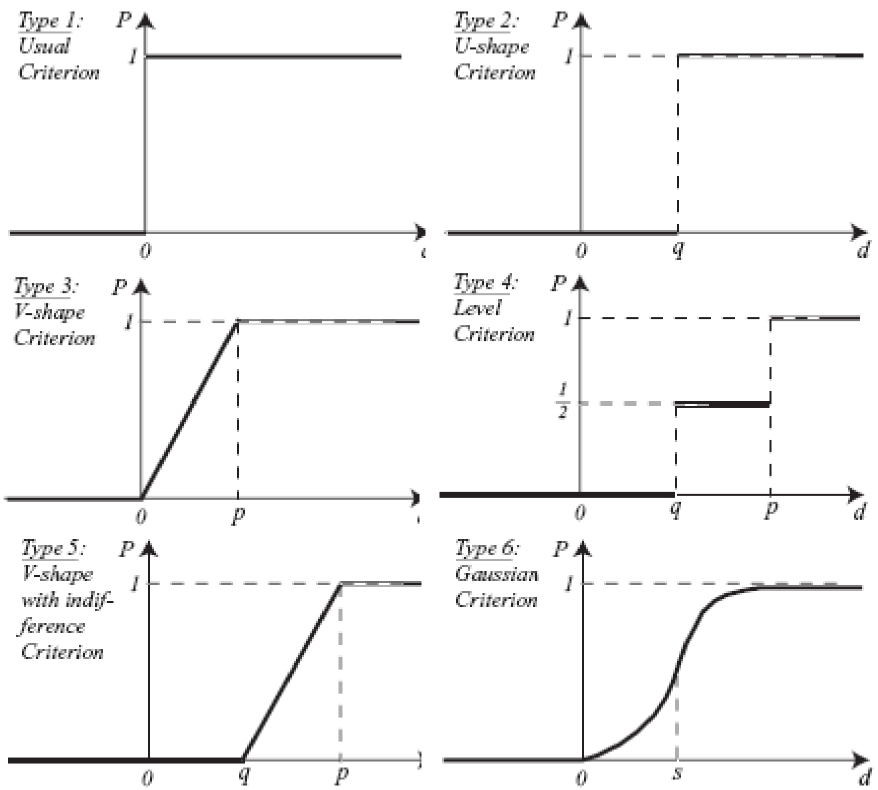

Figure 5.2 Types of preference functions (Figueira et al., 2004)

Two alternatives are considered incomparable, aRb, if alternative a_i has larger leaving flow than alternative a_k, while a_i has smaller entering flow than alternative a_k, or vise verse.

$$a_i \; R \; a_k \text{ if: } \varphi^+(a_i) > \varphi^+(a_k) \text{ and } \varphi^-(a_i) > \varphi^-(a_k) \text{ or}$$

$$\varphi^+(a_i) < \varphi^+(a_k) \text{ and } \varphi^-(a_i) < \varphi^-(a_k)\,. \tag{5.7}$$

Since PROMETHEE I evaluation produces indifference and incomparability situations between alternatives, it provides partial rankings. If the decision maker wants to obtain a complete ranking, PROMETHEE II uses the net flow of each alternative which quantifies the position of each alternative with respect to the remaining alternatives. On the other hand, the larger the net flow, the better the alternative.

$$\phi(a) = \phi^+(a) - \phi^-(a) \text{ net flow} \tag{5.9}$$

5.3 A multi-criteria adaptive control scheme based on neural networks and PROMETHEE

In the previous chapter, the proposed methodology, MCDRC-FIS, is described in detailed. In this chapter, the second approach, MCDRC-PRO, for real time scheduling of DRC manufacturing systems is introduced. MCDRC-PRO also schedules machines and operators through DPRs and worker assignment rules. In addition to DPRs and worker assignment rules, routing decisions are also determined dynamically based on the changing states. The difference from MCDRC-FIS is that MCDRC-PRO alters the multi-criteria scheduling decisions through PROMETHEE. The methodology provides a mechanism that is an interface with the shop floor monitoring and controlling the states and actual performance measures of the manufacturing system.

As seen in Figure 5.3, MCDRC-PRO also consists of three modules; simulation, Artificial Neural Networks (ANNs), and PROMETHEE. Simulation and ANNs modules are the same as those of MCDRC-FIS. As mentioned in previous chapters, simulation is mainly used to generate a sample data to train and test ANNs. ANNs are then used to estimate performance measures generated by candidate DPR, routing rule and worker assignment rule combinations at each decision point. PROMETHEE then aggregates the performance values of the combinations of the decision variables at each decision point generated by ANNs and provides the user with a global rating of each alternative. The decision maker can then determine which decision variable combinations to use based on this overall performance.

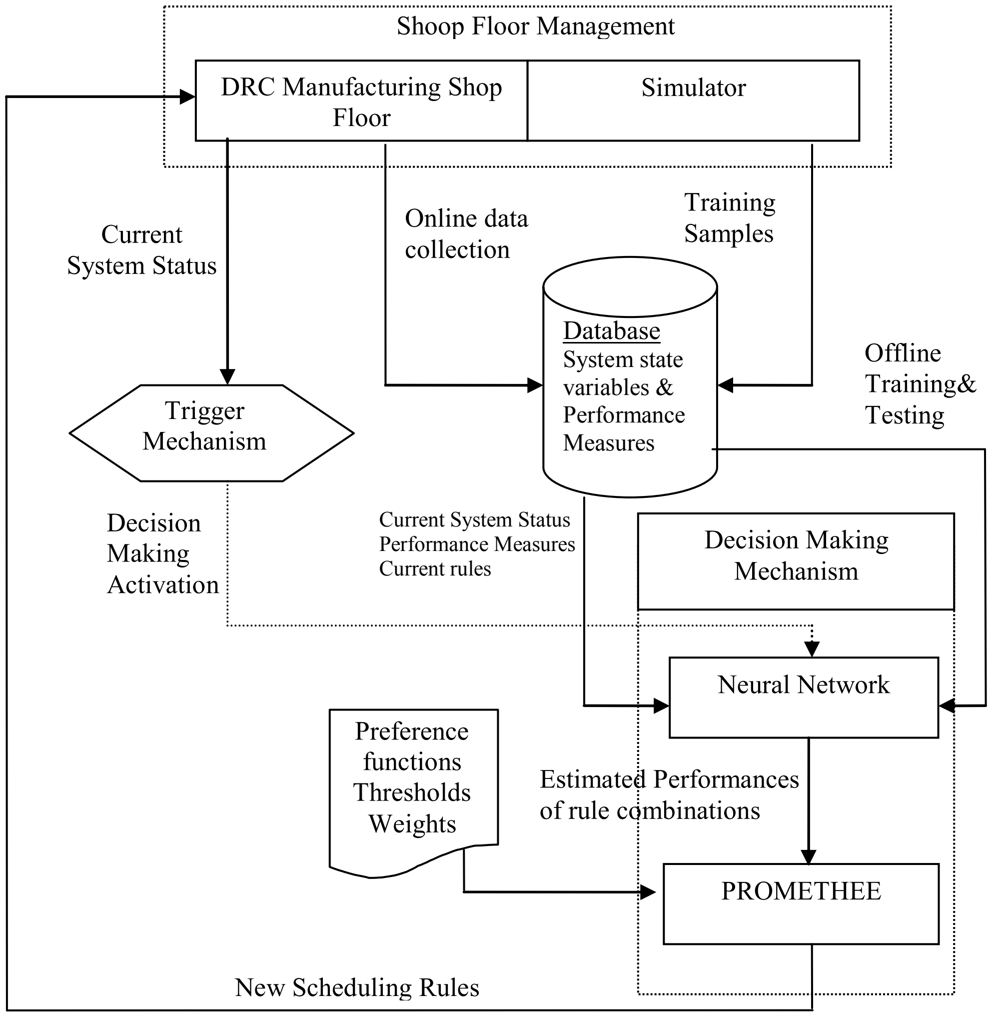

Figure 5.3 MCDRC-PRO architecture

Similar to MCDRC-FIS, MCDRC-PRO operates in two phases: An offline module development phase and an online scheduling phase. Before the methodology for the real-time scheduling is applied, ANN and PROMETHEE modules must be built in the offline phase.

The detailed description of the simulator was given in the Chapter 4. Recall that the simulator is mainly used to create necessary data for training and testing ANNs.

ANNs are used to estimate the corresponding performance measures, obtained by applying the candidate DPR, routing rule and worker assignment rule combinations, at each decision point. The detailed descriptions of the ANN models are also given in Chapter 4. Therefore, in this chapter, the use of PROMETHEE module is focused.

5.3.1 Multi-criteria evaluation of the alternatives by PROMETHEE

In order to evaluate the performance of alternative rule sets, they must be compared in an objective and quantifiable way. Due to the conflicting nature of the performance measures, it is difficult to assess the quality of a rule set. A rule set with a superior performance on some performance indicators (criteria) can perform poorly in another performance indicator. Different rule sets may be the best performers on different criteria. However, finding a satisfactory compromise solution between objectives is more important than finding the best solution for only one objective. In order to obtain a satisfactory compromise solution, generally an aggregated cost function is used as a comparison measure. However, in real life, construction of the cost function is a difficult task because of incommensurable nature of some performance measures such as the number of tardy jobs, mean tardiness, mean flow time, and average machine utilization, etc.

In MCDRC-PRO, a PROMETHEE-based aggregation methodology is proposed to evaluate alternative rule combinations. PROMETHEE enables the methodology to deal with qualitative and quantitative variables, to manage compensatory effects, to understand relations between criteria, and to compare the alternatives in a quantifiable way.

The PROMETHEE should be developed in the offline phase based on preferences of the decision maker. It is clear that if the preferences of a decision maker change during scheduling periods, the parameters of PROMETHEE can be updated to represent the new requirements of the decision maker. The basic steps of this phase are summarized in Figure 5.4.

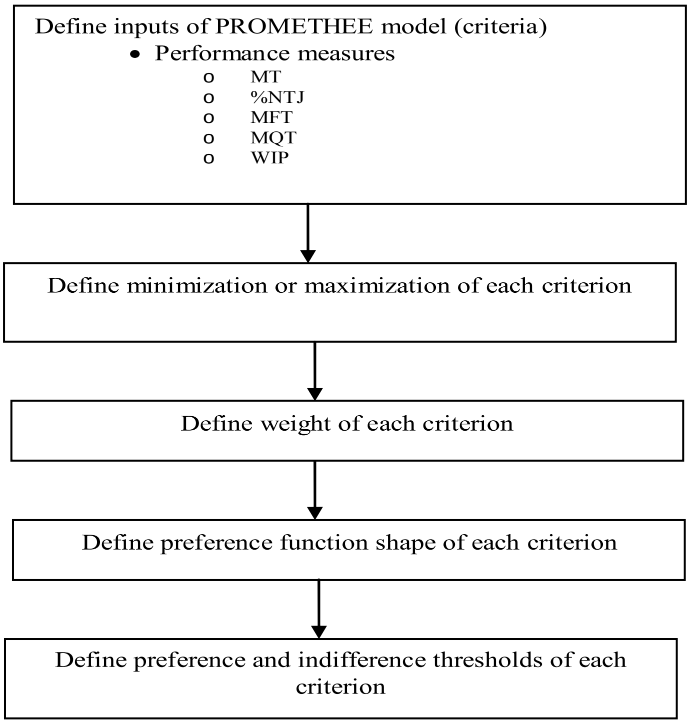

Figure 5.4 Inputs of PROMETHEE

MCDRC-PRO periodically reviews the system status and, at each scheduling point (decision point), the performances of all alternative rule sets that include the DPR, routing rule and worker assignment rule are determined via ANN models. At this point, PROMETHEE finds the net flow value of each alternative through Equations 5.1-5.9 (Figure 5.5). The alternative scheduling rule combination with the highest net flow value is selected as the one to be used during the next scheduling period. This new rule set is utilized till the next scheduling point.

In order to show the effectiveness of MCDRC-PRO, the case problem defined in Chapter 4 is utilized again in the following section.

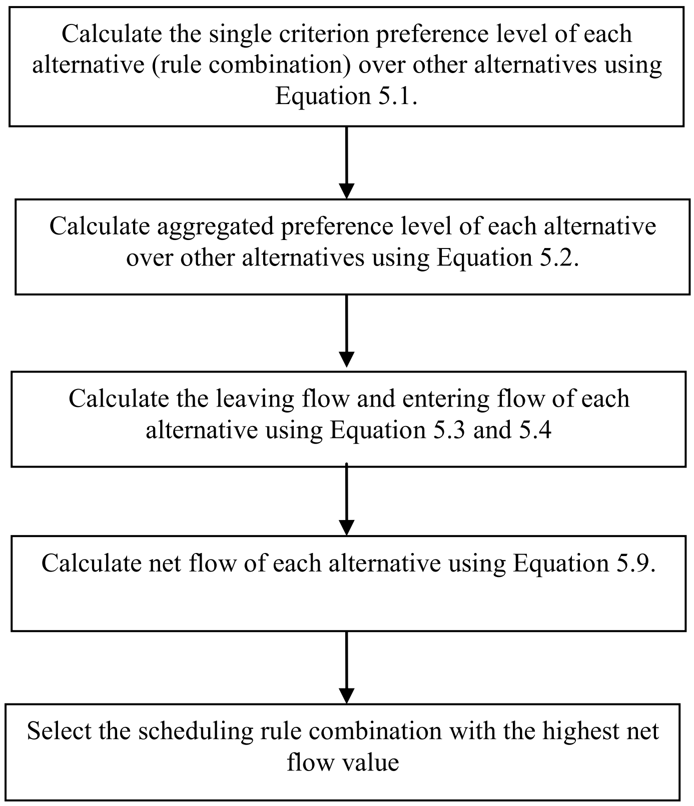

Figure 5.5 Selection of best scheduling rule combination through PROMETHEE

5.4 An Illustrative Example

The hypothetic DRC manufacturing system discussed in Chapter 3 is considered again in this chapter to show the applicability of the proposed methodology. As mentioned above, MCDRC-PRO consists of three modules. Since the simulation and ANN modules are the same as the modules of MCDRC-FIS, the simulation and ANN models developed in Chapter 4 are used in the experiments. Therefore, the development of PROMETHEE module is focused in this section. Then, the results of MCDRC-PRO for the case problems are discussed and compared with those of MCDRC-FIS. Finally, this section is concluded with the sensitivity analysis of the PROMETHEE.

5.4.1 The PROMETHEE Module

The inputs of the PROMETHEE are the performance measures previously defined, which are also called "criterion" in the remaining of this chapter. The parameters of the model, e.g. the weights, indifference and preference thresholds, and preference functions types, should be determined first by the decision maker. These parameters are given in Table 5.1. The linear preference function has been chosen to define the preference relation between the alternatives. The values of all performance measures are normalized between 0-100 according to minimum and maximum values of each performance measures at each rescheduling point.

Table 5.1 Parameters for PROMETHEE

Evaluation criteria	Obj.	Weight	*q*	*p*
MT	Min	0.25	1	5
%NTJ	Min.	0.20	1	5
MFT	Min.	0.25	2	10
MQT	Min.	0.15	1	5
WIP	Min.	0.15	2	8

After PROMETHEE is constructed through the Decision Lab 2000 software, the three cases, which are also described in the previous chapter and deal with the comparison of the proposed scheduling approach with other scheduling approaches for different variation levels, are exploited to evaluate the performance of MCDRC-PRO. Three different levels of system variation, LOW, MEDIUM and HIGH, are also considered. In order to compare the performance of MCDRC-PRO with MCDRC-FIS under the same conditions, the manufacturing system is periodically monitored at every 5000 minutes to consider the system state changes. At the end of each period, the best DPR is chosen with respect to the selected performance measures by both approaches. The results of both approaches at each scheduling point are then compared.

Firstly, the LOW variation case problem is considered. In the first scheduling point (at the end of the first period), in which the time is 20000 minute, all ANNs are fed forward. Each ANN provides the corresponding predicted performance measure values of all alternative rule combinations. The values of the performance measures of each candidate rule combination are transmitted to PROMETHEE to select the best rule set. $\phi^+(a)$ and $\phi^-(a)$ of each alternative are calculated from PROMETHEE, and the alternatives are ranked from the best to the worst with respect to their net flow values. The normalized values of the performance measures, and ϕ^+, ϕ^- and ϕ_{net} values of the best 20 alternatives are given in Table 5.2.

Table 5.2 The evaluation matrix

Alternative	v1	v2	V3	v4	MT	%NTJ	MFT	MQT	WIP	ϕ^+	ϕ^-	ϕ_{net}
81	2	1	4	1	19	14	18	6	18	0.824	0.047	0.777
74	2	1	4	2	8	20	9	7	16	0.820	0.067	0.753
58	2	2	4	1	27	10	16	3	33	0.815	0.068	0.747
67	2	1	4	3	18	7	26	19	19	0.810	0.070	0.741
53	2	2	4	2	17	17	1	13	33	0.813	0.080	0.733
46	2	2	4	3	17	4	23	18	35	0.812	0.080	0.732
22	2	3	7	3	23	8	24	22	17	0.793	0.073	0.720
25	2	3	4	3	0	10	28	17	31	0.799	0.090	0.709
71	2	1	7	2	24	18	25	8	0	0.773	0.084	0.689
29	2	3	7	2	27	20	14	7	21	0.776	0.090	0.686
50	2	2	7	2	44	14	4	10	18	0.777	0.101	0.676
78	2	1	7	1	34	12	29	6	0	0.773	0.099	0.675
32	2	3	4	2	1	23	12	7	39	0.781	0.111	0.670
43	2	2	7	3	43	2	22	17	19	0.769	0.108	0.661
36	2	3	7	1	36	14	23	1	21	0.760	0.099	0.661
41	2	3	4	1	9	17	28	0	40	0.763	0.119	0.644
61	2	2	7	1	57	8	13	1	15	0.757	0.130	0.628
72	2	1	6	2	30	18	22	8	29	0.735	0.112	0.623
64	2	1	7	3	30	6	39	23	2	0.750	0.133	0.617
51	2	2	6	2	39	15	0	14	40	0.742	0.132	0.610

If the mean tardiness were assumed as the sole criterion, alternative 25 should be selected. However, because of the poor performance of the alternative 25 on other criteria, PROMETHEE ranks this alternative in the 8th rank order. It should also be noted that although one alternative is better than other alternatives with respect to only one criterion, it is outranked by the others because of the worse performance on the other criteria. According to the PROMETHEE results, alternatives 81, 74 and 58 are the best three performers.

In order to highlight the effectiveness of the PROMETHEE, the performances of the rule combination selected by PROMETHEE is compared with those of the five different alternatives selected based on only one performance measure at a time. For example, the first alternative has the minimum MT while the others minimizes %NTJ, MFT, MQT and WIP, respectively. The results are shown in Figure 5.6. The net flow value, which shows the strength of the alternative, of the alternative selected by PROMETHEE and the other alternatives are also plotted in the figure.

Similar to the results obtained in Chapter 4, there is no alternative scheduling rule combination better than the other alternative solutions for all performance measures. Although five different solution alternatives have superior performances for different criteria, they perform badly in the others. In other words, they do not offer such a compromise solution. Therefore, the net flow values of these alternatives are low. On the other hand, the alternative selected by PROMETHEE has somewhat good performance in all criteria. Therefore, PROMETHEE is as efficient and flexible to obtain a compromise solution as the FIS approach.

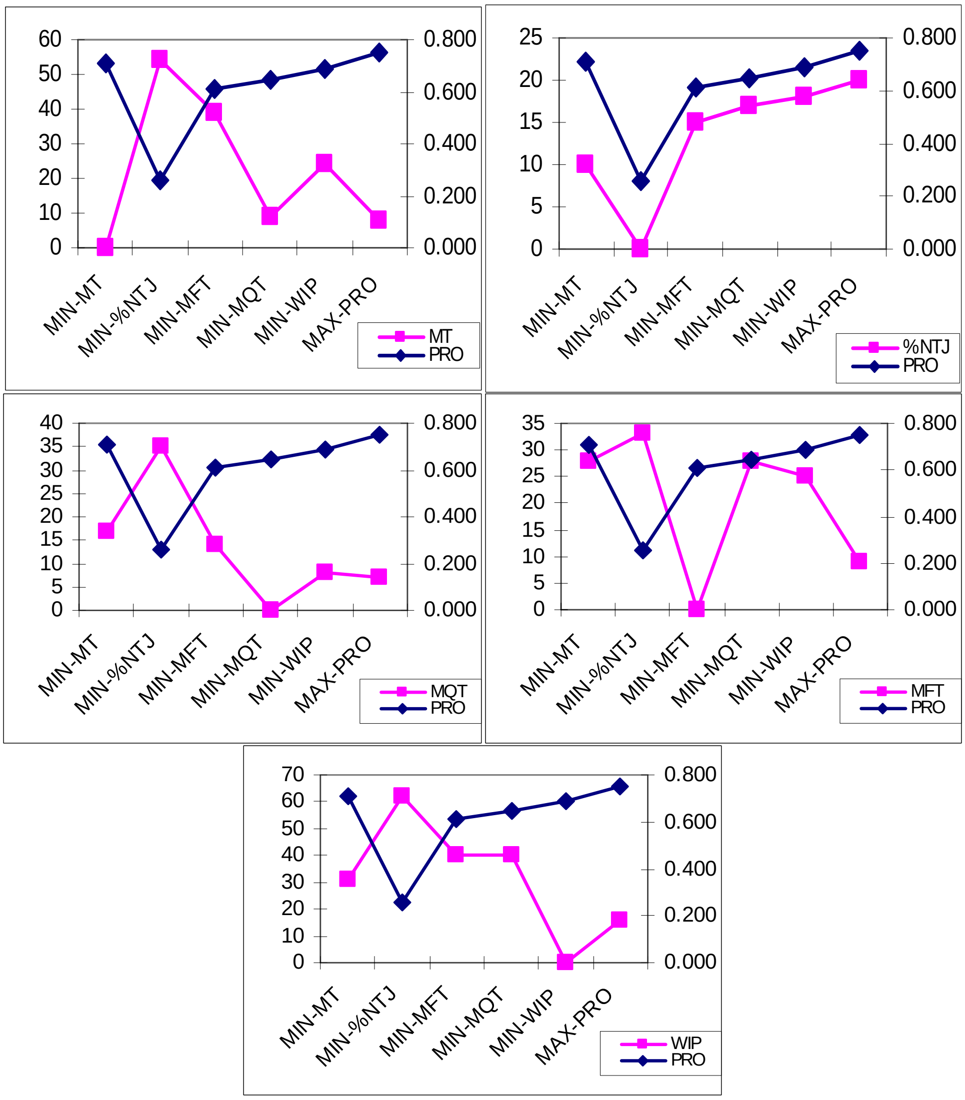

Figure 5.6 The results of comparison of PROMETHEE and single objective for the first step

In the light of the results, it can be noted that the best compromise solution is the 81th alternative, which represents the following rules: “when” labor assignment rule is “Decentralized Rule”, “where” labor assignment rule is “LWT”, selection of machines by part is “LNQ”, selection of parts by machine is “SRPT”. After this schedule is selected from the PROMETHEE results, it is used in the scheduling system until the next scheduling period. In the second scheduling point, in which the time is 25000 minutes, MCDRC-PRO is applied again to select the best scheduling rule set for the next scheduling period. After the values of performance measures of each alternative are derived from the ANN models, PROMETHEE is recalled to evaluate the alternatives. Figure 5.7 shows the PROMETHEE results at the second scheduling point. This procedure is repeated in the next scheduling periods.

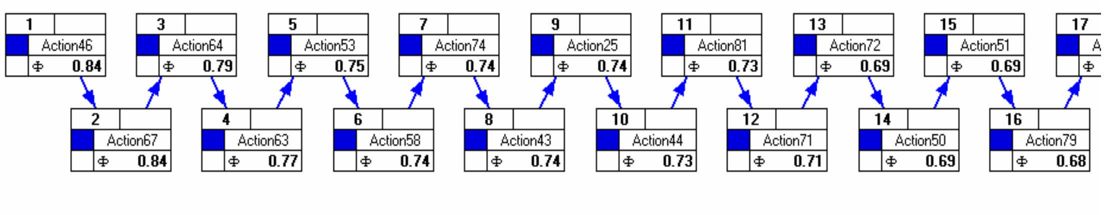

Figure 5.7 The PROMETHEE results for the second step

5.4.2 Results and Discussion

In this section, the performance of MCDRC-PRO is evaluated by comparing it with the fixed, multi-pass and MCDRC-FIS approaches. The random scheduling approach is not considered in this section because it already gives the worst performance in the previous chapter. As remembered, the fixed scheduling selects a scheduling rule combination according to the performance of the simulation results at the beginning of the scheduling period. The multi-pass scheduling algorithm, called MULTIFIS, selects a combination of decision variables at each rescheduling point from the results of a series of discrete event simulation performed under each rule combination. As mentioned before, it is extended with FIS so that it can deal with multiple performance measures. MCDRC-FIS explained in the previous chapter is also compared with MCDRC-PRO.

Recall from chapter 4 that three different levels of system variation, LOW, MEDIUM and HIGH, are considered. The detailed information about the variation levels of the test problem is given in Table 3.17. The rule combination of 2343 (v1=2, v2=3, v3=4, v4=3) is selected as the fixed scheduling rule to be employed, which is also the initial scheduling rule combination for all other methods. It should be remembered that this rule combination has the best performance among all fixed rule combinations.

The simulation results of the different scheduling approaches for the LOW case problem are shown in Table 5.3. Mean improvement percentages are given for each method at each decision point. As remembered, improvement percentages were computed as $((PM_{Sk})- PM_{ik})/ PM_{ik})100$, where PM_{ik} is the value of the kth performance measure for method i (i = 1, 2, 3, and k = 1, 2…5) and PM_{sk} is the value of the kth performance measure for the fixed scheduling. In the table, there are nine decision points for each method. Each row represents percentage improvements of the performance measures derived from the methods with respect to the fixed scheduling rule combination at each decision point. The changes on the performance measures during the scheduling periods are also shown in Figure 5.9.

Table 5.3 % improvement with respect to the fixed scheduling for VR=L and p=5000

Method	v1	v2	v3	v4	% difference fixed scheduling rule 2343				
					MT	%NTJ	MFT	MQT	WIP
MULTIFIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	2	7	3	15.38	5.03	24.04	12.73	3.12
	2	1	6	3	14.13	3.89	18.13	3.14	12.77
	2	4	3	3	14.56	8.34	18.12	3.23	15.00
	2	2	1	3	13.44	9.85	17.82	12.79	0.61
	2	1	7	3	17.26	6.24	17.06	16.46	0.36
	1	2	6	3	29.57	11.74	22.62	19.79	8.36
	2	3	7	3	23.28	14.67	28.26	36.77	16.71
	1	4	7	3	37.89	15.20	45.61	56.41	42.59
MCDRC-FIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	2	6	1	21.42	3.40	26.55	19.72	12.24
	2	2	7	1	31.70	2.07	26.28	19.68	23.15
	2	3	4	1	37.30	8.07	28.60	24.59	26.87
	2	2	6	1	43.29	9.60	31.70	38.22	19.02
	2	1	4	1	47.83	10.06	32.20	42.77	18.37
	2	1	7	3	53.65	11.53	35.42	49.61	23.80
	1	2	4	1	37.36	7.60	33.76	44.24	22.69
	2	2	7	1	47.12	7.85	48.79	60.61	46.88
MCDRC-PRO	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	1	4	1	28.04	5.37	29.67	23.69	13.35
	2	2	4	3	31.46	4.10	26.48	20.42	21.51
	2	1	4	3	28.85	8.38	24.76	17.25	22.17
	2	2	4	1	34.50	9.87	27.64	31.21	13.72
	2	2	4	1	39.48	10.06	28.09	35.84	13.41
	2	1	6	3	47.75	11.96	32.34	44.84	20.03
	2	2	4	3	41.70	14.72	36.38	49.80	26.22
	2	2	4	3	51.67	15.21	51.26	64.69	48.44

It should be noted from the table that the strategies that select a new dispatching rule combination during the scheduling period yield considerably better performance than the fixed scheduling. It should be highlighted that MCDRC-PRO gives the best improvement according to the fixed scheduling at the end of the scheduling periods. Although the system states are changed dynamically, MCDRC-PRO performs well for each performance measure. At the end of the scheduling periods, the MFT is reduced by 51.26%, the MT is reduced by 51.67%, the %NTJ is reduced by 15.21%, the MQT is reduced by 64.691%, and the WIP is reduced by 48.44%.

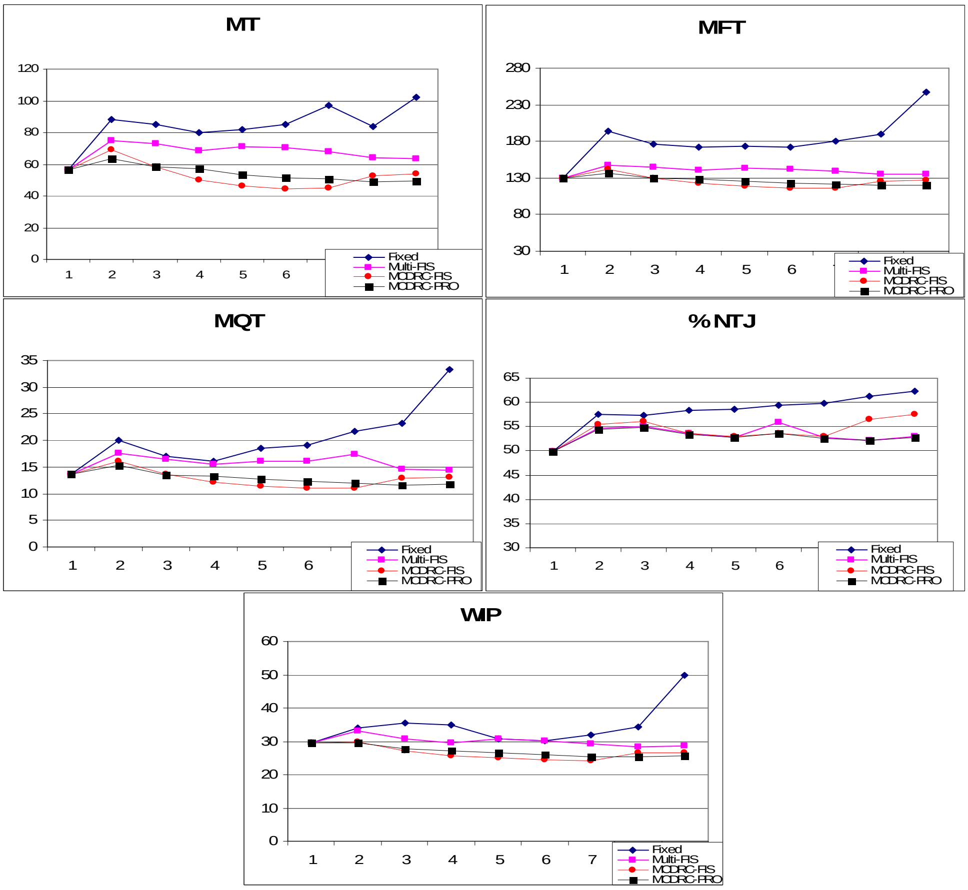

Figure 5.8 Simulation results for variation L (VR=L) and p=5000

As seen in Figure 5.8, MCDRC-PRO gives close results to MCDRC-FIS and MULTIFIS under the LOW variation level. Since MCDRC-FIS and MCDRC-PRO have similar structures, MCDRC-PRO has the same advantages over the fixed scheduling and MULTIFIS. In the previous chapter, MCDRC-FIS and MULTIFIS outperformed the fixed scheduling according to the results of the paired-t test.

Therefore, differences between the fixed scheduling and MCDRC-PRO are not investigated in this experiment, because MCDRC-PRO outperforms the fixed scheduling for each variation level of the DRC manufacturing system. Therefore, in this section, the results of MCDRC-PRO are compared with those of MCDRC-FIS. The results for the LOW variation level show that MCDRC-FIS and MCDRC-PRO provide good results for the real time scheduling of the DRC manufacturing system. In addition, PROMETHEE provides a flexible and efficient tool to aggregate the performance measures. In addition to these results, the performances of the scheduling methods under medium and high variation levels are shown in Table 5.4 and 5.5, and in Figure 5.9 and 5.10, respectively.

Table 5.4 % improvement with respect to the fixed scheduling for VR=M and p=5000

Method	v1	v2	v3	v4	% difference fixed scheduling rule 2343				
					MT	%NTJ	MFT	MQT	WIP
MULTIFIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	4	2	3	19.53	0.91	11.05	35.96	18.72
	2	3	2	1	28.35	12.42	11.81	36.34	19.43
	2	4	6	1	38.23	9.86	13.07	38.91	20.45
	2	4	2	3	34.89	15.01	13.23	38.92	20.46
	1	1	4	3	32.02	14.40	12.57	38.07	19.95
	2	1	4	3	28.46	16.48	12.29	37.43	19.65
	1	4	7	3	26.54	18.53	11.94	36.75	19.33
	2	3	2	1	15.02	24.70	12.10	9.59	19.63
MCDRC-FIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	2	7	1	30.98	-1.71	12.24	37.19	20.13
	2	1	7	3	33.03	8.27	11.85	36.51	19.43
	2	1	4	1	39.48	6.70	12.64	37.84	20.01
	2	2	6	3	29.73	11.76	11.10	34.95	18.83
	1	2	4	1	31.79	11.90	11.62	35.07	19.41
	2	2	4	1	31.47	14.65	12.21	36.32	19.67
	1	2	7	1	31.14	16.63	12.15	35.93	19.54
	2	1	7	3	17.95	22.82	11.89	7.54	19.41
MCDRC-PRO	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	1	4	1	28.21	0.52	12.06	36.81	19.87
	2	1	4	1	33.87	11.33	12.09	35.83	19.70
	2	1	4	3	37.37	8.88	12.32	37.03	19.70
	1	2	4	3	31.77	14.07	11.80	35.67	19.10
	2	1	7	1	32.52	13.33	11.92	35.97	19.71
	2	1	6	3	30.09	15.63	12.04	36.41	19.38
	1	1	4	3	27.34	18.07	11.59	35.42	18.98
	2	1	4	3	13.31	24.27	11.32	6.33	18.72

Table 5.5 % improvement with respect to the fixed scheduling for VR=H and p=5000

Method	v1	v2	v3	v4	% difference fixed scheduling rule 2343				
					MT	%NTJ	MFT	MQT	WIP
MULTIFIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	4	2	3	-5.79	2.90	-3.83	-35.28	-0.85
	2	3	2	1	-2.15	2.76	-2.88	-16.80	-1.13
	1	4	6	1	-30.99	-1.51	-23.17	-74.29	-26.02
	2	4	2	3	-57.03	-1.66	-39.53	-108.91	-49.48
	2	1	4	3	-76.17	-1.38	-51.22	-153.30	-63.89
	1	1	4	3	-102.98	-1.67	-65.97	-197.43	-87.72
	2	4	7	3	-123.72	-1.90	-78.80	-260.30	-115.92
	2	3	2	1	-195.88	-2.41	-78.40	-270.27	-140.78
MCDRC-FIS	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	2	7	1	16.95	4.18	8.93	6.99	11.97
	2	1	7	3	23.28	3.99	12.84	19.72	16.31
	2	1	4	1	28.21	4.25	16.25	24.84	16.25
	2	2	6	3	26.68	4.21	15.14	22.81	16.56
	2	2	4	1	28.66	4.02	16.42	24.26	18.54
	1	2	4	1	28.32	3.81	15.99	24.72	19.40
	2	2	7	1	32.63	3.97	18.74	29.49	18.77
	1	1	7	3	30.29	3.87	17.20	26.61	17.47
MCDRC-PRO	2	3	4	3	0.00	0.00	0.00	0.00	0.00
	2	1	4	1	16.95	4.18	8.93	6.99	11.97
	2	1	4	3	22.15	4.44	12.30	19.22	14.93
	1	2	4	1	27.79	4.58	16.08	23.98	16.34
	1	1	4	3	26.82	4.65	15.39	23.73	16.31
	2	2	4	3	26.40	4.62	15.14	22.11	15.82
	2	1	4	3	25.44	4.68	14.39	20.86	15.57
	2	2	6	1	26.97	4.55	15.30	22.11	15.43
	2	2	6	1	27.17	4.40	15.31	22.73	16.15

As seen from Tables 5.4 and 5.5 and Figures 5.10 and 5.11, MCDRC-FIS and MCDRC-PRO provide similar results and outperform other scheduling approaches in terms of solution quality and response time. The difference between MCDRC-FIS, which utilizes FIS, and MCDRC-PRO, which utilizes PROMETHEE, lies only in their aggregation methods used to evaluate alternatives under multiple criteria. The differences between the two approaches are investigated statistically in terms of all performance measures through the paired-t test. The results are given in Table 5.6.

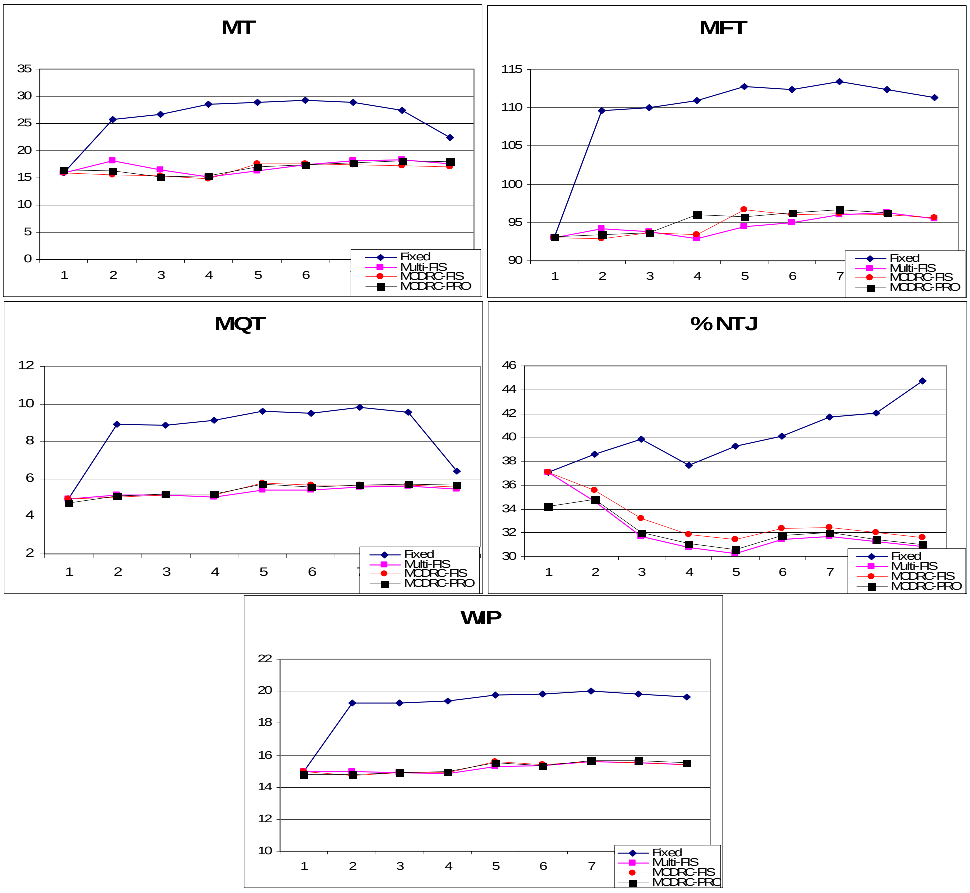

Figure 5.9 Simulation results for variation M (VR=M) and p=5000

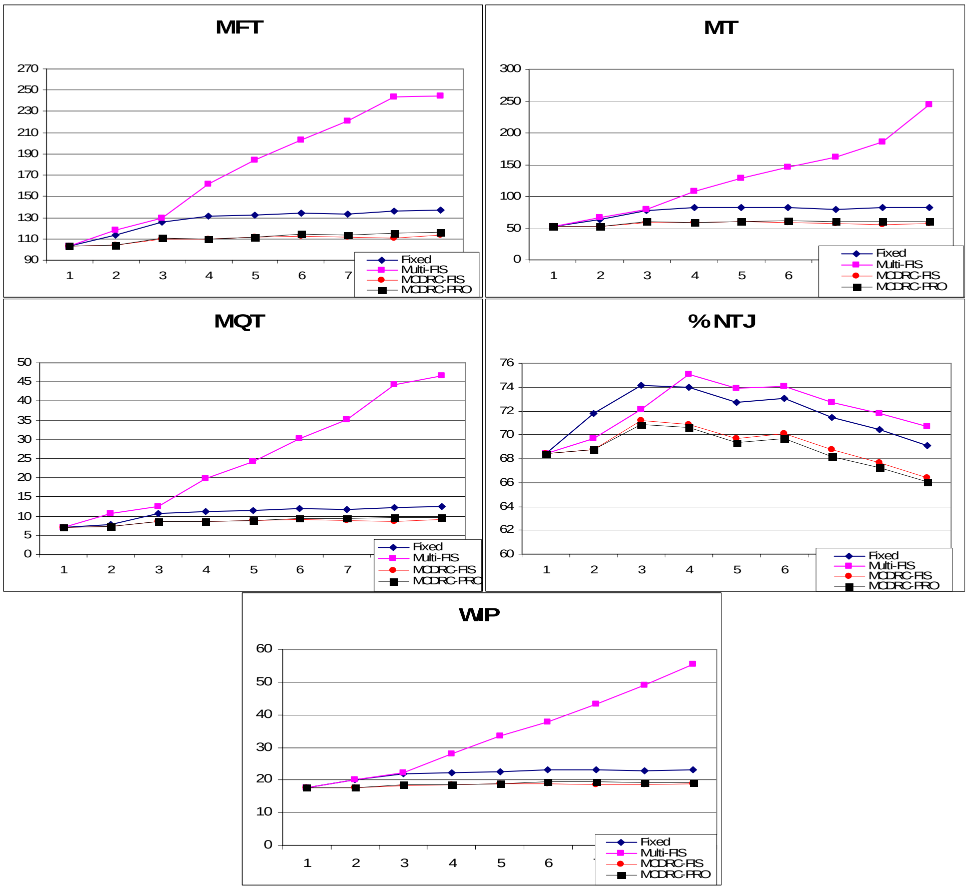

Figure 5.10 Simulation results for variation M (VR=H) and p=5000

Table 5.6 Results of the paired *t*-test

VR	Performance Measures	95 % CI FOR MEAN DIFFERENCE	t-value	p-value
L	MT	(-6.39; 3.19)	-0.79	0.454
L	%NTJ	(-0.11; 3.07)	2.20	0.064
L	MFT	(-6.22; 4.03)	-0.51	0.629
L	MQT	(-1.15; 0.83)	-0.38	0.715
L	WIP	(-1.49; 0.45)	-1.28	0.242
M	MT	(-0.78; 0.15)	-1.61	0.152
M	%NTJ	(0.49; 0.87)	8.65	0.00*
M	MFT	(-0.48; 0.33)	-0.44	0.676
M	MQT	(-0.07; 0.04)	-0.69	0.512
M	WIP	(-0.09; 0.03)	-1.05	0.327
H	MT	(-2.94; -0.21)	-2.72	0.03*
H	%NTJ	(0.19; 0.48)	5.44	0.001*
H	MFT	(-2.86; -0.06)	-2.47	0.043*
H	MQT	(-0.55; 0.01)	-2.29	0.056
H	WIP	(-0.66; -0.07)	-2.91	0.023*

* There is a difference in the two means at a significance level of 0.05.

As seen in Table 5.6, the test results show that the differences between MCDRC-FIS and MCDRC-PRO are not statistically significant at the 95% confidence level for each performance measure in the low variation level. In the medium variation level, there is a difference in only the %NTJ performance measure at a significance level of 0.95. According to the confidence interval of the mean difference between MCDRC-FIS and MCDRC-PRO, it is concluded that MCDRC-PRO gives better solution than MCDRC-FIS for the %NTJ performance measure. But, there is no difference statistically between their results with respect to the other performance measures. Furthermore, the difference between MCDRC-FIS and MCDRC-PRO in the high level variation is statistically significant at the 95% confidence level for all performance measure, except for MQT. Considering the confidence intervals of the mean difference for MT, MFT and WIP, it can be said that MCDRC-PRO outperforms MCDRC-FIS. However, MCDRC-FIS outperforms MCDRC-PRO for %NTJ. When the variation levels of the system increase, the difference between MCDRC-FIS and MCDRC-PRO becomes more significant.

Consequently, all analyses show that MCDRC-FIS and MCDRC-PRO provide flexible, efficient and quick solutions for the real time scheduling of DRC manufacturing systems. Both FIS and PROMETHEE modules of the proposed approaches successfully ensure the multi-criteria evaluation of the scheduling rule combinations. Both of them provide compromise solutions according to the decision maker’s preferences.

As mentioned earlier, the performance of the PROMETHEE models depends on the parameters selected in the model development phase. These parameters are selected by the decision maker according to his/her preferences. In the next section, the sensitivity analysis of the parameters is performed for the PROMETHEE.

5.4.3 Sensitivity analysis for PROMETHEE

In this section, the robustness of MCDRC-PRO is tested. Every multi-criteria method requires the determination of some parameters, e.g. some thresholds, and weights. It is important to know the influence they have on the rankings when small changes occur in their values, because decision makers generally cannot fix correctly their exact values (Brans et al., 1986). The robustness of the rankings must be demonstrated by analyzing the sensitivity in the change of the parameters.

Besides the ‘‘base case’’, i.e. the parameters in Table 5.1, a number of sensitivity analyses should be carried out at the medium variation level.

• The values of indifference and preference thresholds are increased with respect to the ‘‘basic solution’’ by +25%, +50% and +100%.

• The values of indifference and preference thresholds are decreased with respect to the ‘‘basic solution’’ by -25%, -50% and -100%.

Firstly, the thresholds of the indifference and preference are altered. Then, in the first scheduling point, the scheduling rule combination to be applied is selected through MCDRC-PRO. The simulation results of the experiments are compared to the ‘‘fixed scheduling approach’’ derived at the second scheduling point. A summary of the results obtained is given in Table 5.7. It can be seen from the table that small changes in the threshold values do not cause any change in the selected alternative rule combination. If considerable changes occur in the threshold values, a different scheduling rule combination may be selected. Therefore, it can be concluded that the small changes in the values of the thresholds do not have a strong effect on the results of MCDRC-PRO.

Table 5.7 Results of the difference thresholds (weights: 0.25, 0.20, 0.25, 0.15, and 0.15 for MT, %NTJ, MFT, MQT and WIP, respectively; preference function: linear)

Experiments*	Indiference Threshold	Preference Threshold	DVs				Performance Measures				
			v1	v2	v3	v4	MT	%NTJ	MFT	MQT	WIP
B	1	5	2	1	4	1	16.23	34.80	93.10	5.06	14.78
1	1.25	6.25	2	1	4	1	16.23	34.80	93.10	5.06	14.78
2	1.5	7.5	2	1	4	1	16.23	34.80	93.10	5.06	14.78
3	2	10	2	1	4	1	16.23	34.80	93.10	5.06	14.78
4	0.75	3.75	2	1	4	1	16.23	34.80	93.10	5.06	14.78
5	0.5	2.5	2	1	4	1	16.23	34.80	93.10	5.06	14.78
6	0	0	2	1	4	1	16.23	34.80	93.10	5.06	14.78
Fixed			2	3	4	3	22.61	34.98	105.87	8.01	18.45

* B is base case, 1-2-3: Increased threshold by 25%, 50%, 100%, 4-5-6 : Decreased threshold by 25%, 50%, 100%

To show the effects of the weights on the performance of the PROMETHEE model, a second experiment is conducted. In order to reflect the relative importance of performance measures for different decision makers, different weight structures are generated. Table 5.8 shows the alternative solutions according to a decision maker's point of view. As it is expected, the results show that different weight combinations may give different solutions at each decision point.

Table 5.8 Results of the difference weights (Preference function: Linear, Indifference threshold: 1, Preference threshold: 5, DVs: decision variables)

Weight					DVs				Performance Measures				
MT	%NTJ	MFT	MQT	WIP	v1	v2	v3	v4	MT	%NTJ	MFT	MQT	WIP
0.6	0.1	0.1	0.1	0.1	2	1	4	2	15.03	36.90	93.38	4.32	18.26
0.1	0.6	0.1	0.1	0.1	2	2	7	3	17.49	29.63	91.48	4.60	14.17
0.1	0.1	0.6	0.1	0.1	2	3	7	1	18.24	41.11	89.23	4.30	13.81
0.1	0.1	0.1	0.6	0.1	2	2	4	1	16.12	41.09	89.48	4.14	13.87
0.1	0.1	0.1	0.1	0.6	2	1	7	1	15.92	41.21	89.29	4.31	13.68
0.2	0.2	0.2	0.2	0.2	2	3	7	1	15.74	41.11	89.23	4.30	13.81
0.3	0.3	0.2	0.1	0.1	2	3	7	3	15.68	39.04	91.73	4.64	14.21
0.35	0.2	0.35	0.05	0.05	2	3	4	1	15.47	40.97	89.37	4.73	14.84

Furthermore, it should be pointed out that, for a given weight structure, there are several scheduling rule combinations that have PROMETHEE II net flow values close to those of the best scheduling rule combination. The results in Table 5.9 are obtained based on the base case described in Table 5.1. It should be noted that all of the rule combinations in Table 5.9 can be selected for the next scheduling period, since all of them provide very close performances on all criteria**.**

Table 5.9 Results of the best six alternatives

Alternatives	v1	v2	V3	v4	MT	%NTJ	MFT	MQT	WIP	ϕ^{+}	ϕ^{-}	ϕ_{net}
81	2	1	4	1	16.23	34.80	93.10	5.06	14.78	0.824	0.047	0.777
74	2	1	4	2	15.03	36.90	93.38	4.32	18.26	0.820	0.067	0.753
58	2	2	4	1	16.12	41.09	89.48	4.14	13.87	0.815	0.068	0.747
67	2	1	4	3	16.54	41.08	89.47	4.36	14.07	0.810	0.070	0.741
53	2	2	4	2	17.18	40.98	90.32	4.36	14.03	0.813	0.080	0.733
46	2	2	4	3	17.26	41.37	90.54	4.40	13.99	0.812	0.080	0.732

It is obvious that a decision maker can find different solutions by using different weight structures that reflect her/his preferences. The results show that the appropriate selection of the parameters has a significant effect on the performance. Hence, the sensitivity analysis of the parameters should be performed at the developing phase of the PROMETHEE.

5.4. Summary

Scheduling of DRC manufacturing systems has inherently multi-criteria features. Decision makers may be interested in more than one performance measures simultaneously, such as mean flow time and mean tardiness. However, to the best of our knowledge, the multi-criteria real-time scheduling of DRC systems has not yet been studied. Therefore, effective methodologies that have the capability of evaluating and continually monitoring the performance of DRC manufacturing systems and selecting the appropriate scheduling rule combinations considering system changes are needed.

In this chapter, a multi-criteria real time scheduler, MCDRC-PRO, was presented. This scheduler deals with the dynamic selection of appropriate set of scheduling rules with regard to multiple performance criteria of interest by integrating a simulation model, ANNs and a well known multi-criteria decision aid method, PROMETHEE. All analyses show that MCDRC-PRO provides flexible, efficient and fast solutions for the real time scheduling of DRC manufacturing systems.

As discussed in previous chapters, this research proposes three different real time scheduling procedures for DRC systems. In the next chapter, the third one, a fuzzy priority based real time DRC scheduler, is proposed that incorporates simulation, fuzzy sets and ANNs.

CHAPTER SIX
A FUZZY PRIORTY RULE BASED REAL-TIME SCHEDULING APPROACH FOR DRC SYSTEMS

6.1 Introduction

As mentioned in earlier chapters, there are some shortcomings of dispatching rules (Subramaniam et al., 2000): (i) they do not consider all of the available resources at the same time, (ii) they do not allow for the use of multiple criteria in the scheduling process, (iii) their rigid structure excludes the use of other useful information that may be available for scheduling, (iv) there is no single universal dispatching rule, and the choice of a suitable dispatching rule depends on the nature of the scheduling problem and the performance measure of interest.

MCDRC-FIS and MCDRC-PRO overcome the abovementioned shortcomings through dynamically selecting appropriate dispatching rules (DPRs), worker assignment rules and job routes to determine the best rule set *within some predetermined sets* with regard to multiple performance criteria of interest. The rule set with the best compromise performance is then applied in the shop floor until the next rescheduling point determined through either a certain time period or predetermined thresholds of the performance measures. However, they inherit the drawback of the fact that these *predetermined sets* may limit their performances, i.e. their performances are subject to the performances of the *predetermined* dispatching rule sets.

To cope with the drawbacks above, many approaches based on fuzzy logic have been proposed for machine-only constrained systems. As discussed in Chapter 2, some of these studies use a fuzzy inference system (FIS) to prioritize and rank the alternative dispatching rules or routing alternatives, (e.g. see Geneste and Grabot, 1997; Yu et al., 1999; Subramaniam et al.,2000; Caprihan et al., 2006), some of them perform multi-criteria evaluation of part dispatching rules through fuzzy arithmetic (Chan et al., 2002; Petroni and Rizzi, 2002), while some others develop a fuzzy priority index to prioritize routing alternatives (Chan et al., 2002). Yet most studies deal with the FMS scheduling problem and focus on part dispatching and routing selection. To the best of our knowledge, a fuzzy-based scheduling approach has not been developed for DRC manufacturing systems. Furthermore, most of them do not consider multiple decision points simultaneously, and aim either to determine the part dispatching rule or to select the routing alternative. Different from these studies, Chan et al. (2002) propose a fuzzy decision system for an FMS to assign priorities to the parts waiting to be processed and to determine the parts routes. However, the authors did not provide any adaptive control scheme in their approach to allow the decision maker to alter his/her preferences.

This chapter proposes an adaptive fuzzy-based real-time scheduling system to overcome the abovementioned difficulties. This approach, called MCDRC-Fuzzy, defines fuzzy priorities for the parts and routes considering multiple performance measures, instead of using standard dispatching rules and routing rules, and introduces novel “fuzzy where” rules. Moreover, instead of using traditional centralized and decentralized “when” rules, one set of “Sugeno type” rules is proposed. To the best of the author’s knowledge, the “fuzzy-where-rule” and “fuzzy-when-rule” concepts have not been considered before in DRC research.

Different from the previous fuzzy-based approaches, an indirect estimation procedure for the parameters specified by the decision maker, such as weights of fuzzy goals, is also developed. The system parameters are altered by the help of reverse NN metamodeling in order to satisfy the decision maker’s objectives. The use of the fuzzy priorities, routes, “where” and “when” rules provides a compromise solution that represents the decision maker’s point of view more realistically.

The rest of the chapter is organized as follows. In section 6.2, a brief description of the proposed methodology is given. Section 6.3 is devoted to experimental studies. Finally, a chapter summary is given in section 6.4.

6.2 A Fuzzy Priority Rule Based Real-Time Scheduling Approach for DRC Systems

The methodology is illustrated in Figure 6.1. MCDRC-Fuzzy schedules the system continuously using the real time system status information. Fuzzy-based scheduler helps to define priorities of alternatives for scheduling decisions considering all of the traditional rules. Additionally, MCDRC-Fuzzy allows the decision maker to define desired performance measures for the next scheduling period. The parameters of the fuzzy scheduler are then updated using the ANN model.

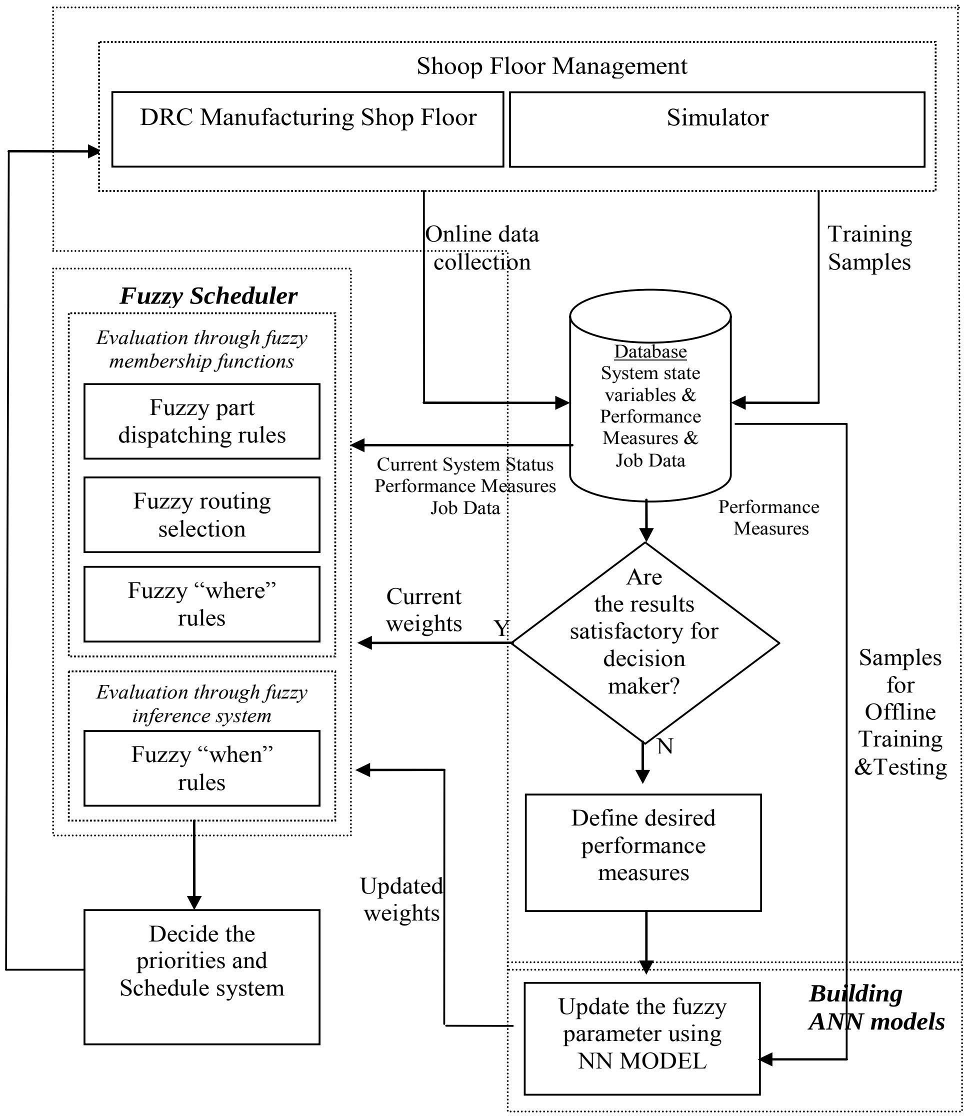

Figure 6.1 The flow of the proposed methodology

As seen in Figure 6.1, three sub-modules exist in the methodology: (1) simulator, (2) ANN module, (3) fuzzy scheduler. The simulation module is the same as that of MCDRC-FIS and MCDRC-PRO. As mentioned in previous chapters, simulation is mainly used to generate sample data to train and test ANNs. The fuzzy scheduler module uses some fuzzy rules in guiding the scheduling process. Different from the previous studies, it realizes four multi-criteria scheduling decisions simultaneously. The ANN module must be built in the offline phase. Recall that ANN models were used to estimate performance measures generated by candidate DPR and worker assignment rule combinations at each decision point in MCDRC-FIS and MCDRC-PRO. ANN models are also trained for reverse simulation metamodeling and used to update the parameters of the fuzzy membership functions of the fuzzy goals in MCDRC-Fuzzy. In the next section, brief descriptions of these modules are given.

6.2.1 Simulator

Recall that the simulator is used to create necessary data for training and testing ANNs and to represent the DRC shop floor in the experiments. In addition to the simulation models described in previous chapters, the simulation model developed in this chapter features real-time adaptive fuzzy scheduling. In other words, the fuzzy scheduler is embedded into the simulation model. The decisions about the jobs waiting to be processed in the queues, alternative routes of each job to be moved from one machine to another, when the workers should be transferred from one machine to another, and where the worker should move are evaluated in real-time. Although the simulator schedules production with the fuzzy scheduler module, it is also able to schedule production using traditional job dispatching rules, alternative routes and when and where rules.

6.2.2 ANN module

In MCDRC-FIS and MCDRC-PRO, the efforts have been directed to develop direct simulation metamodelings through ANNs in order to estimate performance measures generated by candidate DPR rules and worker assignment rules at each decision point based on the system state. Contrarily, in MCDRC-Fuzzy, a reverse ANN model is used. In reverse simulation metamodeling approaches, contrarily to direct metamodeling approaches, the outputs of the simulation (performance measures) are used as the inputs and design parameters of the system as the outputs for the metamodel.

The main advantage of the reverse simulation metamodeling approach is that it is less iterative than the direct simulation metamodeling approach (Nasereddin and Mollaghasemi, 1999). Once a metamodel is built, it is used for determining design parameters according to required performance measures determined by decision makers. However, in the direct simulation metamodeling approach, a simulation metamodel is built to determine the best design at each decision phase. Hence, it takes a longer time. The steps of the reverse ANNs developed are summarized in Figure 6.2.

In MCDRC-Fuzzy, system parameters, system status variables, current system performance measures, and expected achievement levels of performance measures are taken as the input of the neural network model, and the parameters of fuzzy goals are taken as the output of the neural network model. By this way, parameters of the fuzzy priority functions are updated according to the decision maker’s aspiration levels (desired performance measures) for the next production period.

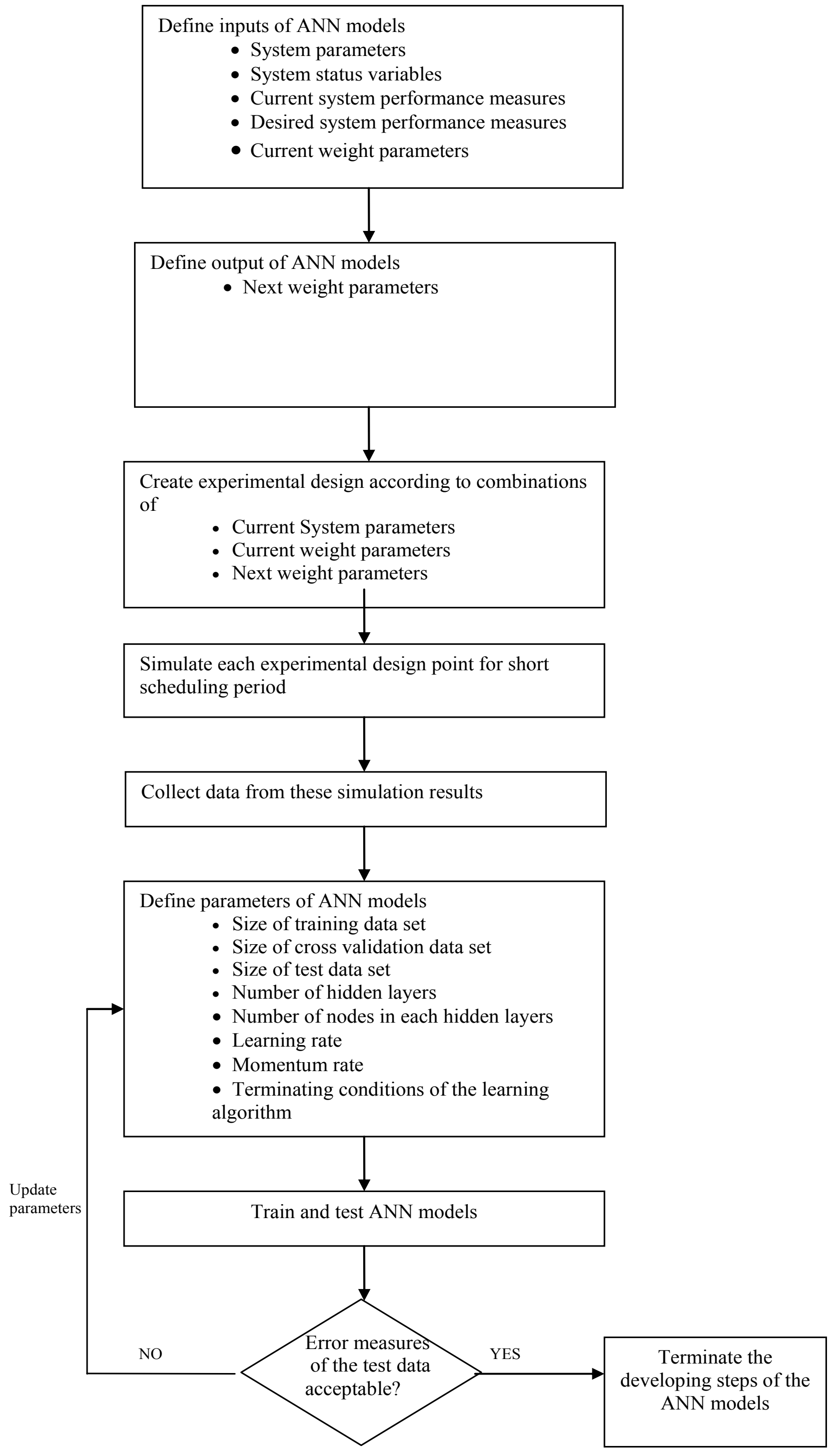

Figure 6.2 Basic steps of developing reverse ANN models

6.2.3 Fuzzy Scheduler

In a DRC manufacturing system, generally there are four decision points (DPs). The first two arise when a part arrives in the system or a machine becomes idle, as in all manufacturing environments. When a machine becomes idle and more than one part awaits in the queue, a part has to be selected to be processed next (DP1). When a part releases the machine, the part should select its next route (DP2). The third and fourth DPs are special for DRC manufacturing systems and related to decisions on the timing of worker transfers ("when" rules, DP3) and the selection of the next work center ("where" rules, DP4).

The proposed fuzzy scheduler includes two types of fuzzy based approaches. In the first approach, the fuzzy set theory is employed to model the compromises between criteria and membership functions to balance the elementary rules. In the second approach, a fuzzy inference model is developed. The first approach is used for selecting part routes (DP1), sequencing the parts for machining (DP2) and deciding which work centre a worker is to be transferred to (DP4). On the other hand, a FIS is defined to determine whether it is necessary to transfer a worker to another work center (DP3). It should be highlighted that fuzzy based scheduling approaches have not yet been proposed for DRC manufacturing systems. Furthermore, recall that the use of a fuzzy inference for "when" rules is also a novelty.

The proposed fuzzy scheduling rules for each DP are discussed in the following subsections.

6.2.3.1 Fuzzy Part Selection by Machines

As mentioned before, MCDRC-FIS and MCDRC-PRO use dispatching rules for determining the sequence of the jobs for machining and provide some simplified guidelines. In the literature, numerous dispatching rules exist, each of which operates in such a way that only one objective is satisfied. For example, many studies show that the shortest processing time (SPT) rule minimizes mean flow time (MFT), while the earliest due date (EDD) rule minimizes mean tardiness (MT).

Recall that there are five performance measures (objectives) considered in this research, namely MFT, MT, percentage of number of tardy job (%NTJ), mean queue time (MQT), and work-in-process (WIP). Since the individual rules are often dependent on the selected performance criterion, the characteristics of the shop, or the jobs themselves (Caprihan et al., 2006), the proposed methodology applies fuzzy set theory to form aggregated fuzzy dispatching rules to minimize the abovementioned performance measures. In other words, the goal is to obtain a comprise priority to satisfy all objectives at some level. In order to determine the fuzzy priorities of job *i* to be processed on machine *m*, a fuzzy dispatching strategy is developed based on four input variables: the processing time of job *i* on machine *m*, the slack time of job *i*, the waiting time of job *i* in the input buffer of machine *m*, and the remaining processing time of job *i*. Note that each of these input variables is used in defining some elementary dispatching rules. One can satisfy all objectives simultaneously at some level by aggregating them. A fuzzy membership function is then set up for each input as follows to evaluate the contribution of the attributes of each job to be processed to the compromise solution:

- For the processing time of job *i*:

$$\mu_{PT} = \begin{cases} 1 & \text{if } P_{i,m} \le P_{\min} \\ \dfrac{P_{\max} - P_{i,m}}{P_{\max} - P_{\min}} & \text{if } P_{\min} < P_{i,m} < P_{\max} \\ 0 & \text{if } P_{i,m} \ge P_{\max} \end{cases} \tag{6.1}$$

where

$P_{i,m}$ is the processing time of *i*th job on *m*th machine,

i is the job number and $i = 1, 2,..., I$

m is the machine number and $m = 1, 2,\ldots, M$

r is the route number and $r = 1, 2,\ldots, R$

P_{max} is maximum processing time,
P_{min} is minimum processing time.

- For the slack time of job *i*:

$$\mu_{SL} = \begin{cases} 1 & if\ S_i \le S_{\min} \\ \dfrac{S_{\max} - Slack_i}{S_{\max} - S_{\min}} & if\ S_{\min} < Slack_i < S_{\max} \\ 0 & if\ Slack_i \ge S_{\max} \end{cases} \tag{6.2}$$

where
$Ddate_i$ is due date of job *i*,
$Slack_i$ is $Ddate_i$ minus current time,
S_{max} is maximum slack,
S_{min} is minumum slack.

- For the waiting time of job *i*:

$$\mu_{w} = \begin{cases} 1 & if\ Wait_{i,m} \ge W_{\max} \\ \dfrac{Wait_{i,m} - W_{\min}}{W_{\max} - W_{\min}} & if\ W_{\min} < Wait_{i,m} < W_{\max} \\ 0 & if\ Wait_i \le W_{\min} \end{cases} \tag{6.3}$$

where
$Wait_{i,\,m}$ is waiting time of job *i* in input buffer of machine *m,*
W_{max} is maximum waiting time,
W_{min} is minumum waiting time.

- For the remaining processing time of job *i*:

$$\mu_{RP} = \begin{cases} 1 & \text{if } R_i \le RP_{\min} \\ \dfrac{RP_{\max} - R_i}{RP_{\max} - RP_{\min}} & \text{if } RP_{\min} < R_i < RP_{\max} \\ 0 & \text{if } R_i \ge RP_{\max} \end{cases} \tag{6.4}$$

where

R_i is remaining processing time of job i,

RP_{max} is maximum remaining time,

RP_{min} is minimum remaining time.

The fuzzy membership functions of these four inputs are illustrated in Figure 6.3.

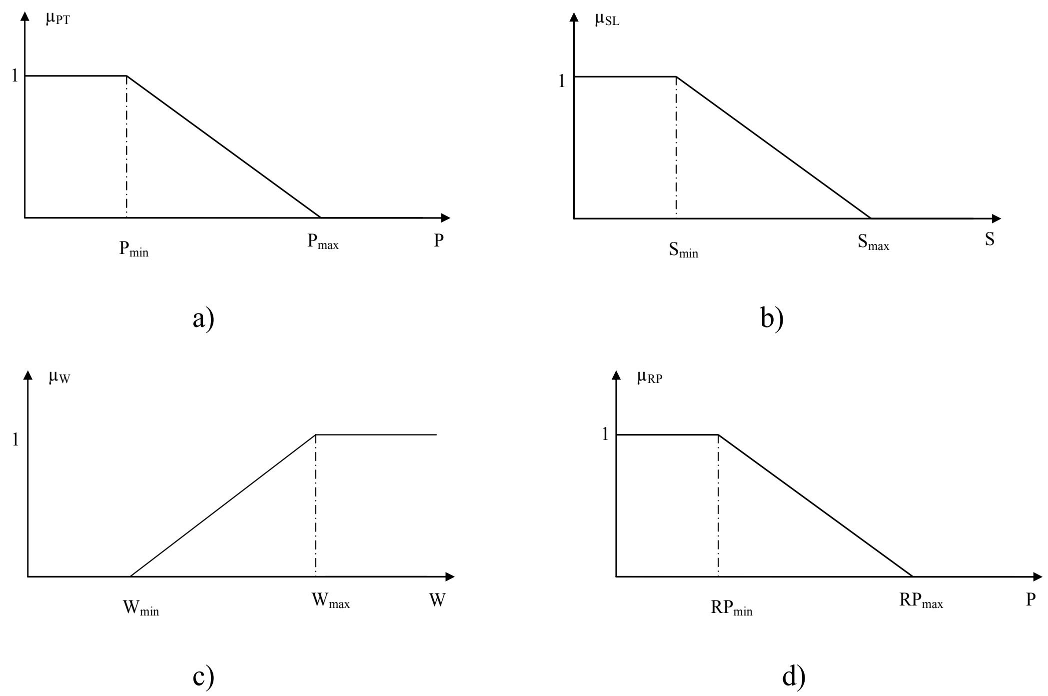

Figure 6.3 Membership functions of processing time (a), slack time (b), waiting time (c), remaining time (d)

For each part in the queue, the membership functions provide individual fuzzy priorities in terms of all the inputs. To obtain a compromise fuzzy priority, these individual priorities should be aggregated. Chan et al. (2002) proposed a weighted additive approach to find the final membership of all alternative routings. The weighted additive model selects the part with the maximum weighted sum of the achievement levels of the fuzzy goals as follows.

$$\mu_{DPR_i} = \sum_{j=1}^{k} \left(\frac{(W_j)}{\sum_{j=1}^{n} W_j} \mu_{i,j} \right) \tag{6.5}$$

where

W_j= weight of objective j; j=1,…,J;

$\mu_{i,j}$= membership of part i to goal j,

μ_{DPRi}= final priority of part i.

The part with max $\{\mu_{DPRi}\}$ is then selected.

Up to date, numerous methods have been proposed to determine the weights of the objectives such as analytic hierarchy process (AHP) (Saaty, 1980), weighted least square method (Chu, Kalaba, & Spingarn, 1979), and the entropy method (Shannon, 1948). Additionally, several fuzzy approaches have been developed to determine weights in a fuzzy environment. A detailed explanation of these approaches can be found in the work of Lai & Hwang (1994).

It is clear that the weighted additive approach is fully compensatory. In this study, besides the weighted additive approach, two other aggregation functions, which have already been used in other multi-criteria decision making problems, are also proposed to find the fuzzy priority of parts. These functions are defined as follows:

- Max-Max approach:
  The priority of part i:
  $\mu_{DPR_i} = \mu_{i,1} \cup \mu_{i,2} \cup .... \cup \mu_{i,J} = \max[\mu_{i,1}, \mu_{i,2}, ..., \mu_{i,J}]$
  The part with max $\{\mu_{DPRi}\}$ is then selected.

- “Fuzzy or” approach:
  The priority of part i:

$$\mu_{DPR_i} = \gamma \max[\mu_{i,1}, \mu_{i,2}, \dots, \mu_{i,J}] + (1-\gamma)\sum_{j=1}^{k}\left(\frac{(W_j)}{\sum_{j=1}^{n} W_j} \mu_{i,j} \right) \quad (6.6)$$

where γ is the coefficient of compensation defined within the interval [0,1]. The part with max { μ_{DPRi}} is then selected.

It can easily be seen that while weighted additive approach is fully compensatory, Max-max approach does not allow that the goals with a high degree of membership are not traded off against the goals with a low degree of membership. On the other hand, "fuzzy or" approach involves both a compensatory operator and a non-compensatory operator. It is clear that various fuzzy operators can be proposed for scheduling problems in the same manner.

Each time a sequencing of parts needs to be obtained, MCDRC-Fuzzy evaluates the aggregated fuzzy priorities for each part in the queue. Then the part with the highest priority is selected to be processed.

6.2.3.2 Fuzzy Routing Selection

In the same manner with the fuzzy part selection, MCDRC-Fuzzy performs routing selection using an aggregated fuzzy membership function. In this case, the output variable is an aspiration level of the routing decision (μ_{RSr}), which defines the priority of route *r*. Each time a part needs to be dispatched, MCDRC-Fuzzy evaluates fuzzy priorities for each potential route given the four inputs: (*i*) the number of the parts in the queue of the next machine in route *r*, (*ii*) total processing time of all parts in the queue of the next machine in route *r*, (*iii*) utilization of the next machine in route *r*, (*iv*) the total remaining time of the part in route *r*. The route with the highest fuzzy priority is then selected as the target route of the part (similar as Chan et al., 2002). In a similar fashion with the fuzzy part selection, one of the three types of aggregation functions can be used to find the final fuzzy priority.

Unlike most approaches, in which when a route is selected for a part, the route does not change during the simulation, e.g. see Chan et al., 2002, MCDRC-Fuzzy allows the route to change during the simulation according to the changes in the system state. This improves the scheduling flexibility, hence its performance.

To perform the routing selection, the membership functions of the goals should be defined as follows:

- For the number of the parts in the queue of the next machine in each alternative route:

$$\mu_{NQ_r} = \begin{cases} 1 & if\ NQ_r \leq NQ_{\min} \\ \dfrac{NQ_{\max} - NQ_r}{NQ_{\max} - NQ_{\min}} & if\ NQ_{\min} < NQ_r < NQ_{\max} \\ 0 & if\ NQ_r \geq NQ_{\max} \end{cases} \tag{6.7}$$

where

NQ_r is number of parts in the next queue in route r

NQ_{max} is maximum number of parts in queue

NQ_{min} is minimum number of parts in queue

- For the total processing time of all parts in the queue of the next machine in route r:

$$\mu_{TPT_r} = \begin{cases} 1 & if\ TPT_r \leq TPT_{\min} \\ \dfrac{TPT_{\max} - TPT_r}{TPT_{\max} - TPT_{\min}} & if\ TPT_{\min} < TPT_r < TPT_{\max} \\ 0 & if\ TPT_r \geq TPT_{\max} \end{cases} \tag{6.8}$$

where

TPT_r is total processing time of all parts (including the processing time of the job to be routed) in the queue of the next machine in route r

TPT_{max} is maximum value of total processing time

TPT_{min} is minimum value of total processing time

- For the average utilization of the next machine in each alternative route:

$$\mu_{UTI_r} = \begin{cases} 1 & \text{if } UTI_r \le UTI_{\min} \\ \dfrac{UTI_{\max} - UTI_r}{UTI_{\max} - UTI_{\min}} & \text{if } UTI_{\min} < UTI_r < UTI_{\max} \\ 0 & \text{if } UTI_r \ge UTI_{\max} \end{cases} \tag{6.9}$$

where

UTI_r is average utilization of the next machine in route r,

NQ_{max} is maximum utilization,

NQ_{min} is minimum utilization.

- For the remaining processing time of the part being processed in each alternative route:

$$\mu_{RT_r} = \begin{cases} 1 & \text{if } RT_r \le RT_{\min} \\ \dfrac{RT_{\max} - RT_r}{RT_{\max} - RT_{\min}} & \text{if } RT_{\min} < RT_r < RT_{\max} \\ 0 & \text{if } RT_r \ge RT_{\max} \end{cases} \tag{6.10}$$

where

RT_r is the remaining processing time of the part being processed in route r,

RT_{max} is maximum remaining processing time of the part,

RT_{min} is minimum remaining processing time of the part.

The aggregated membership function is then calculated by using one of the three types of aggregation functions explained in section 6.2.3.1.

6.2.3.3 Fuzzy "Where" Rule

As discussed before, the appropriate selection of worker assignment rules in addition to dispatching rules is one of the most important decisions in DRC manufacturing systems. "Where" rules are used to select the department to which the worker will be transferred. Recall that an appropriate "where" rule is selected from a list of candidate rules in MCDRC-FIS and MCDRC-PRO based on the prevailing conditions in the system. These rules are LNQ (the work center with the most jobs in queue), LWT (the work center with the job with the longest waiting time in queue), MTPT (the work center with the minimum total processing time and traveling time), EDDS (the work center with the job with the earliest due date). However, similar to job DPRs in machine-only constrained manufacturing systems, it has been indicated that the efficiency of the worker assignment rules highly depends on the performance criteria of interest and on the system state conditions. However, just as job DPRs, there is no worker assignment rule that is globally better than all the others. Therefore, the proposed fuzzy scheduler would be a good alternative to decide which machine is selected by a worker to be transferred. To the best of our knowledge, a fuzzy "where" rule is a novelty in DRC research.

Each time a worker is ready to be transferred, MCDRC-Fuzzy evaluates fuzzy priorities for each potential machine based on the four inputs: the number of the parts in the queue of machine *m*, the longest waiting time of the parts in this queue, the sum of the total processing times of the parts in this queue and the transfer time of the worker to machine *m*, and the earliest due date of the parts in this queue. The machine with the highest fuzzy priority is then selected as the next machine the worker will be transferred to. In a similar fashion with the fuzzy part selection and route selection, one of the three types of aggregation functions can be used to find the final fuzzy priority.

Membership functions of the fuzzy goals can then be defined as follows:

- For the number of the parts in the queue of machine *m*:

$$\mu_{NQ_m} = \begin{cases} 0 & if\ NQ_m \le NQ_{\min} \\ \dfrac{NQ_m - NQ_{\min}}{NQ_{\max} - NQ_{\min}} & if\ NQ_{\min} < NQ_m < NQ_{\max} \\ 1 & if\ NQ_m \ \ge NQ_{\max} \end{cases} \tag{6.11}$$

where
NQ_m is number of parts in the queue of *m*th machine
NQ_{max} is maximum number of part in queue
NQ_{min} is minimum number of part in queue

- For the longest waiting time of the parts in the queue of machine *m*:

$$\mu_{wt_m} = \begin{cases} 1 & if\ Wait_m \ge W_{\max} \\ \dfrac{Wait_m - W_{\min}}{W_{\max} - W_{\min}} & if\ W_{\min} < Wait_m < W_{\max} \\ 0 & if\ Wait_m \ \le W_{\min} \end{cases} \tag{6.12}$$

where
$Wait_M$ is longest waiting time of jobs in the input buffer of machine *m*
W_{max} is maximum waiting time
W_{min} is minumum waiting time

- For the sum of the total processing time of the part waiting in the queue of machine *m* and transfer time of the worker to machine *m*

$$\mu_{TPTm} = \begin{cases} 1 & if\ TPT2_m \le TPT2_{\min} \\ \dfrac{TPT2_{\max} - TPT2_m}{TPT2_{\max} - TPT2_{\min}} & if\ TPT2_{\min} < TPT2_m < TPT2_{\max} \\ 0 & if\ TPT2_m \ \ge TPT2_{\max} \end{cases} \tag{6.13}$$

where

$TPT2_m$ is the sum of the total processing time of the part waiting in the queue of machine *m* and traveling time of the worker to machine *m*,

$TPT2_{max}$ is maximum value of the sum of the of total processing time of the part waiting in the queue of machine *m* and traveling time of worker to machine *m*

$TPT2_{min}$ is minimum value of the sum of total processing time of the part waiting in the queue of machine *m* and traveling time of worker to machine *m*.

- For the earliest due date of the parts in the queue of machine *m*:

$$\mu_{wt_m} = \begin{cases} 1 & if\ SL_{i,m} \leq SL_{\min} \\ \dfrac{SL_{\max} - SL_{i,m}}{SL_{\max} - SL_{\min}} & if\ SL_{\min} < SL_{i,m} < SL_{\max} \\ 0 & if\ SL_{i,m} \geq SL_{\max} \end{cases} \tag{6.14}$$

where

$SL_{i,m}$ is slack time of the job *i* with earliest due date in the input buffer of machine *m*,

SL_{max} is maximum slack time,

SL_{min} is minimum slack time.

The aggregated membership function is then defined through one of the three types of aggregation functions explained in previous sections. In this methodology, each aggregated priority membership function is calculated at each decision point to schedule the jobs and operators dynamically.

6.2.3.4 Fuzzy "When" Rule

As mentioned before, "when" rules are used to dictate the frequency of worker transfers (Kher, 2000). The most commonly used "when" rules are the centralized and decentralized rules. The decentralized "when" rule may be less flexible compared to the centralized rule (Kher and Fry, 2001) because it considers worker transfers only when the work centre becomes idle. In this research, a novel fuzzy "when" rule is also proposed which lies in between the decentralized and centralized rule.

The proposed fuzzy "when" rule is based on Sugeno type FIS and aims to answer the question of when it is necessary to transfer a worker to another work center. The use of a fuzzy inference in determining when to transfer a worker is also a novelty.

The Sugeno type FIS considers two linguistic variables: the number of the jobs in queue (NQ) and the urgency of the jobs in queue (UQ). These variables take three imprecise values: low, medium and high. Their membership functions are given in Figure 6.4.

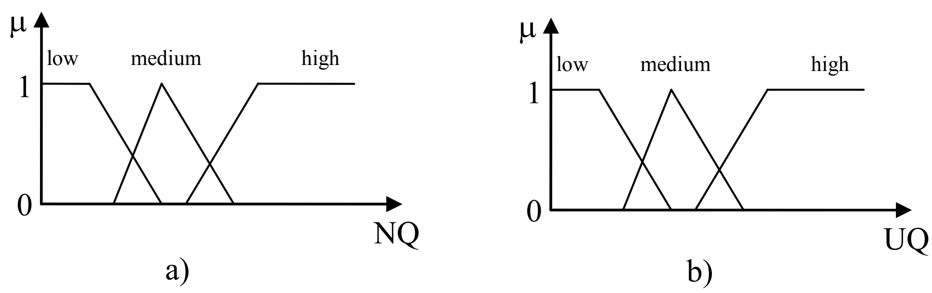

Figure 6.4 Fuzzy membership functions to represent the number of jobs in queue (a) and the urgency of jobs in queue (b).

Recall from chapter 3 that the antecedent of Sugeno type FIS involves some linguistic variables and the consequent is a crisp action with associated weights. Therefore, there are two crisp consequences: transfer (T) or do not transfer (DNT). Since each of NQ and UQ has three states, the number of the total rules is nine. Table 6.1 gives these rules.

Table 6.1 Fuzzy rules

		Fuzzy Rules								
		k								
		1	2	3	4	5	6	7	8	9
IF	NQ	Low	Low	Low	Medium	Medium	Medium	High	High	High
AND	UQ	Low	Medium	High	Low	Medium	High	Low	Medium	High
THEN		T	DNT	DNT	DNT	DNT	DNT	T	T	DNT

Since MCDRC-Fuzzy uses a zero order Sugeno model, the constant output value (z_k) of making "transfer (T)" decision is set to one while the constant value (z_k) of making "do not transfer (DNT)" decision is set to zero (see figure 6.5). The output level of each rule is weighted by the firing strength w_k of the rule (Matlab toolbox, 2007). The firing strength of each rule can be calculated using "and operator" as follows:

$w_k = \min\{\mu_{NQ}(nq), \mu_{UQ}(uq)\}$, where μ_{NQ} and μ_{UQ} are the membership functions for inputs NQ and UQ, respectively. The final output (FO) is the weighted average of all the outputs of the rules, defined as

$$FO = \frac{\sum_{k=1}^{K} w_k z_k}{\sum_{k=1}^{K} w_k} \tag{6.15}$$

Decision D is then defined as follows:

$$D = \begin{cases} DNT & if \quad FO \le 0.5 \\ T & otherwise \end{cases} \tag{6.16}$$

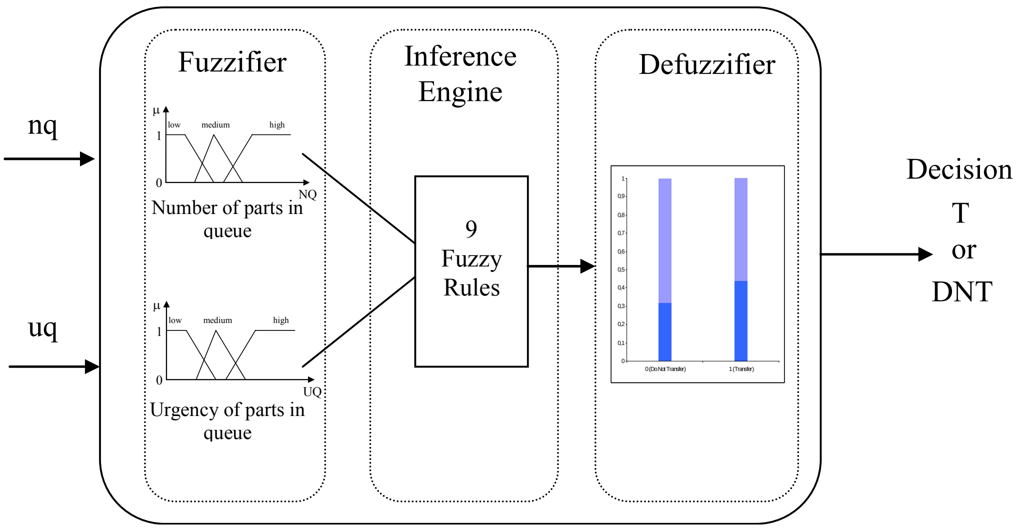

Figure 6.5 The proposed fuzzy model framework for fuzzy "when" rule

An illustrative case study is given in the next section to demonstrate the methodology and to address some issues.

6.3 Experimental Studies

The issues addressed in the experiments are:

a) Does each of fuzzy part selection, fuzzy routing selection, fuzzy “where” and fuzzy “when” rules have an impact on the performance measures?

b) Does MCDRC-Fuzzy outperform MCDRC-FIS and MCDRC-PRO?

c) Does the proposed “max-max” and “fuzzy or” aggregation functions outperform the weighted additive approach?

d) Does MCDRC-Fuzzy also perform well under different situations such as multi level flexible and heterogeneous workers?

e) Can the performance of MCDRC-Fuzzy be improved by the help of ANNs by updating the parameters of fuzzy functions?

6.3.1 Experiment 1 – the performances of fuzzy rules versus elementary rules

Hypothesis 1: Since the proposed fuzzy scheduler assigns priorities to parts, routes and machines based on the conditions prevailing in the system, its performance cannot be inferior to other dispatching rules, route selection rules or worker assignment rules.

To verify hypothesis 1, the individual performances of fuzzy rules are compared with those of the elementary rules. First of all, the performance of the fuzzy part dispatching rule (FDPR) is compared with those of the traditional dispatching rules in terms of the five performance measures. In order to find the final fuzzy priorities of the parts, the weighted additive approach is used with a weight structure of (0.30, 0.30,0.20, 0.20) for processing time, slack time, waiting time and remaining processing time objectives, respectively. In this comparison, a rule combination of 233 (v1=2 (decentralized), v2=3 (MSPT), v4=3 (LAUF)) is selected for other decision points respectively; i.e. the “when” rule, the “where” rule and route selection rule. These rules are fixed in the first experiment.

Eight simulation runs, seven for the traditional dispatching rules and one for the fuzzy rule, are conducted over a period of 50,000 hours under the medium variation level. The results are illustrated in Figure 6.6. Duncan’s multiple range test and Fisher least significant difference (LSD) test were used to compare traditional dispatching rules and fuzzy dispatching rule. The mean differences were separated with Duncan’s test at 0.1% level of significance for each performance measures, as can be seen in Table 6.2 - 6.6. In the tables, different groups show that there are significant differences between pairs of the mean of DPRs. In addition to the multiple range test, the results of Fisher’s LSD test are given in Appendix B.

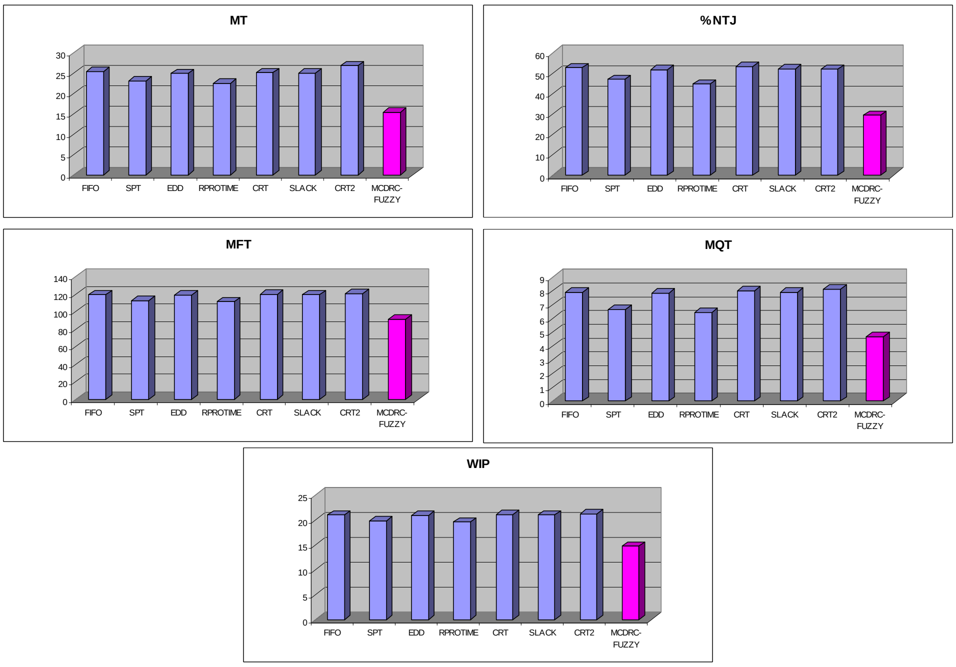

Figure 6.6 Comparison of different part dispatching rules

Table 6.2 Duncan's Multiple Range Test for MT (Subset for alpha = .01)

V3	N	Duncan Group	
		1	2
Fuzzy-DPR	20	15.44	
RPROTIME	20		22.45
SPT	20		23.03
EDD	20		24.89
MST	20		25.05
CRT	20		25.09
FIFO	20		25.44
CRT'	20		26.84
Sig.		1.000	.162

Table 6.3 Duncan's Multiple Range Test for %NTJ

V3	N	Subset for alpha = .01		
		1	2	3
Fuzzy-DPR	20	29.3862		
RPROTIME	20		44.71	
SPT	20		46.96	46.96
EDD	20		51.69	51.69
CRT2	20		51.92	51.92
MST	20		52.22	52.22
FIFO	20		52.81	52.81
CRT	20			53.40
Sig.		1.000	.015	.057

Table 6.4 Duncan's Multiple Range Test for MFT

V3	N	Subset for alpha = .01		
		1	2	3
Fuzzy-DPR	20	91.54		
RPROTIME	20		111.32	
SPT	20		112.56	112.56
EDD	20		118.96	118.96
FIFO	20		119.29	119.29
MST	20		119.29	119.29
CRT	20			119.92
CRT2	20			120.41
Sig.		1.000	.010	.013

Table 6.5 Duncan's Multiple Range Test for MQT

V3	N	Subset for alpha = .01		
		1	2	3
Fuzzy-DPR	20	4.67		
RPROTIME	20		6.43	
SPT	20		6.65	6.65
EDD	20		7.85	7.85
MST	20		7.91	7.91
FIFO	20		7.91	7.91
CRT	20			8.03
CRT2	20			8.12
Sig.		1.000	.015	.018

Table 6.6 Duncan's Multiple Range Test for WIP

V3	N	Subset for alpha = .01	
		1	2
Fuzzy-DPR	20	14.79	
RPROTIME	20		19.61
SPT	20		19.84
EDD	20		20.96
FIFO	20		21.02
MST	20		21.02
CRT	20		21.14
CRT2	20		21.22
Sig.		1.000	.018

The Duncan's test and LSD test show that there are significant differences between traditional dispatching rules and the fuzzy DPR. The results can also be seen in Figure 6.6. All the results demonstrated that the fuzzy scheduler outperforms the other dispatching rules with respect to all criteria. Note that each of the traditional dispatching rules considers only one criterion, while the fuzzy scheduler considers all the criteria. For example, the SPT rule considers only the part with the shortest processing time, and EDD the part with earliest due date. The mean tardiness and mean flow time benefited the most from the fuzzy approach.

In order to investigate the performance of the fuzzy routing selection, each combination of the route selection rules is simulated using each of these rules in turn. During these experiments, the other decision variables are set to the rule combination of 234 (v1=2 (decentralized), v2=3 (MSPT), v3=4 (RPT)) for the “when” rule, “where” rule and part dispatching rule, respectively. To find the final fuzzy priorities of the alternative routes, the weighted additive approach is used with a weight structure of (0.30, 0.30, 0.20, 0.20) for the number of parts in queue, sum of the total processing time and transfer time, utilization, and remaining processing time objectives, respectively.

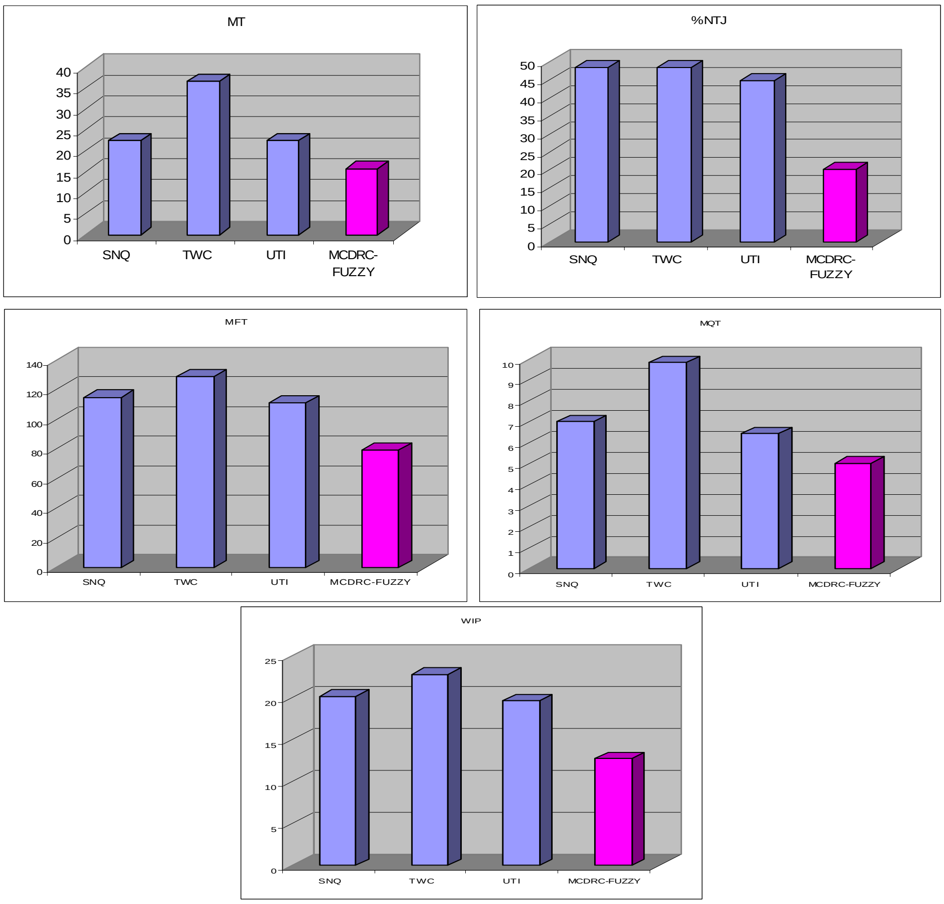

Figure 6.7 Comparison of different route selection rules

The results in Figure 6.7 highlight the superiority exhibited by the fuzzy route selection over other traditional rules. The results of Duncan’s and Fisher’s LSD tests given in Appendix B also confirm these results. These results are in harmony with the findings in the related literature. Some researchers also indicate that fuzzy based part dispatching rules (e.g. see Tedford and Lowe, 1999; Chan et al., 2002; Canpolat and Gundogar, 2004; Chan et al., 2003) and fuzzy route selection rules (e.g. see Chan et al., 2002; Chan et al., 2003; Sirino et al., 2006) outperform the traditional rules. However, recall that fuzzy worker assignment rules have not yet been developed for DRC systems. Therefore, the analysis of the fuzzy worker assignment rules is the major concern in this section.

Recall that this chapter proposes a novel fuzzy “where” rule for DRC systems through the combination of the four important criteria considered by the traditional “where” rules separately. These are the number of parts in the queue of machine *m*, the longest waiting time of the parts in this queue, the sum of the total of the processing times of the parts in this queue and transfer time of the worker to machine *m* from this machine, and the earliest due date of the parts in this queue. It is clear that to apply a balance between the elementary rules, these criteria should be aggregated through a function. Similar to the part and route selection, the weighted additive approach is used for the aggregation with a weight structure of (0.30, 0.20, 0.30, 0.20).

Figure 6.8 shows a comparison of the multi-criteria performance measures of the traditional “where” rules with the results of MCDRC-Fuzzy. The proposed fuzzy “where” rule outperforms other conventional “where” rules in terms of all criteria. An important advantage of the proposed fuzzy “where” rule is that it adapts to changes in the system.

While the conventional “where” rules perform relatively well in some criteria, they yield poor performance on the other criteria. For example, the longest waiting time (LW) rule provides good results on MQT and %NTJ while it is the worst performer on the other criteria. On the other hand, the proposed fuzzy “where” rule improves the performance of the DRC system in terms of all criteria.

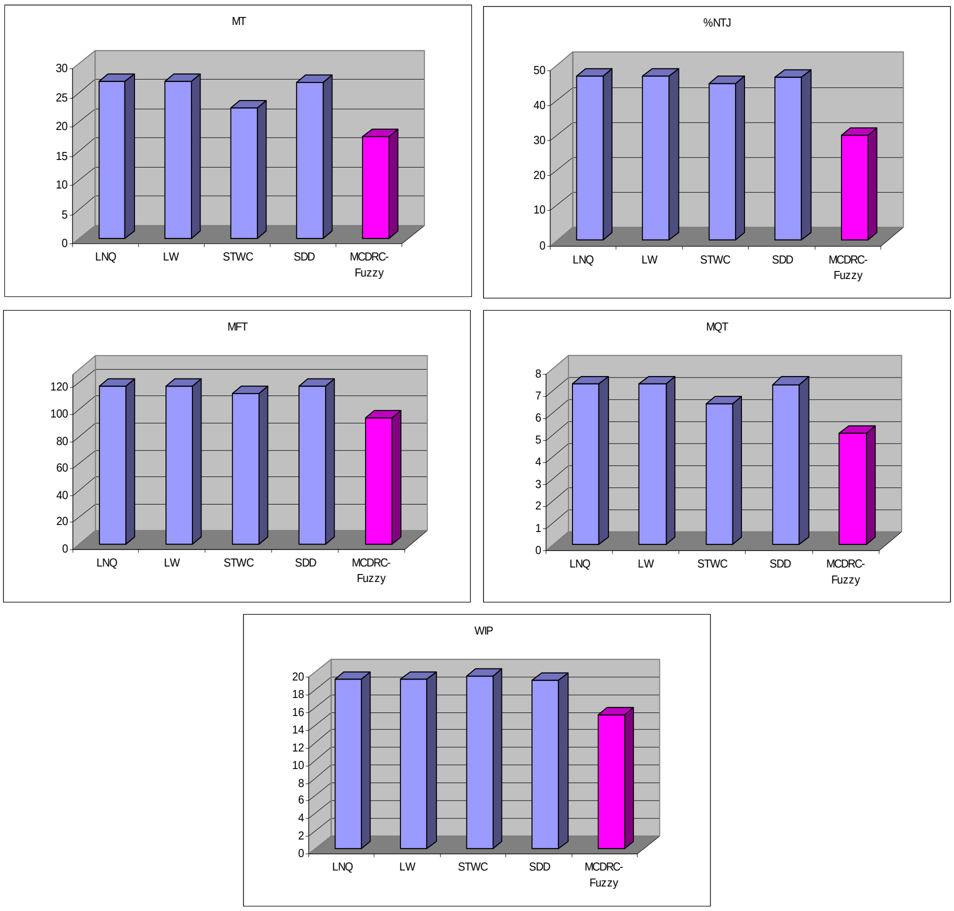

Figure 6.8 Comparison of different "where" rules

Finally, to show the effectiveness of the proposed fuzzy "when" rule, it is compared with two traditional "when" rules, centralized and decentralized. The results are in Figure 6.9. As mentioned before, the proposed fuzzy "when" rule is based on Sugeno-type FIS model and operates using pre-defined fuzzy rules. These rules involve two linguistic variables: number of parts in queue and urgency of jobs in queue. Therefore, the proposed fuzzy "when" rule incorporates information about both urgency of parts and the number of parts while the traditional rules consider only certain conditions.

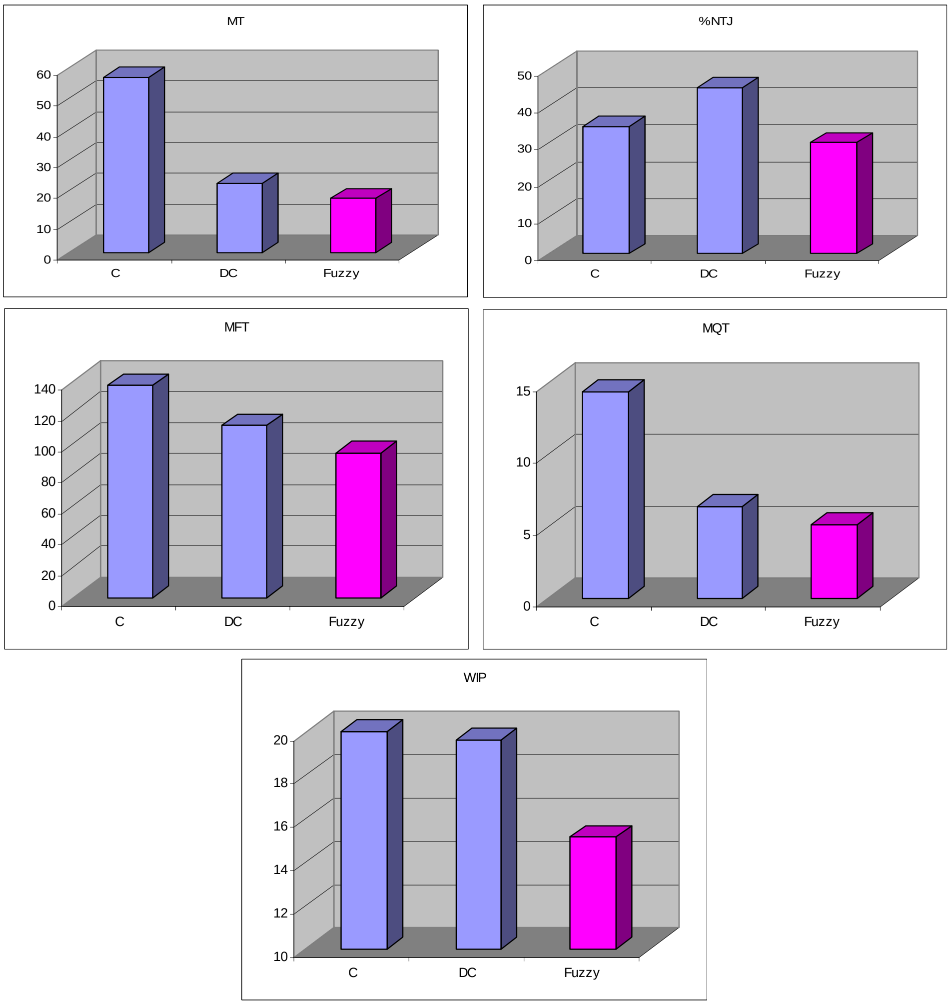

Figure 6.9 Comparison of different “when” rules

The results in Figure 6.9 highlight that the proposed fuzzy “when” rule works superior to both centralized and decentralized rules in all the performance measures. The major advantage of the fuzzy “when” rule is that it can operate as both centralized and decentralized rules according to prevailing shop conditions. If the number of parts in the queue is high and some of them are urgent, then the fuzzy “when” rule operates in a similar fashion with the decentralized rule and do not allow the worker transfer. On the other hand, if the number of parts in the queue is low and their average urgencies are also quite low, then the fuzzy “when” rule operates as the centralized rule and allows the worker to be transferred before the input buffer of the machine becomes empty. It should be pointed out that the decentralized rule works better than the centralized rule in terms of MT, MFT, MQT and WIP objectives. The centralized rule only outperforms the decentralized rule in %NTJ. It is frequently reported in the literature that, in a DRC environment with transfer delays, the decentralized “when” rule is recommended instead of the centralized rule. The results of Duncan’s and Fisher’s LSD tests given in Appendix B also confirm these results. Yet this study shows that the proposed fuzzy rule outperforms both rules.

6.3.2 Experiment 2 – Comparison of MCDRC-Fuzzy with MCDRC-FIS and MCDRC-PRO approaches

Since the previous experiments show that MCDRC-PRO and MCDRC-FIS outperform Multi-FIS and all static scheduling approaches, these approaches are not considered in this comparison.

Recall from Chapter 4 that three variation levels were considered in the experiments. In this experiment, low, medium and high variation levels are also considered in comparing the proposed approaches. Furthermore, during the experiments, the scheduling rule combinations obtained by MCDRC-FIS and MCDRC-PRO are updated at every 5000 minutes. Although MCDRC-Fuzzy also has the capability of updating the parameters through the reverse ANN module according to changes in the system, it is assumed that the parameters have been set up in the beginning and fixed until the next scheduling point. Note that, in this experiment, MCDRC-Fuzzy utilizes the fuzzy scheduler for all decision points simultaneously.

The summary results of the scheduling methods under low, medium and high variation levels are in Table 6.7, 6.8 and 6.9, respectively, and in Figure 6.10, 6.11 and 6.12, respectively. While the figures show the results of each approach at each rescheduling point, the tables demonstrate the percentage improvements achieved by MCDRC-Fuzzy relative to MCDRC-FIS and MCDRC-PRO at the end of each rescheduling period.

Table 6.7 % improvement achieved by MCDRC-Fuzzy relative to MCDRC-FIS and MCDRC-PRO for VR=L

	Rescheduling Points	Performance Measures				
		MT	%NTJ	MFT	MQT	WIP
MCDRC-FUZZY vs MCDRC-FIS	1	39.53	20.93	23.77	33.52	29.79
	2	43.19	19.38	26.71	35.95	21.88
	3	29.71	18.48	19.16	24.13	17.17
	4	24.83	16.67	16.25	19.18	14.85
	5	14.46	14.80	11.79	10.32	9.64
	6	9.15	14.57	9.50	5.51	8.96
	7	11.96	15.55	10.68	7.79	9.83
	8	28.61	21.88	18.53	24.81	18.70
	9	31.99	22.47	20.23	27.26	19.48
MCDRC-FUZZY vs MCDRC-PRO	1	39.53	20.93	23.77	33.52	29.79
	2	37.96	17.70	23.45	32.62	20.88
	3	29.95	16.76	18.93	23.43	18.90
	4	33.77	16.39	20.52	26.34	19.99
	5	25.93	14.55	16.74	19.45	15.19
	6	21.68	14.56	14.68	15.72	14.17
	7	21.89	15.14	14.75	15.75	14.08
	8	23.29	15.36	15.18	16.48	14.82
	9	25.58	15.74	16.18	18.87	17.04

These results are in agreement with the results obtained in the previous section where it was noted that individual fuzzy rules outperform each traditional rule in terms of all criteria. Since the performances of MCDRC-FIS and MCDRC-PRO are subject to those of the traditional rules, MCDRC-Fuzzy outperforms these approaches for each variation level in terms of all criteria. Results of Duncan's multiple range tests and the LSD test are also given in Appendix B. Test results show MCDRC-Fuzzy outperforms these approaches for each variation level in terms of all criteria except for MT and MQT for low variation level and MQT for high variation level. In the low variation level, the MT and MQT performance in MCDRC-PRO and MCDRC-Fuzzy are not statistically distinguishable. Additionally, differences between performance of MQT for MCDRC-FIS and MCDRC-Fuzzy are not statistically significant for the high variation level. However, note that the variation level of the system parameters could affect the system performance. MCDRC-FIS and MCDRC-PRO show similar performance for all performance measures in all variation levels.

Table 6.8 % improvement achieved by MCDRC-Fuzzy relative to MCDRC-FIS and MCDRC-PRO for VR=M

	Rescheduling Points	Performance Measures				
		MT	%NTJ	MFT	MQT	WIP
MCDRC-FUZZY vs MCDRC-FIS	1	51.98	21.55	19.35	30.14	18.84
	2	36.69	22.34	17.36	24.92	16.59
	3	36.69	23.97	17.49	24.36	17.04
	4	30.52	23.44	16.51	21.82	16.44
	5	34.96	23.74	17.84	25.03	17.73
	6	35.45	22.43	17.94	26.45	17.77
	7	36.26	21.78	18.07	27.05	18.12
	8	35.59	22.04	18.04	27.28	17.88
	9	36.27	22.15	18.23	27.73	18.08
MCDRC-FUZZY vs MCDRC-PRO	1	51.98	21.55	19.35	30.14	18.84
	2	39.12	20.60	17.53	25.37	16.86
	3	35.88	21.35	17.26	25.17	16.76
	4	32.87	21.60	16.81	22.83	16.77
	5	33.02	21.70	17.19	24.18	17.46
	6	34.75	21.15	17.66	25.43	17.46
	7	37.51	20.87	18.22	26.95	18.41
	8	38.96	20.67	18.56	27.86	18.45
	9	39.68	20.65	18.76	28.67	18.77

Table 6.9 % improvement achieved by MCDRC-Fuzzy relative to MCDRC-FIS and MCDRC-PRO for VR=H

	Rescheduling Points	Performance Measures				
		MT	%NTJ	MFT	MQT	WIP
MCDRC-FUZZY vs MCDRC-FIS	1	33.87	9.13	22.27	36.07	23.89
	2	34.72	9.52	22.84	38.33	20.05
	3	24.03	10.08	17.95	23.79	16.71
	4	21.83	9.69	16.62	19.76	16.51
	5	20.44	9.01	16.00	18.13	14.59
	6	19.79	9.12	15.42	17.51	12.77
	7	20.98	10.37	16.04	17.64	12.09
	8	15.67	10.94	13.37	11.73	13.23
	9	19.19	11.16	15.33	16.07	15.10
MCDRC-FUZZY vs MCDRC-PRO	1	33.87	9.13	22.27	36.07	23.89
	2	34.72	9.52	22.84	38.33	20.05
	3	25.13	9.66	18.46	24.27	18.06
	4	22.28	9.38	16.79	20.67	16.41
	5	20.30	8.60	15.76	17.14	14.84
	6	22.26	8.55	16.69	19.78	15.59
	7	24.04	9.55	17.60	21.65	16.08
	8	22.21	10.40	16.88	20.09	16.66
	9	22.65	10.67	17.22	20.29	16.43

Figure 6.10 Simulation results for VR=L

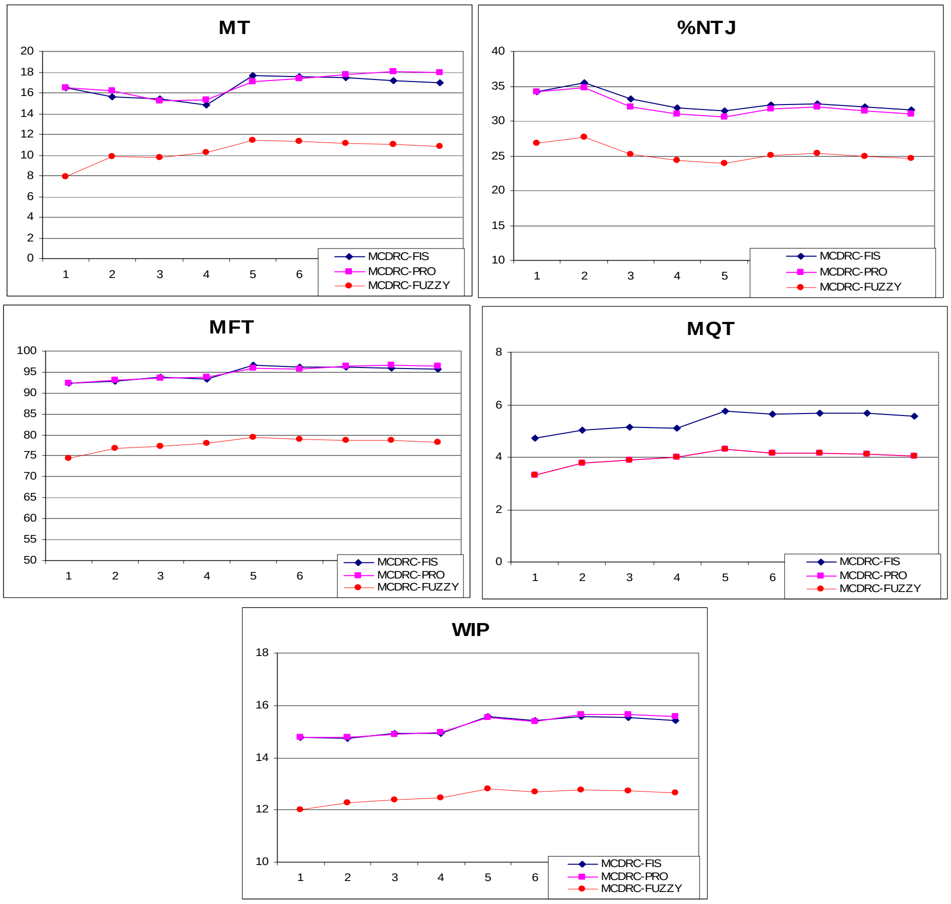

Figure 6.11 Simulation results for VR=M

Although MCDRC-Fuzzy provides better results in all cases, the difference between the performance measures is more significant in the medium variation level. This is probably because it is relatively easy to achieve a good performance for all the proposed approaches in the low variation. Additionally, the high variation in the system parameters may result in a progressively increasing deterioration in the system performance under all scheduling approaches. However, the results obtained in previous chapters and this chapter show that the proposed approaches provide robust performances in all variation levels.

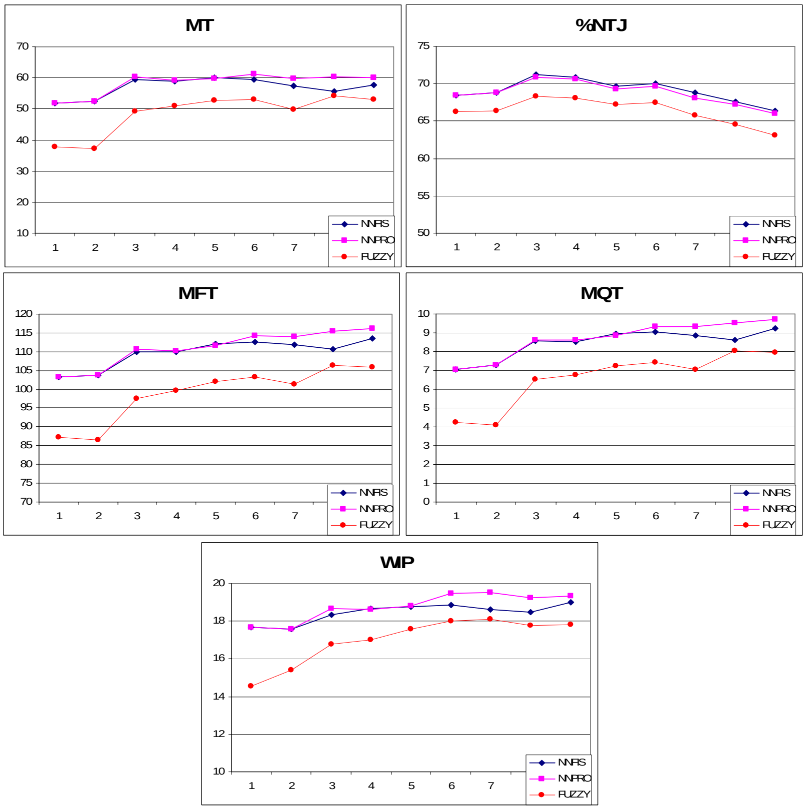

Figure 6.12 Simulation results for VR=H

It should also be indicated that the performance of MCDRC-Fuzzy can be improved in real-time by updating its parameters according to the changes in the system state. This issue will be discussed in detail in further sections.

Although the fuzzy approach outperforms MCDRC-FIS and MCDRC-PRO, one cannot easily conclude that it should be selected as the scheduling strategy for DRC systems. The proposed approaches should also be compared considering the applicability criteria. MCDRC-FIS and MCDRC-PRO require the extensive information about the system status only at each rescheduling point. On the other hand, in MCDRC-Fuzzy, after each operation, an on-line control decision is required to select a part to be processed, to determine its route, to determine when a worker should be transferred to another work center, or to determine which work center needs a worker. All of these decisions require a detailed monitoring and control of the shop floor. In such environments, any information delay deteriorates the system performance. Building such a highly automated information system may be very expensive. This is the major drawback of MCDRC-Fuzzy like other real-time scheduling approaches.

6.3.3 Experiment 3 – Comparison of Different Aggregation Functions

As mentioned before, MCDRC-Fuzzy needs an aggregation function to obtain final priorities for part selection, route selection and "where" rule decisions. In this study, besides the weighted additive approach, "max-max" and "fuzzy-or" approaches are proposed as the alternative aggregation functions for the evaluation of alternative scheduling decisions. During this experiment, the efficiencies of the aggregation functions are investigated in the medium variation level.

Recall that the weighted additive and max-max aggregation functions are special cases of the "*fuzzy or*" function. In the "*fuzzy or*" function, if one sets the coefficient of compensation γ to zero, the function becomes the weighted additive one. Contrarily, the "*fuzzy or*" function can be used as the max-max function by setting the value of γ to one. Figure 6.13 shows the relative performance of the fuzzy approach for different values of γ.

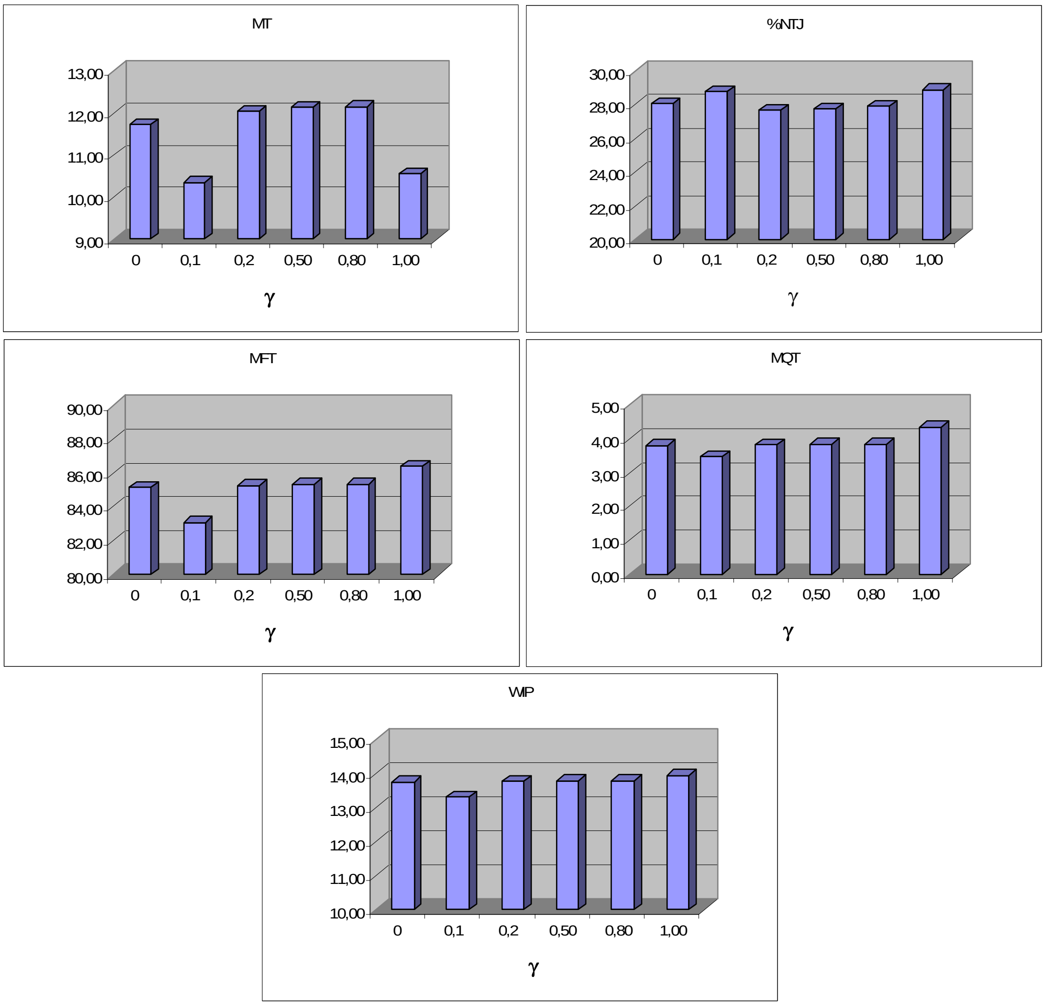

Figure 6.13 The results of MCDRC-Fuzzy for different values of γ .

In the light of the results in Figure 6.13, it can be pointed out that MCDRC-Fuzzy provides different solutions for different values of γ . However, it should be indicated that MCDRC-Fuzzy with γ=0.1 gives better results in almost all objectives, except for %NTJ, than the weighted additive approach (γ=0). This shows that the use of "*fuzzy or*" function provides a promising alternative framework in solving scheduling problems of DRC systems.

6.3.4 Experiment 4 – Testing the performance of MCDRC-Fuzzy in the case of varying worker efficiency

As mentioned before, in a DRC system, the number of workers is typically less than the number of available machines, and workers are cross trained so that they can process jobs in different departments (Kher, 2000). In this study, so far, it is assumed that each worker has the ability to work at each work center, and workers have homogenous efficiencies. However, in most real-life DRC cases, workers can process jobs with varying efficiency levels, and some workers are unable to work at some work centers. The objective of this comparison is to examine the claim that MCDRC-Fuzzy, which uses fuzzy rules in the scheduling of DRC systems, achieves better results even in the case of varying worker efficiency than the traditional "when" and "where" rules.

In order to perform this experiment, small changes have been made in the simulation model of the manufacturing system. Varying efficiency levels are defined for each worker and the processing times of the parts are updated according to a new worker efficiency structure (see Appendix A). Furthermore, an additional "where" rule, which is the most frequently used method in such cases, is incorporated into the model. This rule, called "Most efficient (ME)", assigns the workers to those work centers where they are most efficient (Treleven, 1989). The fuzzy membership function is also defined for this rule and embedded into the fuzzy scheduler module.

In DRC research with transfer delays, the decentralized "when" rule is recommended (Kher, 2000; Malhotra and Kher, 1994), while the centralized rule is recommended if workers process parts with varying efficiency levels (Kher, 2000; Malhotra and Kher, 1994). Some prior studies have also recommended the "most efficient where" rule in the case of both transfer delay and varying worker efficiency levels (Malhotra and Kher, 1994). Recall that the case problem considered in this section models both transfer delays and varying worker efficiency levels. Therefore, in order to show the efficiency of MCDRC-Fuzzy in such cases, it is compared with two alternatives that combine recommended traditional rules. The first rule combination (DC) includes decentralized “when” rule, ME “where” rule, RPT part dispatching rule and LAUF route selection rule. In the second alternative (C), the centralized control is the “when” rule. The comparison is performed for the medium variation level. The results are in Figure 6.14.

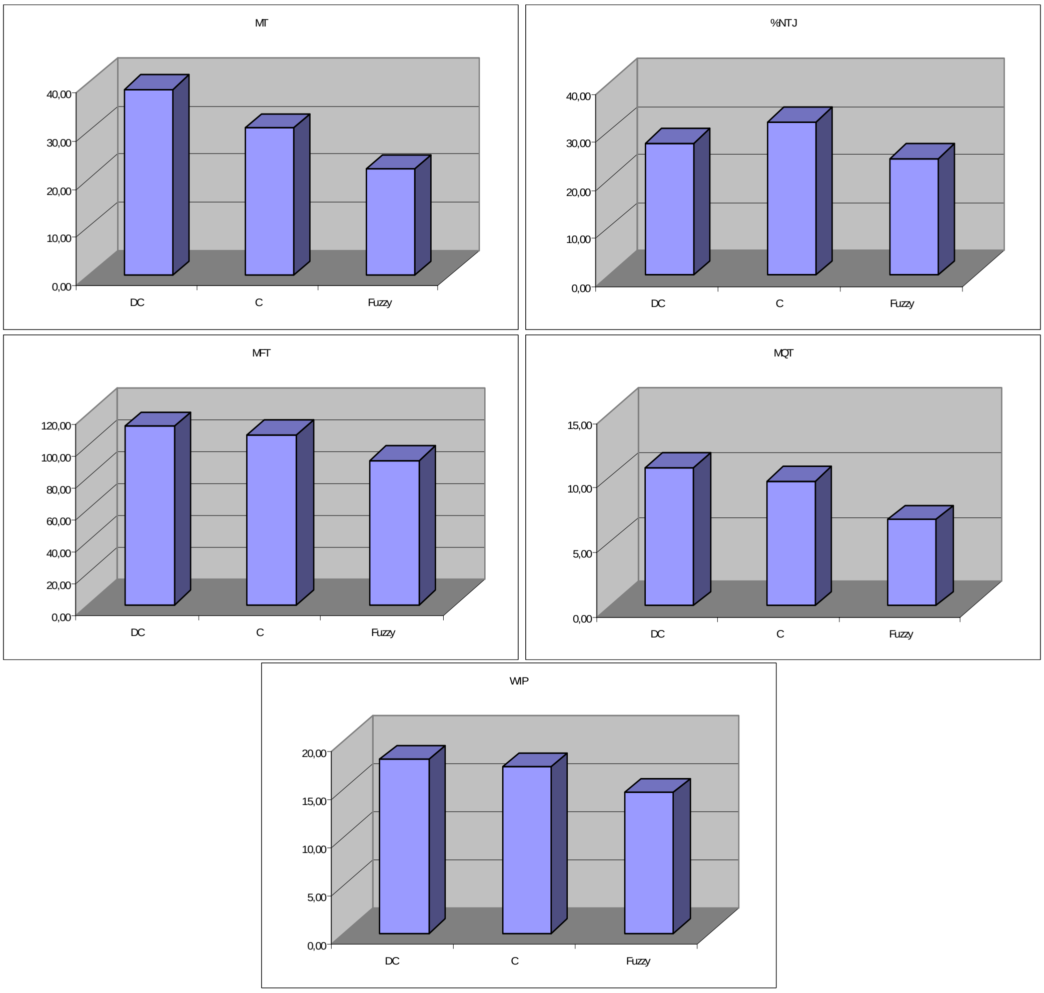

Figure 6.14 Comparison of MCDRC-Fuzzy with the traditional rule pairs

As can be remembered, in the base case of this dissertation that models only transfer delays, the decentralized “when” rule provided a better performance than the centralized rule in terms of all criteria. However, when both transfer delays and worker efficiencies are considered, the traditional rule pair that includes the centralized rule outperforms those including the decentralized rule in the four criteria. On the other hand, MCDRC-Fuzzy, which includes fuzzy “when” and “where” rules, significantly improves the DRC system performance.

6.3.5 Experiment 5 – Improving the performance of MCDRC-Fuzzy through ANNs

The results of the experiments discussed above reveals that the performance of MCDRC-Fuzzy can be improved by changing its parameters. Changing the weights of fuzzy goals is a possible way. However, some issues then arise related to adjusting the weights. At this point, this research proposes the use of reverse ANNs to determine the weights of fuzzy goals considering the changes in the system states and the decision makers' aspiration levels.

In order to build the ANN model, DRC manufacturing systems is simulated for a lengthy period, which consists of a sequence of short production intervals, i.e. 5000 minutes. Data collection is performed in two steps. In the first step, the simulation run is executed for a number of scheduling periods using a random sequence of the weights of fuzzy goals. The number of scheduling periods and the weights of fuzzy goals for each period are determined arbitrarily. This step is executed to reach a random point in DRC manufacturing system state space (e.g. Arzi and Iaroslavitz, 1999). In the second step, the values of the current system status, the performance measures and the current weights of the fuzzy goals are observed at the end of the previous production interval, i.e. period t-1. A new set of weights of fuzzy goals for the next production interval, i.e. period t, is then randomly selected. At the end of the current production interval, the system status at the end of the previous production interval, i.e. period t-1, the performance measures at the end of period t and the weights of the fuzzy goals used in the period t are collected. In the same manner, 2200 data sets, which consist of the combination of the weights of fuzzy goals, are randomly generated. During the production intervals, the current and next combination of weights are also randomly selected.

1760 and 220 of these 2200 data set are used to train and cross validation of the ANN models, respectively. NeuroSolutions 4.0 software is used to develop the ANN models. The backpropagation learning algorithm is applied to train the ANN models. When the number of learning epochs is greater than 20,000 or the mean square error is less than 0.0001, the learning process stops. The remaining 220 combinations are used for the testing.

As discussed before, the performance of neural networks depends on several design parameters, e.g. the number of hidden layers, the number of nodes in each hidden layer, the transfer function type, the learning rate, and momentum rate. Some error measures, e.g. mean error (ME), mean absolute error (MAE), mean squared error (MSE), root MSE (RMSE), percentage error (%error), are calculated for the validity of the neural network. The test and design parameters of the trained ANN models are given in Table 6.10.

Table 6.10 Design parameter and test result for the ANN model

# of Hidden Layer	# of neuron in Hidden Layer	ME	MAE	MSE	RMSE	% Error
1	60	-0.02	0.01	0.00	0.03	3.28

To update the parameters at each state, the reverse ANN model, which has already been trained and tested, is run with the inputs of the system parameters, system status variables, current system performance measures and new aspiration levels of each performance measure. The outputs are the new value of weights of the fuzzy goals. It is assumed that the decision maker updates the parameters at the beginning of each production interval, i.e. at each 5000 minutes.

In order to demonstrate how the performance of MCDRC-Fuzzy can be improved through reverse ANNs, a hypothetic case problem with fixed system parameters is considered. Different from the case problems considered in the previous sections, the system parameters, i.e. *K*, *A* and *N*, is fixed to 2, 4.5 and 10, respectively, in order to be able to show the effects of the weights of fuzzy goals on the system performances more clearly. Furthermore, since the primary interest is the effect of the current weights of fuzzy goals on the system performance during the current production interval, the performance measures observed only in the current interval are considered instead of the cumulative ones. The results of the proposed approach, called FuzzyD-NN, are compared with those of two different methods.

In the first method, it is assumed that once the parameters of MCDRC-Fuzzy are determined, it is not allowed to change these parameters during the whole scheduling horizon (FuzzyS). The same set of parameters with those used in previous experiments is also used in this situation. It should be noted that it is already verified that these parameters provide superior performance over all other approaches. In the second method, the weights of the fuzzy goals are randomly changed at the beginning of each production interval. Two randomly selected weight structures, called FuzzyD-RND1 and FuzzyD-RND2, are compared with FuzzyD-NN.

In FuzzyD-NN case, it is assumed that the decision maker updates the parameters at the beginning of each production interval. However, it is possible that the rescheduling points can be determined by the decision maker with continuous review approach. In such cases, if the decision maker is satisfied with the current performance, he does not need to update the parameters during the scheduling period. During the experiments, it is assumed that the decision maker set the aspiration levels of the goals to the best values of the performance measures obtained during the simulation experiments. The initial values of the parameters are the same set of parameters with those used in previous experiments. The comparative results are given in Figure 6.15 and Table 6.11.

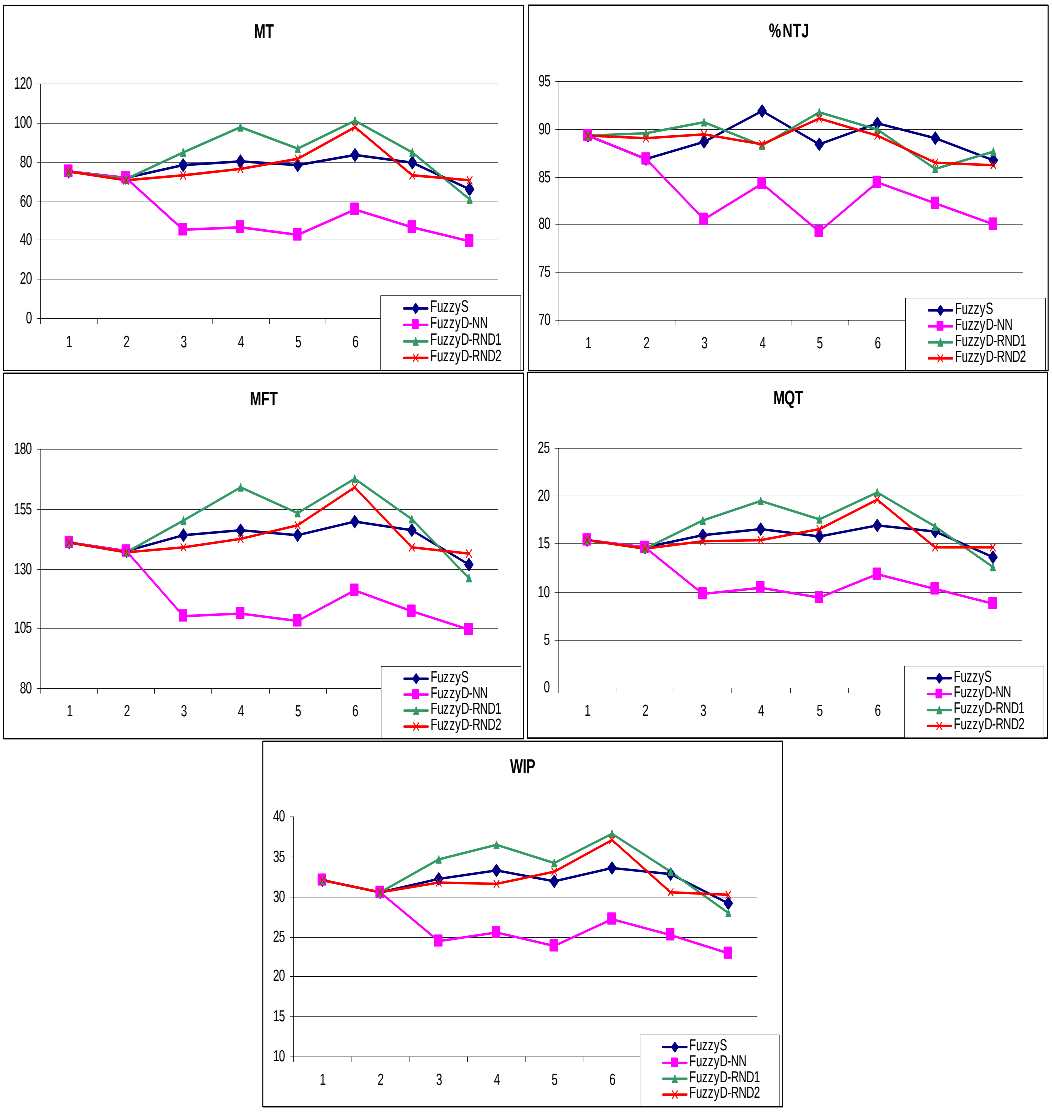

Figure 6.15 Comparison of the dynamic and fixed weights

Table 6.11 Simulation Results for Alternative Weight Update Methods

Method	Time	MT	%NTJ	MFT	MQT	WIP
FuzzyS	25000	74.95	89.31	141.13	15.41	32.08
	30000	72.29	86.89	137.60	14.70	30.54
	35000	78.49	88.71	144.16	15.90	32.28
	40000	80.53	91.85	146.10	16.54	33.36
	45000	78.19	88.41	144.06	15.75	31.99
	50000	83.66	90.58	150.00	16.96	33.63
	55000	79.99	89.12	146.21	16.31	32.87
	60000	66.28	86.79	131.68	13.65	29.17
FuzzyD-NN	25000	74.95	89.31	141.13	15.41	32.08
	30000	72.29	86.89	137.60	14.70	30.54
	35000	45.16	80.52	110.05	9.81	24.48
	40000	46.70	84.31	111.41	10.40	25.48
	45000	43.04	79.27	108.04	9.43	23.87
	50000	55.46	84.47	121.18	11.83	27.15
	55000	46.94	82.26	112.49	10.32	25.22
	60000	39.61	80.08	104.41	8.84	22.95
FuzzyD-RND1	25000	74.95	89.31	141.13	15.41	32.08
	30000	71.04	89.62	136.83	14.56	30.56
	35000	85.19	90.72	150.51	17.49	34.66
	40000	98.21	88.30	164.02	19.53	36.43
	45000	86.87	91.83	153.44	17.54	34.25
	50000	101.31	89.95	167.57	20.43	37.88
	55000	84.77	85.87	150.59	16.86	33.11
FuzzyD-RND2	25000	74.95	89.31	141.13	15.41	32.08
	30000	71.00	89.04	136.72	14.50	30.56
	35000	73.56	89.51	138.89	15.32	31.79
	40000	76.64	88.44	142.49	15.46	31.59
	45000	81.73	91.15	148.13	16.60	33.20
	50000	97.81	89.28	163.97	19.68	37.06
	55000	73.19	86.48	139.05	14.73	30.52
	60000	70.95	86.19	136.29	14.62	30.29

The weights of fuzzy goals used in each production interval are given in Table 6.12-6.14.

Table 6.12 Weight Combinations for FuzzyD-RND1

Time	w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12
25000	0.30	0.30	0.20	0.20	0.30	0.30	0.20	0.20	0.30	0.30	0.20	0.20
30000	0.07	0.91	0.83	0.02	0.37	0.19	0.85	0.51	0.13	0.90	0.09	0.03
35000	0.80	0.85	0.63	0.93	0.50	0.54	0.06	0.19	0.02	0.42	0.82	0.71
40000	0.56	0.84	0.68	0.03	0.63	0.35	0.28	0.38	0.99	0.11	0.45	0.33
45000	0.06	0.77	0.99	0.47	0.72	0.60	0.67	0.42	0.21	0.75	0.26	0.21
50000	0.04	0.85	0.57	0.58	0.48	0.83	0.97	0.16	0.88	0.61	0.34	0.99
55000	0.13	0.69	0.19	0.24	0.47	0.78	0.37	0.95	0.22	0.26	0.39	0.35
60000	0.73	0.12	0.64	0.61	0.92	0.25	0.44	0.13	0.32	0.32	0.94	0.04

Table 6.13 Weight Combinations for FuzzyD-RND2

Time	w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12
25000	0.30	0.30	0.20	0.20	0.30	0.30	0.20	0.20	0.30	0.30	0.20	0.20
30000	0.41	0.00	0.32	0.30	0.41	0.31	0.11	0.22	0.41	0.42	0.10	0.10
35000	0.10	0.53	0.10	0.41	0.00	0.49	0.28	0.20	0.32	0.20	0.21	0.21
40000	0.22	0.50	0.29	0.05	0.21	0.43	0.22	0.21	0.20	0.42	0.18	0.22
45000	0.11	0.68	0.12	0.11	0.52	0.21	0.11	0.22	0.12	0.43	0.32	0.14
50000	0.27	0.23	0.33	0.11	0.71	0.03	0.22	0.10	0.04	0.28	0.31	0.41
55000	0.22	0.12	0.43	0.32	0.31	0.29	0.09	0.28	0.32	0.31	0.31	0.11
60000	0.12	0.32	0.31	0.42	0.32	0.30	0.21	0.22	0.21	0.21	0.21	0.41

Table6. 14 Weight Combinations for FuzzyD-NN

Time	w1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12
25000	0.30	0.30	0.20	0.20	0.30	0.30	0.20	0.20	0.30	0.30	0.20	0.20
30000	0.26	0.13	0.37	0.24	0.23	0.14	0.02	0.54	0.05	0.53	0.19	0.28
35000	0.20	0.08	0.43	0.29	0.53	0.11	0.00	0.47	0.33	0.37	0.11	0.17
40000	0.20	0.25	0.21	0.29	0.35	0.19	0.00	0.55	0.11	0.43	0.16	0.33
45000	0.16	0.18	0.32	0.28	0.55	0.15	0.03	0.47	0.21	0.42	0.10	0.25
50000	0.16	0.36	0.25	0.24	0.36	0.15	0.02	0.65	0.22	0.41	0.10	0.31
55000	0.84	0.84	0.04	0.74	0.74	0.84	0.05	0.04	0.04	0.84	0.04	0.84
60000	0.03	0.51	0.61	0.16	0.18	0.01	0.04	0.80	0.17	0.58	0.25	0.17

As seen in Figure 6.15, the parameters directly affect the MCDRC-Fuzzy performance. The results from this set of experiments show that updating the parameters of MCDRC-Fuzzy through ANN will create a better result than both applying in a single parameter combination in a static manner and changing the parameters randomly. It should be indicated that updating the parameters can improve the performance even if the initial parameters are selected randomly. However, it is recommended to determine the initial parameters through the trained ANN model.

6.4 Summary

In this chapter, a real-time scheduling system incorporating an adaptive fuzzy system, called MCDRC-Fuzzy, was proposed. MCDRC-Fuzzy defines fuzzy priorities for the parts and routes considering multiple performance measures, instead of using traditional dispatching rules and routing rules. Moreover, fuzzy “where” and “when” rules were proposed for the first time in DRC research. The results of the experiments indicate that MCDRC-Fuzzy outperforms the other approaches proposed in Chapter 4 and 5.

CHAPTER SEVEN
CONCLUSION

7.1 Summary and Concluding Remarks

Increasing attention towards responsive manufacturing systems not only raises the importance of real-time scheduling of manufacturing systems, but also increases the significance of considering multiple performance measures in this decision making process. Extensive literature review indicates that numerous real-time scheduling approaches have been proposed for machine-only constrained systems. However, real-time scheduling of dual resource constrained (DRC) systems, which share a significant portion of manufacturing systems, have not been extensively explored. Furthermore, numerous researchers have paid considerable attention to evaluate different dispatching rule and worker assignment rule combinations in DRC systems. Although all these applications are inherently multi-criteria decision making problems, the literature review reveals that there is no sufficient effort on multi-criteria scheduling of DRC systems.

This research has focused on the development of adaptive real-time DRC schedulers capable of reacting to the changes in the system in a timely manner and satisfying the multiple objectives simultaneously. Considering these facts, this research has proposed three multi-criteria real-time scheduling approaches for DRC manufacturing systems. The first two approaches focus on the dynamic selection of appropriate set of rules, and use artificial neural networks (ANNs) and some multi-criteria decision making techniques to reduce computational complexity and cope with multiple performance measures. The first approach uses a fuzzy inference system (FIS), while the second utilizes a well-known multi-criteria decision making technique, PROMETHEE. The third approach proposed a fuzzy-based real-time scheduling approach for DRC manufacturing systems.

In the first methodology, called MCDRC-FIS, candidate DPRs, routing rules and worker assignment rules were selected dynamically based on the changing states.

The decisions about DPRs, routing rules and worker assignment rules to be applied were made for short production intervals and updated at the beginning of each interval (decision point). A simulation module that generates a sample data to train and test ANNs was developed. At the beginning of a scheduling period, ANNs were then used to estimate performances of alternative rule sets for short production interval based on system states. Multiple performance measures of alternative rule combinations were aggregated using a FIS. The rule combination for the next production interval was then determined based on this overall performance. A number of experiments were performed to test the effectiveness of MCDRC-FIS. In the first group of the experimental studies, the performance of MCDRC-FIS was compared with those of fixed, random and multi-pass scheduling approaches. The effects of the length of the scheduling period on the performance of MCDRC-FIS were also investigated through the second group of experiments. The third group of the experiments focused on the comparison of the effects of fixed length and variable length scheduling periods on the performance of MCDRC-FIS.

The results of the experiments indicated that applying MCDRC-FIS provided superior results comparable with those of fixed, random and multi-pass scheduling approaches. Although the results are somewhat dependent on system conditions tested, MCDRC-FIS outperformed fixed and random scheduling approaches at each case. The results also showed that the differences between MCDRC-FIS and the multi-pass approach are not statistically significant in low and medium variation level of the system. However, when the variation increases, MCDRC-FIS provided superior results than the multi-pass approach. Simulation experiments also showed that better results can be obtained by MCDRC-FIS through determining the appropriate length of the scheduling period. An important aspect of a real-time scheduling approach is its ability to make required decisions in short times (Arzi and Iaroslavitz, 1999). In MCDRC-FIS, due to the ANN's rapid computation feature and its ability to continually learn and adapt, computation time required to predict the performances of alternative rule combinations is short enough to use MCDRC-FIS in real-time.

In the second approach, called MCDRC-PRO, an alternative real-time multi-criteria DRC scheduler that operates in a similar way to MCDRC-FIS was proposed. Instead of using FIS, the multi-criteria nature of the dynamic scheduling problem was handled by a multi-criteria decision aid method, PROMETHEE. The performance of MCDRC-PRO was evaluated by comparing it with the fixed, multi-pass and MCDRC-FIS approaches. The results of the experiments showed that MCDRC-FIS and MCDRC-PRO provided similar results and outperformed other scheduling approaches in terms of the solution quality and response time. The robustness of MCDRC-PRO was demonstrated by analyzing the sensitivity in the change of the parameters. Experimental results also showed that while the small changes in the values of thresholds do not have a strong effect on the results of MCDRC-PRO, the weights of the performance measures have important impacts on the values of the performance measures.

This research also proposed a real-time scheduling system incorporating an adaptive fuzzy system. The proposed approach, called MCDRC-Fuzzy, defines fuzzy priorities for parts and routes considering multiple performance measures, instead of using standard rule sets. In MCDRC-Fuzzy, “fuzzy where” rules, which aggregate several traditional “where” rules, were developed to select the department to which the worker would be transferred. Moreover, instead of using traditional centralized and decentralized “when” rules, one set of “Sugeno type” rules was developed to support the “when” rules. The experimental results showed that significant improvements can be achieved through MCDRC-Fuzzy. MCDRC-Fuzzy outperformed each combination of traditional rules, MCDRC-FIS and MCDRC-PRO in terms of all criteria. The performance of MCDRC-fuzzy was also investigated under different conditions such as the case of varying worker efficiency. The simulation experiments showed that the proposed fuzzy approach, which uses fuzzy rules in the scheduling of DRC systems, achieves better results even in the case of varying worker efficiency than the traditional “when” and “where” rules in the literature. Furthermore, in this research, a reverse ANN was proposed to determine the weights of fuzzy goals considering the changes in decision makers’ aspiration levels. The results of the experiments indicated that the parameters directly affect the performance of MCDRC-Fuzzy, and updating the parameters of MCDRC-Fuzzy would create a better result than applying in a single parameter combination in a static manner.

From these results, it is concluded that the proposed real-time scheduling approaches may be practically used and can provide satisfactory solutions for real-time scheduling of DRC systems.

7.2 Directions for future research

While this research was conducted, several areas that can be investigated in the future have come to light. Topics worthy of future investigation are listed as follows:

1) MCDRC-FIS and MCDRC-PRO focus on the dynamic selection of appropriate set of dispatching rules (DPRs), worker assignment rules and routing decisions of jobs with regard to multiple performance criteria of interest. Although some case studies proved that the proposed methodologies give satisfactory solutions in practice, their performances are subject to those of pre-determined traditional rules. In this research, only a limited number of rules were used. It is expected that the system's performance can be improved by considering more DPRs, routing rules and worker assignment rules. Furthermore, the proposed approaches only deal with the four important decision in DRC systems; i.e. part dispatching, routing, "where" and "when" worker assignment decisions. Other important decisions can also be studied by including corresponding rules, e.g. dispatching of material handling vehicles.

2) MCDRC-FIS and MCDRC-PRO use ANNs as a look-ahead simulation model that produces the performances of all rule combinations during the next look-ahead window. Although the effects of scheduling period length on the performance of the proposed approaches were investigated, the

effects of the length of the look-ahead window on the ANN performance should also be investigated.

3) In this research, it is assumed that the length of the scheduling period is determined either by constant time periods or pre-determined thresholds. In the latter case, the thresholds need to be adapted to the system configuration, the operating conditions and the production objectives (Pierreval and Mebarki, 1997). Some simulation-optimization techniques may be used to determine these thresholds. Furthermore, it would be interesting to use a fuzzy inference system to determine whether it is necessary to change current scheduling rule combination considering the current system states.

4) More realistic examples which include minor and major machine breakdowns need to be investigated to understand the performance of the proposed approaches under such situations. Kutanoglu and Sabuncuoglu (2001b) indicate that dynamic priority dispatching techniques can be improved using additional policies specifically designed to reduce effects of such disruptions. Therefore, it would be interesting to extend this research by including some reactive policies against machine failures.

5) This research mainly focused on the selection of appropriate “where” and “when” rules based on chancing system states. Besides “where” and “when” rules, Bokhorst et al. (2004) proposed some “who” rules to determine which worker should be transferred to the work centre that requires a worker. This thesis can be extended by considering these “who” rules in the decision making process and exploring their impact on the DRC system.

6) The concept of worker flexibility plays a major role in the success of DRC systems. As discussed in Chapter 2, worker flexibility can also be characterized by different ways, such as homogeneous or heterogeneous, and single-level flexibility or multi-level flexibility. Therefore, the effects of the worker flexibility on the performance of the proposed approaches should

be further investigated. Another interesting area for future research should be to investigate the performance of the proposed approaches when worker attrition and learning effects are considered.

7) In this study, it is assumed that the information access delay is negligible. However, in some real-life DRC shop floors, the type of automation built in the DRC system, the quality of information technologies used and the control strategies executed cause information delays. Caprihan et al.(2006) reported that such delays can cause significant deteriorations in the performance of FMSs. As discussed in Chapter 2, only few research efforts have been directed to deal with information delays in DRC systems. Therefore, one of the further research studies should be to investigate the performance of the proposed approaches on whether they can deal with information delays in DRC systems.

8) The results of MCDRC-fuzzy reveal that its performance can be improved by chancing its parameters. In this research, the parameters of MCDRC-fuzzy were determined at each scheduling period via a reverse ANN based on the desired performance values of the objectives. Therefore, optimizing the parameters for each scheduling period was beyond the scope of this research. However, developing an evolutionary simulation-optimization model, which selects the parameters guaranteeing good compromise solution for all system performances, is still open for future research.

9) In MCDRC-fuzzy, fuzzy "where" rules are obtained using the membership function concept of fuzzy sets while fuzzy inference is utilized to develop fuzzy "when" rules. Developing a fuzzy inference-based "where" rule can also be considered as a future research topic.

10) In MCDRC-PRO, PROMETHEE was used to evaluate alternative rule combinations and select the best one over successive short-time periods based on the current system state. On the other hand, after each operation,

PROMETHEE can be used to evaluate alternative actions, and select a part to be processed, to decide the route of a part, to determine when a worker should be transferred to another work center or to choose which work center needs a worker. One of the further research studies should be to embed PROMETHEE into the shop floor management module.

11) It may also be interesting to apply other multi-criteria decision making approaches, such as ELECTRE and TOPSIS, to real-time scheduling problems.

12) One of the other issues for future research may be to determine the appropriate parameters required for ANNs, such as the number of hidden layers and the number of training epochs, based on an automatic parameter controlling method.

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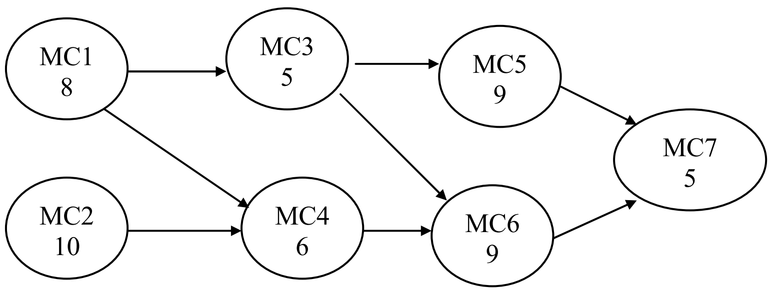
APPENDIX A

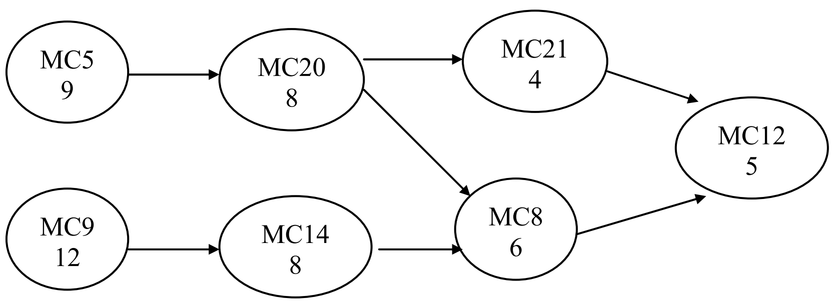
A1. Distance Matrix Between Departments

Machine	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1		0.45	0.30	0.15	0.45	0.30	1.05	0.30	0.30	0.75	0.45	0.15	0.60	0.15	1.20	1.05	0.45	0.60	1.05	0.60	0.90	0.60	0.90	0.75
2			0.15	0.30	0.30	0.15	1.35	0.60	0.45	1.05	0.60	0.30	0.90	0.45	1.50	1.35	0.75	0.15	1.35	0.15	1.20	0.75	1.05	0.90
3				0.15	0.45	0.30	1.20	0.45	0.30	0.90	0.45	0.15	0.75	0.30	1.35	1.20	0.60	0.30	1.20	0.30	1.05	0.60	0.90	0.75
4					0.30	0.15	1.20	0.45	0.45	0.75	0.60	0.15	0.75	0.30	1.35	1.20	0.60	0.30	1.20	0.45	1.05	0.60	0.90	0.75
5						0.15	1.50	0.75	0.75	1.20	0.90	0.45	1.05	0.60	1.65	1.50	0.90	0.15	1.50	0.30	1.35	0.90	1.35	1.20
6							1.35	0.60	0.45	1.05	0.60	0.30	0.90	0.45	1.50	1.35	0.75	0.15	1.35	0.30	1.20	0.75	1.05	0.90
7								0.75	0.90	0.30	0.75	1.05	0.45	0.90	0.15	0.15	0.60	1.50	0.30	1.50	0.15	0.60	0.30	0.45
8									0.30	0.45	0.15	0.30	0.30	0.15	0.90	0.75	0.15	0.75	0.75	0.75	0.60	0.30	0.60	0.45
9										0.60	0.15	0.15	0.45	0.15	1.05	0.90	0.30	0.60	0.90	0.60	0.75	0.30	0.60	0.45
10											0.45	0.75	0.15	0.60	0.45	0.30	0.30	1.20	0.30	1.20	0.15	0.45	0.15	0.30
11												0.30	0.30	0.15	0.90	0.75	0.15	0.75	0.75	0.75	0.60	0.15	0.45	0.30
12													0.60	0.15	1.20	1.05	0.45	0.45	1.05	0.45	0.90	0.45	0.75	0.60
13														0.45	0.75	0.60	0.15	1.05	0.60	1.05	0.45	0.15	0.30	0.15
14															1.05	0.90	0.30	0.60	0.90	0.60	0.75	0.45	0.75	0.60
15																0.30	0.75	1.65	0.45	1.65	0.30	0.75	0.45	0.60
16																	0.60	1.50	0.15	1.50	0.15	0.60	0.30	0.45
17																		0.90	0.60	0.90	0.45	0.15	0.45	0.30
18																			1.50	0.15	1.35	0.90	1.20	1.05
19																				1.50	0.15	0.60	0.30	0.45
20																					1.35	0.90	1.20	1.05
21																						0.45	0.15	0.30
22																							0.30	0.15
23																								0.15
24																								

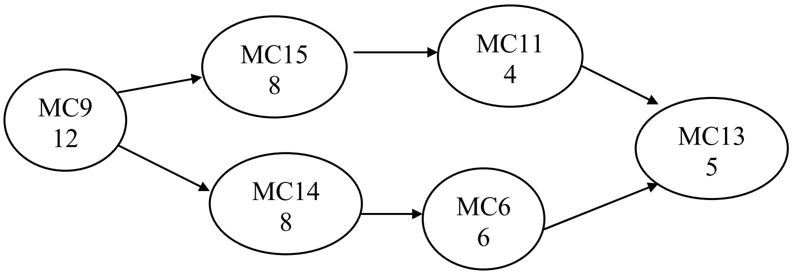
A2. Production Routes and Processing Times for Product Type 1 (MCk is k^{th} machine department)



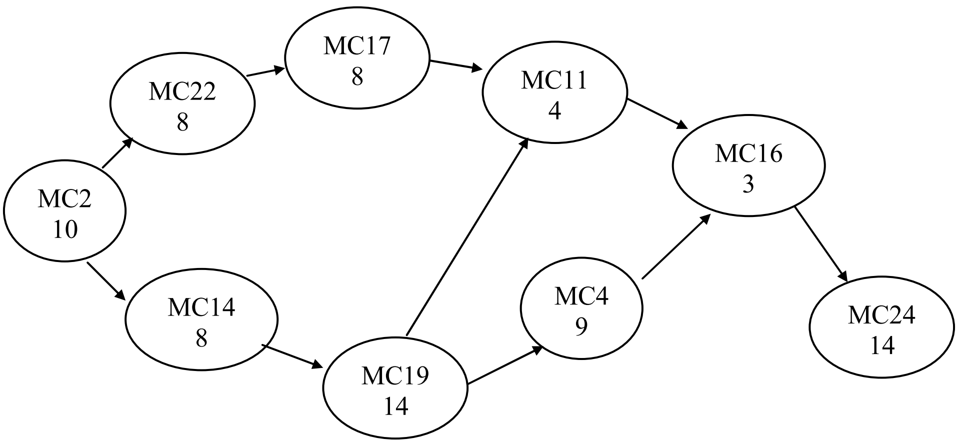
A3. Production Routes and Processing Times for Product Type 2 (MCk is k^{th} machine department)



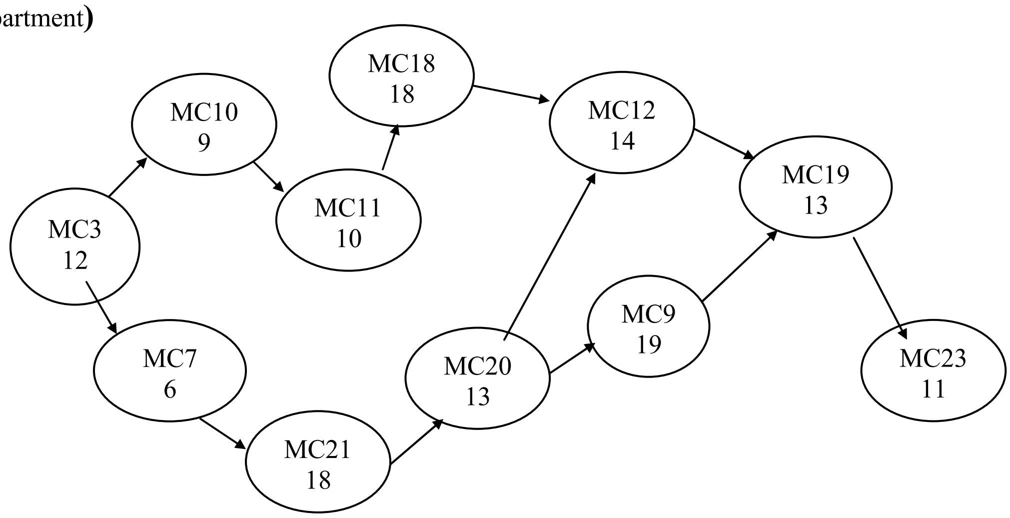
A4. Production Routes and Processing Times for Product Type 3 (MCk is k^{th} machine department**)**



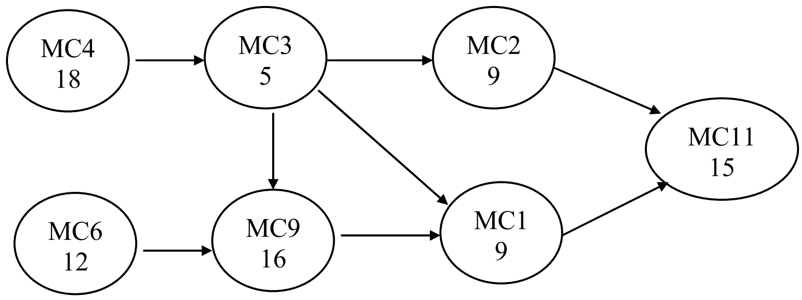
A5. Production Routes and Processing Times for Product Type 4 (MCk is k^{th} machine department**)**



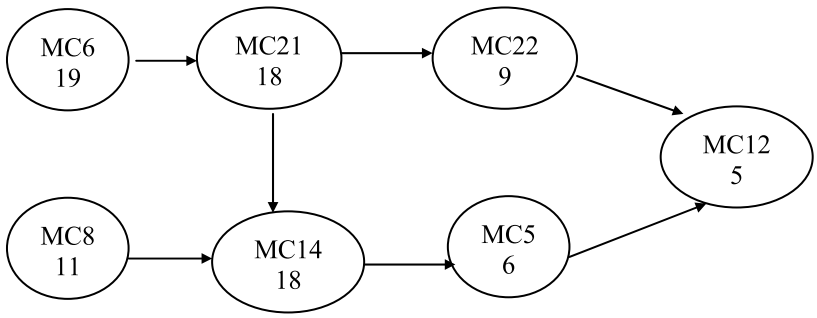
A6. Production Routes and Processing Times for Product Type 5 (MCk is k^{th} machine department**)**



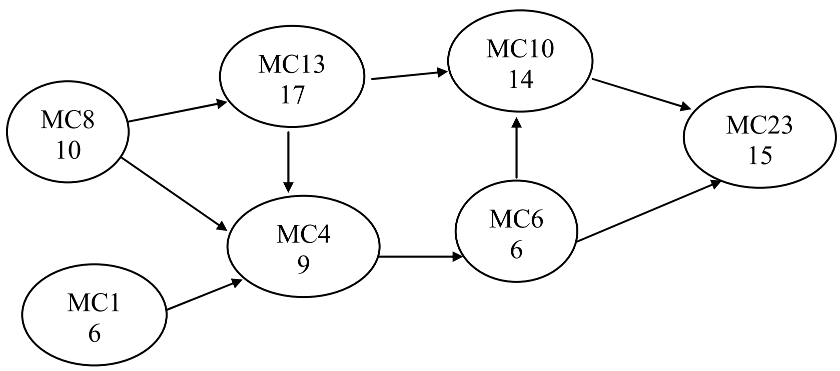
A7. Production Routes and Processing Times for Product Type 6 (MC*k* is *k*th machine department**)**



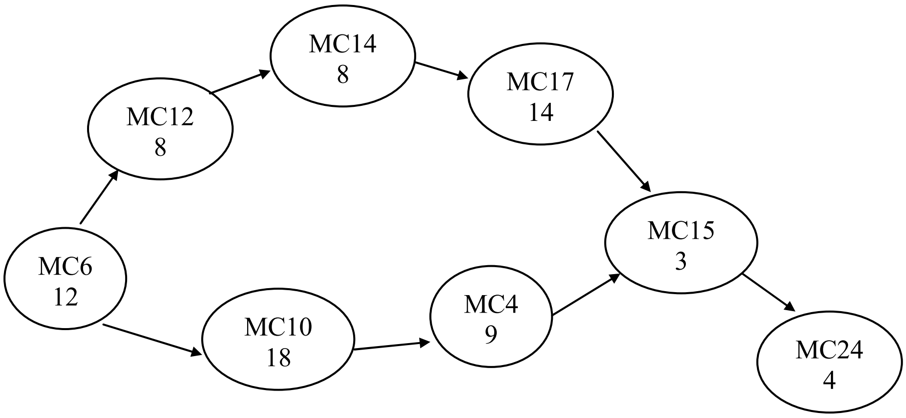
A8. Production Routes and Processing Times for Product Type 7 (MC*k* is *k*th machine department**)**



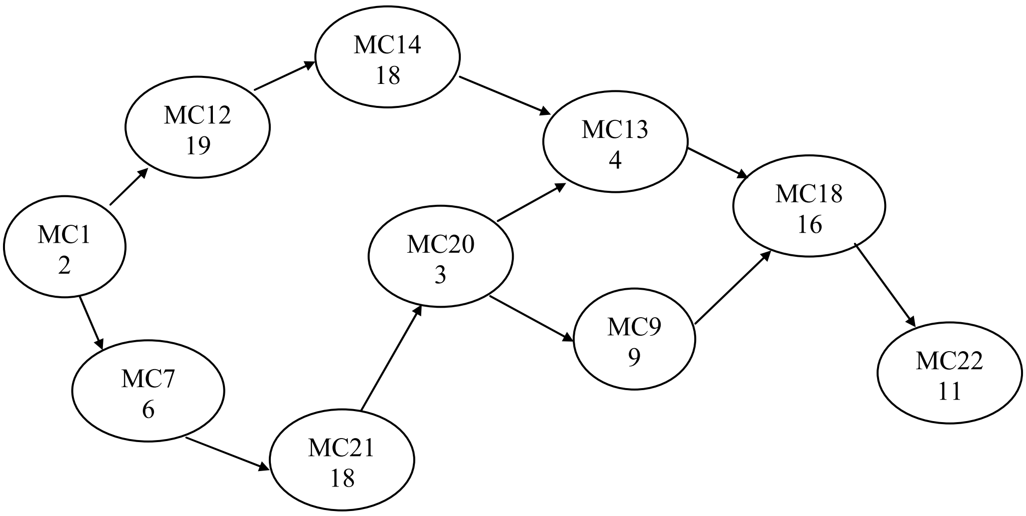
A9. Production Routes and Processing Times for Product Type 8 (MC*k* is *k*th machine department**)**



A10. Production Routes and Processing Times for Product Type 9 (MC*k* is *k*[th] machine department**)**



A11. Production Routes and Processing Times for Product Type 10 (MC*k* is *k*[th] machine department**)**



A12. Worker Efficiency Matrix

		WORKER NUMBER														
DEPARTMENT NUMBER		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	1	1.00	0.90	0.85	0.00	0.00	0.85	1.00	0.90	0.00	0.95	0.00	0.90	1.00	0.00	0.00
	2	0.00	1.00	0.85	0.00	0.00	0.95	0.00	0.90	0.85	1.00	0.00	0.00	0.95	1.00	0.85
	3	0.00	0.00	1.00	0.95	0.85	1.00	0.00	0.85	0.00	0.00	0.90	0.95	1.00	0.00	0.00
	4	0.00	0.95	0.00	1.00	1.00	0.75	1.00	0.00	0.95	0.00	0.90	1.00	0.00	0.85	0.00
	5	0.85	0.95	0.00	0.95	1.00	0.90	0.00	0.85	0.00	0.00	1.00	0.00	0.90	0.00	0.95
	6	0.00	0.95	0.85	0.90	1.00	1.00	0.00	0.00	0.85	0.00	0.95	1.00	0.00	0.00	1.00
	7	1.00	0.00	0.00	0.00	0.95	0.95	1.00	0.00	0.95	0.00	0.85	0.95	0.00	0.85	0.85
	8	1.00	0.00	1.00	0.95	0.90	0.00	0.90	0.85	0.95	0.85	0.00	0.00	0.00	0.00	1.00
	9	0.00	0.95	1.00	0.00	1.00	0.95	0.00	0.00	1.00	0.90	0.85	0.00	0.85	0.00	0.85
	10	0.00	0.00	0.95	1.00	0.00	0.00	0.00	0.90	0.95	1.00	0.85	0.00	0.85	0.00	1.00
	11	0.85	0.00	0.95	0.00	0.00	0.90	0.90	1.00	0.90	0.85	0.00	0.00	0.00	1.00	0.95
	12	1.00	0.85	0.95	1.00	0.85	0.85	0.00	0.00	0.00	0.85	1.00	0.00	0.00	1.00	0.00
	13	0.95	0.85	0.00	0.00	0.90	1.00	0.00	0.90	0.00	0.85	0.00	0.90	1.00	1.00	0.00
	14	1.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.85	0.00	0.90	0.85	0.95	1.00	0.00
	15	1.00	0.85	0.00	0.00	0.90	0.95	1.00	0.00	0.95	0.00	0.00	0.90	0.90	0.00	1.00
	16	0.00	0.95	0.00	0.90	0.00	0.85	0.90	0.00	0.85	1.00	1.00	0.00	0.00	0.90	1.00
	17	1.00	0.00	0.95	0.00	0.90	0.00	0.95	0.90	0.00	0.95	0.00	0.00	1.00	0.00	1.00
	18	1.00	0.00	1.00	0.00	0.95	0.00	0.00	0.90	0.00	0.90	0.00	1.00	0.85	0.90	0.00
	19	0.00	0.00	0.95	1.00	0.00	0.00	0.85	0.85	0.00	0.00	1.00	0.85	0.90	1.00	0.00
	20	0.85	0.85	0.00	1.00	0.00	0.00	0.90	0.00	0.00	0.85	0.95	1.00	0.95	0.00	0.95
	21	0.95	1.00	0.90	1.00	0.00	0.00	0.85	1.00	0.85	0.90	0.00	0.00	0.00	0.95	0.00
	22	0.00	0.00	0.85	0.00	1.00	0.90	1.00	0.00	0.90	0.85	0.90	0.95	0.00	1.00	0.00
	23	0.00	0.00	0.00	0.85	0.00	0.95	1.00	0.00	0.85	1.00	0.85	1.00	0.00	0.00	0.90
	24	0.00	0.95	0.00	1.00	0.95	0.00	1.00	0.95	0.00	0.00	0.00	1.00	0.90	1.00	0.85

APPENDIX B

STATISTICAL TESTS FOR COMPARISION BETWEEN TRADIONAL RULES AND FUZZY RULES USING SPSS 11.0

B.1 ANOVA for part DPRs ($\alpha = 0.01$)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MT	Between Groups	1,761.726	7	251.675	3.536	.002
	Within Groups	10,818.270	152	71.173		
	Total	12,579.997	159			
NTJ	Between Groups	9,148.043	7	1,306.863	14.971	.000
	Within Groups	13,268.660	152	87.294		
	Total	22,416.703	159			
MFT	Between Groups	13,405.781	7	1,915.112	24.187	.000
	Within Groups	12,035.384	152	79.180		
	Total	25,441.166	159			
MQT	Between Groups	205.564	7	29.366	9.680	.000
	Within Groups	461.134	152	3.034		
	Total	666.698	159			
WIP	Between Groups	662.919	7	94.703	27.096	.000
	Within Groups	531.262	152	3.495		
	Total	1,194.181	159			

B.2 Multiple comparison of part DPRs with LSD test for MT (α = 0.01)

Multiple Comparisons

Dependent Variable: MT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	FIFO	(J) MTH	1					
			2	2.4009	2.66782	.370	-4.5582	9.3601
			3	.5466	2.66782	.838	-6.4125	7.5058
			4	2.9853	2.66782	.265	-3.9739	9.9445
			5	.3433	2.66782	.898	-6.6159	7.3025
			6	.3878	2.66782	.885	-6.5713	7.3470
			7	-1.4032	2.66782	.600	-8.3624	5.5560
			8	9.9991*	2.66782	.000	3.0399	16.9583
	SPT	(J) MTH	1	-2.4009	2.66782	.370	-9.3601	4.5582
			2					
			3	-1.8543	2.66782	.488	-8.8135	5.1049
			4	.5844	2.66782	.827	-6.3748	7.5435
			5	-2.0576	2.66782	.442	-9.0168	4.9016
			6	-2.0131	2.66782	.452	-8.9723	4.9461
			7	-3.8041	2.66782	.156	-10.7633	3.1550
			8	7.5982*	2.66782	.005	.6390	14.5573
	EDD	(J) MTH	1	-.5466	2.66782	.838	-7.5058	6.4125
			2	1.8543	2.66782	.488	-5.1049	8.8135
			3					
			4	2.4387	2.66782	.362	-4.5205	9.3979
			5	-.2033	2.66782	.939	-7.1625	6.7559
			6	-.1588	2.66782	.953	-7.1180	6.8004
			7	-1.9498	2.66782	.466	-8.9090	5.0094
			8	9.4525*	2.66782	.001	2.4933	16.4116
	RPR**	(J) MTH	1	-2.9853	2.66782	.265	-9.9445	3.9739
			2	-.5844	2.66782	.827	-7.5435	6.3748
			3	-2.4387	2.66782	.362	-9.3979	4.5205
			4					
			5	-2.6420	2.66782	.324	-9.6012	4.3172
			6	-2.5975	2.66782	.332	-9.5566	4.3617
			7	-4.3885	2.66782	.102	-11.3477	2.5707
			8	7.0138*	2.66782	.009	.0546	13.9730
	CRT	(J) MTH	1	-.3433	2.66782	.898	-7.3025	6.6159
			2	2.0576	2.66782	.442	-4.9016	9.0168
			3	.2033	2.66782	.939	-6.7559	7.1625
			4	2.6420	2.66782	.324	-4.3172	9.6012
			5					
			6	.0445	2.66782	.987	-6.9147	7.0037
			7	-1.7465	2.66782	.514	-8.7057	5.2127
			8	9.6558*	2.66782	.000	2.6966	16.6150
	MST	(J) MTH	1	-.3878	2.66782	.885	-7.3470	6.5713
			2	2.0131	2.66782	.452	-4.9461	8.9723
			3	.1588	2.66782	.953	-6.8004	7.1180
			4	2.5975	2.66782	.332	-4.3617	9.5566
			5	-.0445	2.66782	.987	-7.0037	6.9147
			6					
			7	-1.7910	2.66782	.503	-8.7502	5.1681
			8	9.6113*	2.66782	.000	2.6521	16.5704
	CRT2	(J) MTH	1	1.4032	2.66782	.600	-5.5560	8.3624
			2	3.8041	2.66782	.156	-3.1550	10.7633
			3	1.9498	2.66782	.466	-5.0094	8.9090
			4	4.3885	2.66782	.102	-2.5707	11.3477
			5	1.7465	2.66782	.514	-5.2127	8.7057
			6	1.7910	2.66782	.503	-5.1681	8.7502
			7					
			8	11.4023*	2.66782	.000	4.4431	18.3615
	FDPR***	(J) MTH	1	-9.9991*	2.66782	.000	-16.9583	-3.0399
			2	-7.5982*	2.66782	.005	-14.5573	-.6390
			3	-9.4525*	2.66782	.001	-16.4116	-2.4933
			4	-7.0138*	2.66782	.009	-13.9730	-.0546
			5	-9.6558*	2.66782	.000	-16.6150	-2.6966
			6	-9.6113*	2.66782	.000	-16.5704	-2.6521
			7	-11.4023*	2.66782	.000	-18.3615	-4.4431
			8					

*. The mean difference is significant at the .01 level.

** RPRO is RPROTIME
***FDPR is Fuzzy DPR

B.3 Multiple comparison of part DPRs LSD test for %NTJ (α = 0.01)

Multiple Comparisons

Dependent Variable: NTJ
LSD

				Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	1	(J) MTH	FIFO					
			SPT	5.8522	2.95455	.049	-1.8550	13.5593
			EDD	1.1163	2.95455	.706	-6.5908	8.8234
			RPRO	8.0979*	2.95455	.007	.3908	15.8050
			CRT	-.5937	2.95455	.841	-8.3008	7.1135
			MST	.5877	2.95455	.843	-7.1194	8.2949
			CRT2	.8853	2.95455	.765	-6.8218	8.5924
			FDPR	23.4217*	2.95455	.000	15.7145	31.1288
	2	(J) MTH	FIFO	-5.8522	2.95455	.049	-13.5593	1.8550
			SPT					
			EDD	-4.7358	2.95455	.111	-12.4430	2.9713
			RPRO	2.2457	2.95455	.448	-5.4614	9.9529
			CRT	-6.4458	2.95455	.031	-14.1530	1.2613
			MST	-5.2644	2.95455	.077	-12.9716	2.4427
			CRT2	-4.9669	2.95455	.095	-12.6740	2.7403
			FDPR	17.5695*	2.95455	.000	9.8624	25.2766
	3	(J) MTH	FIFO	-1.1163	2.95455	.706	-8.8234	6.5908
			SPT	4.7358	2.95455	.111	-2.9713	12.4430
			EDD					
			RPRO	6.9816	2.95455	.019	-.7256	14.6887
			CRT	-1.7100	2.95455	.564	-9.4171	5.9971
			MST	-.5286	2.95455	.858	-8.2357	7.1785
			CRT2	-.2310	2.95455	.938	-7.9382	7.4761
			FDPR	22.3054*	2.95455	.000	14.5982	30.0125
	4	(J) MTH	FIFO	-8.0979*	2.95455	.007	-15.8050	-.3908
			SPT	-2.2457	2.95455	.448	-9.9529	5.4614
			EDD	-6.9816	2.95455	.019	-14.6887	.7256
			RPRO					
			CRT	-8.6916*	2.95455	.004	-16.3987	-.9844
			MST	-7.5102	2.95455	.012	-15.2173	.1970
			CRT2	-7.2126	2.95455	.016	-14.9197	.4945
			FDPR	15.3238*	2.95455	.000	7.6167	23.0309
	5	(J) MTH	FIFO	.5937	2.95455	.841	-7.1135	8.3008
			SPT	6.4458	2.95455	.031	-1.2613	14.1530
			EDD	1.7100	2.95455	.564	-5.9971	9.4171
			RPRO	8.6916*	2.95455	.004	.9844	16.3987
			CRT					
			MST	1.1814	2.95455	.690	-6.5257	8.8885
			CRT2	1.4790	2.95455	.617	-6.2282	9.1861
			FDPR	24.0153*	2.95455	.000	16.3082	31.7225
	6	(J) MTH	FIFO	-.5877	2.95455	.843	-8.2949	7.1194
			SPT	5.2644	2.95455	.077	-2.4427	12.9716
			EDD	.5286	2.95455	.858	-7.1785	8.2357
			RPRO	7.5102	2.95455	.012	-.1970	15.2173
			CRT	-1.1814	2.95455	.690	-8.8885	6.5257
			MST					
			CRT2	.2976	2.95455	.920	-7.4096	8.0047
			FDPR	22.8340*	2.95455	.000	15.1268	30.5411
	7	(J) MTH	FIFO	-.8853	2.95455	.765	-8.5924	6.8218
			SPT	4.9669	2.95455	.095	-2.7403	12.6740
			EDD	.2310	2.95455	.938	-7.4761	7.9382
			RPRO	7.2126	2.95455	.016	-.4945	14.9197
			CRT	-1.4790	2.95455	.617	-9.1861	6.2282
			MST	-.2976	2.95455	.920	-8.0047	7.4096
			CRT2					
			FDPR	22.5364*	2.95455	.000	14.8292	30.2435
	8	(J) MTH	FIFO	-23.4217*	2.95455	.000	-31.1288	-15.7145
			SPT	-17.5695*	2.95455	.000	-25.2766	-9.8624
			EDD	-22.3054*	2.95455	.000	-30.0125	-14.5982
			RPRO	-15.3238*	2.95455	.000	-23.0309	-7.6167
			CRT	-24.0153*	2.95455	.000	-31.7225	-16.3082
			MST	-22.8340*	2.95455	.000	-30.5411	-15.1268
			CRT2	-22.5364*	2.95455	.000	-30.2435	-14.8292
			FDPR					

*. The mean difference is significant at the .01 level.

B.4 Multiple comparison of part DPRs with LSD test for MFT (α = 0.01)

Multiple Comparisons

Dependent Variable: MFT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval Lower Bound	99% Confidence Interval Upper Bound
(I) MTH	1	(J) MTH	FIFO					
			SPT	6.7294	2.81390	.018	-.6109	14.0696
			EDD	.3304	2.81390	.907	-7.0098	7.6707
			RPRO	7.9659*	2.81390	.005	.6257	15.3061
			CRT	-.6302	2.81390	.823	-7.9704	6.7100
			MST	-.0059	2.81390	.998	-7.3462	7.3343
			CRT2	-1.1269	2.81390	.689	-8.4671	6.2134
			FDPR	27.7492*	2.81390	.000	20.4090	35.0895
	2	(J) MTH	FIFO	-6.7294	2.81390	.018	-14.0696	.6109
			SPT					
			EDD	-6.3989	2.81390	.024	-13.7391	.9413
			RPRO	1.2365	2.81390	.661	-6.1037	8.5768
			CRT	-7.3595*	2.81390	.010	-14.6998	-.0193
			MST	-6.7353	2.81390	.018	-14.0755	.6049
			CRT2	-7.8562*	2.81390	.006	-15.1964	-.5160
			FDPR	21.0199*	2.81390	.000	13.6797	28.3601
	3	(J) MTH	FIFO	-.3304	2.81390	.907	-7.6707	7.0098
			SPT	6.3989	2.81390	.024	-.9413	13.7391
			EDD					
			RPRO	7.6355*	2.81390	.007	.2952	14.9757
			CRT	-.9606	2.81390	.733	-8.3008	6.3796
			MST	-.3364	2.81390	.905	-7.6766	7.0039
			CRT2	-1.4573	2.81390	.605	-8.7975	5.8829
			FDPR	27.4188*	2.81390	.000	20.0786	34.7590
	4	(J) MTH	FIFO	-7.9659*	2.81390	.005	-15.3061	-.6257
			SPT	-1.2365	2.81390	.661	-8.5768	6.1037
			EDD	-7.6355*	2.81390	.007	-14.9757	-.2952
			RPRO					
			CRT	-8.5961*	2.81390	.003	-15.9363	-1.2559
			MST	-7.9718*	2.81390	.005	-15.3120	-.6316
			CRT2	-9.0928*	2.81390	.002	-16.4330	-1.7525
			FDPR	19.7834*	2.81390	.000	12.4431	27.1236
	5	(J) MTH	FIFO	.6302	2.81390	.823	-6.7100	7.9704
			SPT	7.3595*	2.81390	.010	.0193	14.6998
			EDD	.9606	2.81390	.733	-6.3796	8.3008
			RPRO	8.5961*	2.81390	.003	1.2559	15.9363
			CRT					
			MST	.6243	2.81390	.825	-6.7160	7.9645
			CRT2	-.4967	2.81390	.860	-7.8369	6.8435
			FDPR	28.3794*	2.81390	.000	21.0392	35.7197
	6	(J) MTH	FIFO	.0059	2.81390	.998	-7.3343	7.3462
			SPT	6.7353	2.81390	.018	-.6049	14.0755
			EDD	.3364	2.81390	.905	-7.0039	7.6766
			RPRO	7.9718*	2.81390	.005	.6316	15.3120
			CRT	-.6243	2.81390	.825	-7.9645	6.7160
			MST					
			CRT2	-1.1209	2.81390	.691	-8.4612	6.2193
			FDPR	27.7552*	2.81390	.000	20.4150	35.0954
	7	(J) MTH	FIFO	1.1269	2.81390	.689	-6.2134	8.4671
			SPT	7.8562*	2.81390	.006	.5160	15.1964
			EDD	1.4573	2.81390	.605	-5.8829	8.7975
			RPRO	9.0928*	2.81390	.002	1.7525	16.4330
			CRT	.4967	2.81390	.860	-6.8435	7.8369
			MST	1.1209	2.81390	.691	-6.2193	8.4612
			CRT2					
			FDPR	28.8761*	2.81390	.000	21.5359	36.2163
	8	(J) MTH	FIFO	-27.7492*	2.81390	.000	-35.0895	-20.4090
			SPT	-21.0199*	2.81390	.000	-28.3601	-13.6797
			EDD	-27.4188*	2.81390	.000	-34.7590	-20.0786
			RPRO	-19.7834*	2.81390	.000	-27.1236	-12.4431
			CRT	-28.3794*	2.81390	.000	-35.7197	-21.0392
			MST	-27.7552*	2.81390	.000	-35.0954	-20.4150
			CRT2	-28.8761*	2.81390	.000	-36.2163	-21.5359
			FDPR					

*. The mean difference is significant at the .01 level.

B.5 Multiple comparison of part DPRs with LSD test for MQT (α = 0.01)

Multiple Comparisons

Dependent Variable: MQT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval Lower Bound	99% Confidence Interval Upper Bound
(I) MTH	1	(J) MTH	FIFO					
			SPT	1.2641	.55080	.023	-.1727	2.7009
			EDD	.0639	.55080	.908	-1.3729	1.5007
			RPRO	1.4839*	.55080	.008	.0471	2.9207
			CRT	-.1136	.55080	.837	-1.5504	1.3231
			MST	.0015	.55080	.998	-1.4352	1.4383
			CRT2	-.2088	.55080	.705	-1.6456	1.2280
			FDPR	3.2451*	.55080	.000	1.8083	4.6819
	2	(J) MTH	FIFO	-1.2641	.55080	.023	-2.7009	.1727
			SPT					
			EDD	-1.2002	.55080	.031	-2.6369	.2366
			RPRO	.2199	.55080	.690	-1.2169	1.6566
			CRT	-1.3777	.55080	.013	-2.8145	.0591
			MST	-1.2625	.55080	.023	-2.6993	.1743
			CRT2	-1.4729*	.55080	.008	-2.9097	-.0361
			FDPR	1.9810*	.55080	.000	.5442	3.4178
	3	(J) MTH	FIFO	-.0639	.55080	.908	-1.5007	1.3729
			SPT	1.2002	.55080	.031	-.2366	2.6369
			EDD					
			RPRO	1.4200	.55080	.011	-.0168	2.8568
			CRT	-.1776	.55080	.748	-1.6143	1.2592
			MST	-.0624	.55080	.910	-1.4992	1.3744
			CRT2	-.2727	.55080	.621	-1.7095	1.1640
			FDPR	3.1812*	.55080	.000	1.7444	4.6179
	4	(J) MTH	FIFO	-1.4839*	.55080	.008	-2.9207	-.0471
			SPT	-.2199	.55080	.690	-1.6566	1.2169
			EDD	-1.4200	.55080	.011	-2.8568	.0168
			RPRO					
			CRT	-1.5976*	.55080	.004	-3.0344	-.1608
			MST	-1.4824*	.55080	.008	-2.9192	-.0456
			CRT2	-1.6928*	.55080	.003	-3.1296	-.2560
			FDPR	1.7611*	.55080	.002	.3244	3.1979
	5	(J) MTH	FIFO	.1136	.55080	.837	-1.3231	1.5504
			SPT	1.3777	.55080	.013	-.0591	2.8145
			EDD	.1776	.55080	.748	-1.2592	1.6143
			RPRO	1.5976*	.55080	.004	.1608	3.0344
			CRT					
			MST	.1152	.55080	.835	-1.3216	1.5520
			CRT2	-.0952	.55080	.863	-1.5320	1.3416
			FDPR	3.3587*	.55080	.000	1.9219	4.7955
	6	(J) MTH	FIFO	-.0015	.55080	.998	-1.4383	1.4352
			SPT	1.2625	.55080	.023	-.1743	2.6993
			EDD	.0624	.55080	.910	-1.3744	1.4992
			RPRO	1.4824*	.55080	.008	.0456	2.9192
			CRT	-.1152	.55080	.835	-1.5520	1.3216
			MST					
			CRT2	-.2104	.55080	.703	-1.6472	1.2264
			FDPR	3.2435*	.55080	.000	1.8067	4.6803
	7	(J) MTH	FIFO	.2088	.55080	.705	-1.2280	1.6456
			SPT	1.4729*	.55080	.008	.0361	2.9097
			EDD	.2727	.55080	.621	-1.1640	1.7095
			RPRO	1.6928*	.55080	.003	.2560	3.1296
			CRT	.0952	.55080	.863	-1.3416	1.5320
			MST	.2104	.55080	.703	-1.2264	1.6472
			CRT2					
			FDPR	3.4539*	.55080	.000	2.0171	4.8907
	8	(J) MTH	FIFO	-3.2451*	.55080	.000	-4.6819	-1.8083
			SPT	-1.9810*	.55080	.000	-3.4178	-.5442
			EDD	-3.1812*	.55080	.000	-4.6179	-1.7444
			RPRO	-1.7611*	.55080	.002	-3.1979	-.3244
			CRT	-3.3587*	.55080	.000	-4.7955	-1.9219
			MST	-3.2435*	.55080	.000	-4.6803	-1.8067
			CRT2	-3.4539*	.55080	.000	-4.8907	-2.0171
			FDPR					

*. The mean difference is significant at the .01 level.

B.6 Multiple comparison of part DPRs with LSD test for WIP (α = 0.01)

Multiple Comparisons

Dependent Variable: WIP
LSD

(I) MTH	(J) MTH	Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
					Lower Bound	Upper Bound
1	FIFO					
	SPT	1.1869	.59120	.046	-.3553	2.7291
	EDD	.0587	.59120	.921	-1.4834	1.6009
	RPRO	1.4127	.59120	.018	-.1295	2.9549
	CRT	-.1134	.59120	.848	-1.6556	1.4288
	MST	-.0008	.59120	.999	-1.5430	1.5414
	CRT2	-.1925	.59120	.745	-1.7347	1.3497
	FDPR	6.2378*	.59120	.000	4.6957	7.7800
2	FIFO	-1.1869	.59120	.046	-2.7291	.3553
	SPT					
	EDD	-1.1281	.59120	.058	-2.6703	.4140
	RPRO	.2258	.59120	.703	-1.3164	1.7680
	CRT	-1.3003	.59120	.029	-2.8424	.2419
	MST	-1.1877	.59120	.046	-2.7298	.3545
	CRT2	-1.3794	.59120	.021	-2.9215	.1628
	FDPR	5.0510*	.59120	.000	3.5088	6.5931
3	FIFO	-.0587	.59120	.921	-1.6009	1.4834
	SPT	1.1281	.59120	.058	-.4140	2.6703
	EDD					
	RPRO	1.3540	.59120	.023	-.1882	2.8961
	CRT	-.1721	.59120	.771	-1.7143	1.3701
	MST	-.0595	.59120	.920	-1.6017	1.4827
	CRT2	-.2512	.59120	.671	-1.7934	1.2909
	FDPR	6.1791*	.59120	.000	4.6369	7.7213
4	FIFO	-1.4127	.59120	.018	-2.9549	.1295
	SPT	-.2258	.59120	.703	-1.7680	1.3164
	EDD	-1.3540	.59120	.023	-2.8961	.1882
	RPRO					
	CRT	-1.5261	.59120	.011	-3.0683	.0161
	MST	-1.4135	.59120	.018	-2.9556	.1287
	CRT2	-1.6052*	.59120	.007	-3.1474	-.0630
	FDPR	4.8251*	.59120	.000	3.2830	6.3673
5	FIFO	.1134	.59120	.848	-1.4288	1.6556
	SPT	1.3003	.59120	.029	-.2419	2.8424
	EDD	.1721	.59120	.771	-1.3701	1.7143
	RPRO	1.5261	.59120	.011	-.0161	3.0683
	CRT					
	MST	.1126	.59120	.849	-1.4296	1.6548
	CRT2	-.0791	.59120	.894	-1.6213	1.4631
	FDPR	6.3512*	.59120	.000	4.8091	7.8934
6	FIFO	.0008	.59120	.999	-1.5414	1.5430
	SPT	1.1877	.59120	.046	-.3545	2.7298
	EDD	.0595	.59120	.920	-1.4827	1.6017
	RPRO	1.4135	.59120	.018	-.1287	2.9556
	CRT	-.1126	.59120	.849	-1.6548	1.4296
	MST					
	CRT2	-.1917	.59120	.746	-1.7339	1.3505
	FDPR	6.2386*	.59120	.000	4.6964	7.7808
7	FIFO	.1925	.59120	.745	-1.3497	1.7347
	SPT	1.3794	.59120	.021	-.1628	2.9215
	EDD	.2512	.59120	.671	-1.2909	1.7934
	RPRO	1.6052*	.59120	.007	.0630	3.1474
	CRT	.0791	.59120	.894	-1.4631	1.6213
	MST	.1917	.59120	.746	-1.3505	1.7339
	CRT2					
	FDPR	6.4303*	.59120	.000	4.8882	7.9725
8	FIFO	-6.2378*	.59120	.000	-7.7800	-4.6957
	SPT	-5.0510*	.59120	.000	-6.5931	-3.5088
	EDD	-6.1791*	.59120	.000	-7.7213	-4.6369
	RPRO	-4.8251*	.59120	.000	-6.3673	-3.2830
	CRT	-6.3512*	.59120	.000	-7.8934	-4.8091
	MST	-6.2386*	.59120	.000	-7.7808	-4.6964
	CRT2	-6.4303*	.59120	.000	-7.9725	-4.8882
	FDPR					

*. The mean difference is significant at the .01 level.

B.7 ANOVA for routing selection rules (α = 0.01)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MT	Between Group	4,657.366	3	1,552.455	17.828	.000
	Within Groups	6,617.945	76	87.078		
	Total	1,275.311	79			
NTJ	Between Group	1,160.153	3	3,720.051	43.365	.000
	Within Groups	6,519.660	76	85.785		
	Total	7,679.813	79			
MFT	Between Group	6,621.024	3	8,873.675	85.750	.000
	Within Groups	7,864.683	76	103.483		
	Total	4,485.707	79			
MQT	Between Group	244.946	3	81.649	21.156	.000
	Within Groups	293.313	76	3.859		
	Total	538.259	79			
WIP	Between Group	1,103.483	3	367.828	84.894	.000
	Within Groups	329.291	76	4.333		
	Total	1,432.775	79			

B.8 DUNCAN Multiple Range Test for MT (Route Selection) (α = 0.05)

MT

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FRT	20	15.7283		
		UTI	20		22.4500	
		SNQ	20		22.4836	
		TWC	20			36.6562
		Sig.		1.000	.991	1.000

Means for groups in homogeneous subsets are displayed.

B.9 DUNCAN Multiple Range Test for %NTJ (Route Selection) (α = 0.05)

NTJ

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	FRT	20	20.0740	
		UTI	20		44.7100
		TWC	20		48.2667
		SNQ	20		48.4252
		Sig.		1.000	.237

Means for groups in homogeneous subsets are displayed.

B.10 DUNCAN Multiple Range Test for MFT (Route Selection) ($\alpha = 0.05$)

MFT

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FRT	20	79.0084		
		UTI	20		111.3200	
		SNQ	20		114.8225	
		TWC	20			128.8315
		Sig.		1.000	.280	1.000

Means for groups in homogeneous subsets are displayed.

B.11 DUNCAN Multiple Range Test for MQT (Route Selection) ($\alpha = 0.05$)

MQT

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FRT	20	5.0216		
		UTI	20		6.4300	
		SNQ	20		7.0231	
		TWC	20			9.8340
		Sig.		1.000	.343	1.000

Means for groups in homogeneous subsets are displayed.

B.12 DUNCAN Multiple Range Test for WI (Route Selection) ($\alpha = 0.05$)

WIP

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FRT	20	12.7414		
		UTI	20		19.6100	
		SNQ	20		20.1998	
		TWC	20			22.7821
		Sig.		1.000	.373	1.000

Means for groups in homogeneous subsets are displayed.

B.13 Multiple comparison of route selection rules with LSD test for MT (α = 0.05)

Multiple Comparisons

Dependent Variable: MT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	SNQ	(J) MTH	SNQ					
			TWC	-14.1726*	2.9509	.0000	-20.0499	-8.2954
			UTI	.0336	2.9509	.9910	-5.8437	5.9108
			FRT	6.7553*	2.9509	.0248	.8781	12.6325
	TWC	(J) MTH	SNQ	14.1726*	2.9509	.0000	8.2954	20.0499
			TWC					
			UTI	14.2062*	2.9509	.0000	8.3290	20.0834
			FRT	20.9279*	2.9509	.0000	15.0507	26.8051
	UTI	(J) MTH	SNQ	-.0336	2.9509	.9910	-5.9108	5.8437
			TWC	-14.2062*	2.9509	.0000	-20.0834	-8.3290
			UTI					
			FRT	6.7217*	2.9509	.0255	.8445	12.5990
	FRT	(J) MTH	SNQ	-6.7553*	2.9509	.0248	-12.6325	-.8781
			TWC	-20.9279*	2.9509	.0000	-26.8051	-15.0507
			UTI	-6.7217*	2.9509	.0255	-12.5990	-.8445
			FRT					

*. The mean difference is significant at the .05 level.

B.14 Multiple comparison of route selection rules with LSD test for %NTJ (α = 0.05)

Multiple Comparisons

Dependent Variable: NTJ
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	SNQ	(J) MTH	SNQ					
			TWC	.1585	2.9289	.9570	-5.6750	5.9919
			UTI	3.7152	2.9289	.2085	-2.1182	9.5486
			FRT	28.3512*	2.9289	.0000	22.5178	34.1846
	TWC	(J) MTH	SNQ	-.1585	2.9289	.9570	-5.9919	5.6750
			TWC					
			UTI	3.5567	2.9289	.2284	-2.2767	9.3902
			FRT	28.1927*	2.9289	.0000	22.3593	34.0262
	UTI	(J) MTH	SNQ	-3.7152	2.9289	.2085	-9.5486	2.1182
			TWC	-3.5567	2.9289	.2284	-9.3902	2.2767
			UTI					
			FRT	24.6360*	2.9289	.0000	18.8026	30.4694
	FRT	(J) MTH	SNQ	-28.3512*	2.9289	.0000	-34.1846	-22.5178
			TWC	-28.1927*	2.9289	.0000	-34.0262	-22.3593
			UTI	-24.6360*	2.9289	.0000	-30.4694	-18.8026
			FRT					

*. The mean difference is significant at the .05 level.

B.15 Multiple comparison of route selection rules with LSD test for MFT (α = 0.05)

Multiple Comparisons

Dependent Variable: MFT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	SNQ	(J) MTH	SNQ					
			TWC	-14.0091*	3.2169	.0000	-20.4160	-7.6021
			UTI	3.5025	3.2169	.2797	-2.9045	9.9094
			FRT	35.8141*	3.2169	.0000	29.4071	42.2210
	TWC	(J) MTH	SNQ	14.0091*	3.2169	.0000	7.6021	20.4160
			TWC					
			UTI	17.5115*	3.2169	.0000	11.1046	23.9185
			FRT	49.8231*	3.2169	.0000	43.4162	56.2301
	UTI	(J) MTH	SNQ	-3.5025	3.2169	.2797	-9.9094	2.9045
			TWC	-17.5115*	3.2169	.0000	-23.9185	-11.1046
			UTI					
			FRT	32.3116*	3.2169	.0000	25.9046	38.7185
	FRT	(J) MTH	SNQ	-35.8141*	3.2169	.0000	-42.2210	-29.4071
			TWC	-49.8231*	3.2169	.0000	-56.2301	-43.4162
			UTI	-32.3116*	3.2169	.0000	-38.7185	-25.9046
			FRT					

*. The mean difference is significant at the .05 level.

B.16 Multiple comparison of route selection rules with LSD test for MQT (α = 0.05)

Multiple Comparisons

Dependent Variable: MQT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	SNQ	(J) MTH	SNQ					
			TWC	-2.8109*	.6212	.0000	-4.0482	-1.5736
			UTI	.5931	.6212	.3427	-.6442	1.8304
			FRT	2.0015*	.6212	.0019	.7642	3.2388
	TWC	(J) MTH	SNQ	2.8109*	.6212	.0000	1.5736	4.0482
			TWC					
			UTI	3.4040*	.6212	.0000	2.1667	4.6413
			FRT	4.8124*	.6212	.0000	3.5751	6.0497
	UTI	(J) MTH	SNQ	-.5931	.6212	.3427	-1.8304	.6442
			TWC	-3.4040*	.6212	.0000	-4.6413	-2.1667
			UTI					
			FRT	1.4084*	.6212	.0262	.1711	2.6457
	FRT	(J) MTH	SNQ	-2.0015*	.6212	.0019	-3.2388	-.7642
			TWC	-4.8124*	.6212	.0000	-6.0497	-3.5751
			UTI	-1.4084*	.6212	.0262	-2.6457	-.1711
			FRT					

*. The mean difference is significant at the .05 level.

B.17 Multiple comparison of route selection rules with LSD test for WIP (α = 0.05)

Multiple Comparisons

Dependent Variable: WIP

LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	SNQ	(J) MTH	SNQ					
			TWC	-2.5822*	.6582	.0002	-3.8932	-1.2713
			UTI	.5898	.6582	.3731	-.7212	1.9008
			FRT	7.4584*	.6582	.0000	6.1474	8.7694
	TWC	(J) MTH	SNQ	2.5822*	.6582	.0002	1.2713	3.8932
			TWC					
			UTI	3.1721*	.6582	.0000	1.8611	4.4831
			FRT	10.0406*	.6582	.0000	8.7296	11.3516
	UTI	(J) MTH	SNQ	-.5898	.6582	.3731	-1.9008	.7212
			TWC	-3.1721*	.6582	.0000	-4.4831	-1.8611
			UTI					
			FRT	6.8686*	.6582	.0000	5.5576	8.1796
	FRT	(J) MTH	SNQ	-7.4584*	.6582	.0000	-8.7694	-6.1474
			TWC	-10.0406*	.6582	.0000	-11.3516	-8.7296
			UTI	-6.8686*	.6582	.0000	-8.1796	-5.5576
			FRT					

*. The mean difference is significant at the .05 level.

B.18 ANOVA for “where” rules (α = 0.05)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MT	Between Groups	1,409.374	4	352.343	5.787	.000
	Within Groups	5,783.613	95	60.880		
	Total	7,192.987	99			
NTJ	Between Groups	4,374.738	4	1,093.685	11.618	.000
	Within Groups	8,942.920	95	94.136		
	Total	13,317.659	99			
MFT	Between Groups	8,278.493	4	2,069.623	37.922	.000
	Within Groups	5,184.634	95	54.575		
	Total	13,463.127	99			
MQT	Between Groups	75.852	4	18.963	7.971	.000
	Within Groups	226.013	95	2.379		
	Total	301.865	99			
WIP	Between Groups	279.030	4	69.757	29.102	.000
	Within Groups	227.714	95	2.397		
	Total	506.744	99			

B.19 DUNCAN Multiple Range Test for MT ("Where" Rules) (α = 0.05)

MT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	FWHR	20	17.4308	
		STWC	20		22.4500
		SDD	20		26.8322
		LNQ	20		26.9042
		LWT	20		26.9177
		Sig.		1.000	.102

Means for groups in homogeneous subsets are displayed.

B.20 DUNCAN Multiple Range Test for %NTJ ("Where" Rules) (α = 0.05)

NTJ

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	FWHR	20	29.9532	
		STWC	20		44.7100
		SDD	20		46.7464
		LNQ	20		46.9648
		LWT	20		46.9830
		Sig.		1.000	.507

Means for groups in homogeneous subsets are displayed.

B.21 DUNCAN Multiple Range Test for MFT ("Where" Rules) (α = 0.05)

MFT

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FWHR	20	93.6701		
		STWC	20		111.3200	
		SDD	20			117.0441
		LWT	20			117.2131
		LNQ	20			117.2288
		Sig.		1.000	1.000	.941

Means for groups in homogeneous subsets are displayed.

B.22 DUNCAN Multiple Range Test for MQT (“Where” Rules) (α = 0.05)

MQT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	FWHR	20	5.0974	
		STWC	20		6.4300
		SDD	20		7.2975
		LWT	20		7.3291
		LNQ	20		7.3315
		Sig.		1.000	.094

Means for groups in homogeneous subsets are displayed.

B.23 DUNCAN Multiple Range Test for WIP (“Where” Rules) (α = 0.05)

WIP

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	FWHR	20	15.1113	
		SDD	20		19.1252
		LWT	20		19.1544
		LNQ	20		19.1629
		STWC	20		19.6100
		Sig.		1.000	.375

Means for groups in homogeneous subsets are displayed.

B.24 Multiple comparison of “where” rules with LSD test for MT (α = 0.05)

Multiple Comparisons

Dependent Variable: MT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	LNQ	(J) MTH	LNQ					
			LWT	-.0135	2.4674	.9957	-4.9119	4.8849
			STWC	4.4542	2.4674	.0742	-.4442	9.3526
			SDD	.0720	2.4674	.9768	-4.8264	4.9704
			FWHR	9.4734*	2.4674	.0002	4.5750	14.3718
	LWT	(J) MTH	LNQ	.0135	2.4674	.9957	-4.8849	4.9119
			LWT					
			STWC	4.4677	2.4674	.0734	-.4307	9.3660
			SDD	.0854	2.4674	.9724	-4.8129	4.9838
			FWHR	9.4869*	2.4674	.0002	4.5885	14.3853
	STWC	(J) MTH	LNQ	-4.4542	2.4674	.0742	-9.3526	.4442
			LWT	-4.4677	2.4674	.0734	-9.3660	.4307
			STWC					
			SDD	-4.3822	2.4674	.0789	-9.2806	.5162
			FWHR	5.0192*	2.4674	.0447	.1209	9.9176
	SDD	(J) MTH	LNQ	-.0720	2.4674	.9768	-4.9704	4.8264
			LWT	-.0854	2.4674	.9724	-4.9838	4.8129
			STWC	4.3822	2.4674	.0789	-.5162	9.2806
			SDD					
			FWHR	9.4015*	2.4674	.0002	4.5031	14.2998
	FWHR	(J) MTH	LNQ	-9.4734*	2.4674	.0002	-14.3718	-4.5750
			LWT	-9.4869*	2.4674	.0002	-14.3853	-4.5885
			STWC	-5.0192*	2.4674	.0447	-9.9176	-.1209
			SDD	-9.4015*	2.4674	.0002	-14.2998	-4.5031
			FWHR					

*. The mean difference is significant at the .05 level.

B.25 Multiple comparison of "where" rules with LSD test for %NTJ (α = 0.05)

Multiple Comparisons

Dependent Variable: NTJ
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	LNQ	(J) MTH	LNQ					
			LWT	-.0182	3.06816	.995	-6.1093	6.0728
			STWC	2.2548	3.06816	.464	-3.8363	8.3458
			SDD	.2183	3.06816	.943	-5.8727	6.3094
			FWHR	17.0116*	3.06816	.000	10.9205	23.1026
	LWT	(J) MTH	LNQ	.0182	3.06816	.995	-6.0728	6.1093
			LWT					
			STWC	2.2730	3.06816	.461	-3.8181	8.3641
			SDD	.2366	3.06816	.939	-5.8545	6.3276
			FWHR	17.0298*	3.06816	.000	10.9387	23.1209
	STWC	(J) MTH	LNQ	-2.2548	3.06816	.464	-8.3458	3.8363
			LWT	-2.2730	3.06816	.461	-8.3641	3.8181
			STWC					
			SDD	-2.0364	3.06816	.508	-8.1275	4.0546
			FWHR	14.7568*	3.06816	.000	8.6657	20.8479
	SDD	(J) MTH	LNQ	-.2183	3.06816	.943	-6.3094	5.8727
			LWT	-.2366	3.06816	.939	-6.3276	5.8545
			STWC	2.0364	3.06816	.508	-4.0546	8.1275
			SDD					
			FWHR	16.7932*	3.06816	.000	10.7022	22.8843
	FWHR	(J) MTH	LNQ	-17.0116*	3.06816	.000	-23.1026	-10.9205
			LWT	-17.0298*	3.06816	.000	-23.1209	-10.9387
			STWC	-14.7568*	3.06816	.000	-20.8479	-8.6657
			SDD	-16.7932*	3.06816	.000	-22.8843	-10.7022
			FWHR					

*. The mean difference is significant at the .05 level.

B.26 Multiple comparison of "where" rules with LSD test for MFT (α = 0.05)

Multiple Comparisons

Dependent Variable: MFT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	LNQ	(J) MTH	LNQ					
			LWT	.0157	2.33613	.995	-4.6221	4.6535
			STWC	5.9088*	2.33613	.013	1.2710	10.5466
			SDD	.1847	2.33613	.937	-4.4531	4.8225
			FWHR	23.5587*	2.33613	.000	18.9209	28.1965
	LWT	(J) MTH	LNQ	-.0157	2.33613	.995	-4.6535	4.6221
			LWT					
			STWC	5.8931*	2.33613	.013	1.2553	10.5309
			SDD	.1690	2.33613	.942	-4.4688	4.8068
			FWHR	23.5430*	2.33613	.000	18.9052	28.1808
	STWC	(J) MTH	LNQ	-5.9088*	2.33613	.013	-10.5466	-1.2710
			LWT	-5.8931*	2.33613	.013	-10.5309	-1.2553
			STWC					
			SDD	-5.7241*	2.33613	.016	-10.3619	-1.0863
			FWHR	17.6499*	2.33613	.000	13.0121	22.2877
	SDD	(J) MTH	LNQ	-.1847	2.33613	.937	-4.8225	4.4531
			LWT	-.1690	2.33613	.942	-4.8068	4.4688
			STWC	5.7241*	2.33613	.016	1.0863	10.3619
			SDD					
			FWHR	23.3740*	2.33613	.000	18.7362	28.0118
	FWHR	(J) MTH	LNQ	-23.5587*	2.33613	.000	-28.1965	-18.9209
			LWT	-23.5430*	2.33613	.000	-28.1808	-18.9052
			STWC	-17.6499*	2.33613	.000	-22.2877	-13.0121
			SDD	-23.3740*	2.33613	.000	-28.0118	-18.7362
			FWHR					

*. The mean difference is significant at the .05 level.

B.27 Multiple comparison of "where" rules with LSD test for MQT (α = 0.05)

Multiple Comparisons

Dependent Variable: MQT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	LNQ	(J) MTH	LNQ					
			LWT	.0024	.48776	.996	-.9660	.9707
			STWC	.9015	.48776	.068	-.0668	1.8698
			SDD	.0340	.48776	.945	-.9343	1.0023
			FWHR	2.2340*	.48776	.000	1.2657	3.2024
	LWT	(J) MTH	LNQ	-.0024	.48776	.996	-.9707	.9660
			LWT					
			STWC	.8991	.48776	.068	-.0692	1.8674
			SDD	.0316	.48776	.948	-.9367	.9999
			FWHR	2.2317*	.48776	.000	1.2633	3.2000
	STWC	(J) MTH	LNQ	-.9015	.48776	.068	-1.8698	.0668
			LWT	-.8991	.48776	.068	-1.8674	.0692
			STWC					
			SDD	-.8675	.48776	.079	-1.8358	.1008
			FWHR	1.3326*	.48776	.008	.3642	2.3009
	SDD	(J) MTH	LNQ	-.0340	.48776	.945	-1.0023	.9343
			LWT	-.0316	.48776	.948	-.9999	.9367
			STWC	.8675	.48776	.079	-.1008	1.8358
			SDD					
			FWHR	2.2000*	.48776	.000	1.2317	3.1684
	FWHR	(J) MTH	LNQ	-2.2340*	.48776	.000	-3.2024	-1.2657
			LWT	-2.2317*	.48776	.000	-3.2000	-1.2633
			STWC	-1.3326*	.48776	.008	-2.3009	-.3642
			SDD	-2.2000*	.48776	.000	-3.1684	-1.2317
			FWHR					

*. The mean difference is significant at the .05 level.

B.28 Multiple comparison of "where" rules with LSD test for WIP (α = 0.05)

Multiple Comparisons

Dependent Variable: WIP
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	LNQ	(J) MTH	LNQ					
			LWT	.0086	.48959	.986	-.9634	.9805
			STWC	-.4471	.48959	.363	-1.4190	.5249
			SDD	.0377	.48959	.939	-.9342	1.0097
			FWHR	4.0517*	.48959	.000	3.0797	5.0236
	LWT	(J) MTH	LNQ	-.0086	.48959	.986	-.9805	.9634
			LWT					
			STWC	-.4556	.48959	.354	-1.4276	.5163
			SDD	.0292	.48959	.953	-.9428	1.0012
			FWHR	4.0431*	.48959	.000	3.0711	5.0151
	STWC	(J) MTH	LNQ	.4471	.48959	.363	-.5249	1.4190
			LWT	.4556	.48959	.354	-.5163	1.4276
			STWC					
			SDD	.4848	.48959	.325	-.4871	1.4568
			FWHR	4.4987*	.48959	.000	3.5268	5.4707
	SDD	(J) MTH	LNQ	-.0377	.48959	.939	-1.0097	.9342
			LWT	-.0292	.48959	.953	-1.0012	.9428
			STWC	-.4848	.48959	.325	-1.4568	.4871
			SDD					
			FWHR	4.0139*	.48959	.000	3.0420	4.9859
	FWHR	(J) MTH	LNQ	-4.0517*	.48959	.000	-5.0236	-3.0797
			LWT	-4.0431*	.48959	.000	-5.0151	-3.0711
			STWC	-4.4987*	.48959	.000	-5.4707	-3.5268
			SDD	-4.0139*	.48959	.000	-4.9859	-3.0420
			FWHR					

*. The mean difference is significant at the .05 level.

B.29 ANOVA for “when” rules (α = 0.01)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MT	Between Groups	18,977.752	2	9,488.876	119.550	.000
	Within Groups	4,524.194	57	79.372		
	Total	23,501.946	59			
NTJ	Between Groups	2,307.071	2	1,153.536	19.193	.000
	Within Groups	3,425.816	57	60.102		
	Total	5,732.888	59			
MFT	Between Groups	19,213.462	2	9,606.731	109.171	.000
	Within Groups	5,015.824	57	87.997		
	Total	24,229.286	59			
MQT	Between Groups	1,005.531	2	502.765	135.934	.000
	Within Groups	210.820	57	3.699		
	Total	1,216.351	59			
WIP	Between Groups	495.217	2	247.608	75.391	.000
	Within Groups	187.207	57	3.284		
	Total	682.424	59			

B.30 DUNCAN Multiple Range Test for MT (“When” Rules) (α = 0.05)

MT

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FWHN	20	16.7768		
		DC	20		22.4500	
		C	20			57.0192
		Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

B.31 DUNCAN Multiple Range Test for %NTJ (“When” Rules) (α = 0.05)

NTJ

			N	Subset for alpha = .05	
				1	2
Duncan[a]	MTH	FWHN	20	29.9453	
		C	20	34.2401	
		DC	20		44.7100
		Sig.		.085	1.000

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 20,000.

B.32 DUNCAN Multiple Range Test for MFT ("When" Rules) (α = 0.05)

MFT

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FWHN	20	93.8075		
		DC	20		111.3200	
		C	20			137.3631
		Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

B.33 DUNCAN Multiple Range Test for MQT ("When" Rules) (α = 0.05)

MQT

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FWHN	20	5.1244		
		DC	20		6.4300	
		C	20			14.3875
		Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

B.34 DUNCAN Multiple Range Test for WIP ("When" Rules) (α = 0.05)

WIP

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	FWHN	20	15.1355		
		DC	20		19.6100	
		C	20			22.0766
		Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

B.35 Multiple comparison of "when" rules with LSD test for MT (α = 0.05)

Multiple Comparisons

Dependent Variable: MT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	C	(J) MTH	C					
			DC	34.5692*	2.81730	.000	28.9276	40.2107
			FWHN	40.2424*	2.81730	.000	34.6008	45.8839
	DC	(J) MTH	C	-34.5692*	2.81730	.000	-40.2107	-28.9276
			DC					
			FWHN	5.6732*	2.81730	.049	.0316	11.3147
	FWHN	(J) MTH	C	-40.2424*	2.81730	.000	-45.8839	-34.6008
			DC	-5.6732*	2.81730	.049	-11.3147	-.0316
			FWHN					

*. The mean difference is significant at the .05 level.

B.36 Multiple comparison of "when" rules with LSD test for %NTJ (α = 0.05)

Multiple Comparisons

Dependent Variable: NTJ
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
(I) MTH	C	(J) MTH	C					
			DC	-10.4699*	2.45157	.000	-15.3791	-5.5607
			FWHN	4.2948	2.45157	.085	-.6144	9.2039
	DC	(J) MTH	C	10.4699*	2.45157	.000	5.5607	15.3791
			DC					
			FWHN	14.7647*	2.45157	.000	9.8555	19.6739
	FWHN	(J) MTH	C	-4.2948	2.45157	.085	-9.2039	.6144
			DC	-14.7647*	2.45157	.000	-19.6739	-9.8555
			FWHN					

*. The mean difference is significant at the .05 level.

B.37 Multiple comparison of "when" rules with LSD test for MFT (α = 0.05)

Multiple Comparisons

Dependent Variable: MFT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
(I) MTH	C	(J) MTH	C					
			DC	26.0431*	2.96643	.000	20.1029	31.9833
			FWHN	43.5556*	2.96643	.000	37.6154	49.4958
	DC	(J) MTH	C	-26.0431*	2.96643	.000	-31.9833	-20.1029
			DC					
			FWHN	17.5125*	2.96643	.000	11.5723	23.4526
	FWHN	(J) MTH	C	-43.5556*	2.96643	.000	-49.4958	-37.6154
			DC	-17.5125*	2.96643	.000	-23.4526	-11.5723
			FWHN					

*. The mean difference is significant at the .05 level.

B.38 Multiple comparison of "when" rules with LSD test for MQT (α = 0.05)

Multiple Comparisons

Dependent Variable: MQT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
(I) MTH	C	(J) MTH	C					
			DC	7.9575*	.60816	.000	6.7396	9.1753
			FWHN	9.2630*	.60816	.000	8.0452	10.4809
	DC	(J) MTH	C	-7.9575*	.60816	.000	-9.1753	-6.7396
			DC					
			FWHN	1.3056*	.60816	.036	.0877	2.5234
	FWHN	(J) MTH	C	-9.2630*	.60816	.000	-10.4809	-8.0452
			DC	-1.3056*	.60816	.036	-2.5234	-.0877
			FWHN					

*. The mean difference is significant at the .05 level.

B.39 Multiple comparison of "when" rules with LSD test for WIP (α = 0.05)

Multiple Comparisons

Dependent Variable: WIP
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	C	(J) MTH	C					
			DC	2.4666*	.57309	.000	1.3190	3.6142
			FWHN	6.9410*	.57309	.000	5.7934	8.0886
	DC	(J) MTH	C	-2.4666*	.57309	.000	-3.6142	-1.3190
			DC					
			FWHN	4.4745*	.57309	.000	3.3269	5.6221
	FWHN	(J) MTH	C	-6.9410*	.57309	.000	-8.0886	-5.7934
			DC	-4.4745*	.57309	.000	-5.6221	-3.3269
			FWHN					

*. The mean difference is significant at the .05 level.

B.40 ANOVA for proposed three approaches for VR=L (α = 0.05)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MT	Between Groups	3,196.328	2	1,598.164	2.668	.078
	Within Groups	34,143.435	57	599.008		
	Total	37,339.764	59			
NTJ	Between Groups	1,722.878	2	861.439	21.328	.000
	Within Groups	2,302.249	57	40.390		
	Total	4,025.127	59			
MFT	Between Groups	7,164.163	2	3,582.081	5.888	.005
	Within Groups	34,675.860	57	608.348		
	Total	41,840.023	59			
MQT	Between Groups	129.823	2	64.912	2.596	.083
	Within Groups	1,425.205	57	25.004		
	Total	1,555.028	59			
WIP	Between Groups	309.503	2	154.751	5.659	.006
	Within Groups	1,558.626	57	27.344		
	Total	1,868.129	59			

B.41 DUNCAN Multiple Range Test for MT for VR=L (proposed approaches) (α = 0.05)

MT

			N	Subset for alpha = .05 1	Subset for alpha = .05 2
Duncan	MTH	MCDRC-FUZZY	20	36.7320	
		MCDRC-PRO	20	49.3584	49.3584
		MCDRC-FIS	20		54.0067
		Sig.		.108	.550

Means for groups in homogeneous subsets are displayed.

B.42 DUNCAN Multiple Range Test for % NTJ for VR=L (proposed approaches) (α = 0.05)

NTJ

			N	Subset for alpha = .05		
				1	2	3
Duncan	MTH	MCDRC-FUZZY	20	44.5142		
		MCDRC-PRO	20		52.8869	
		MCDRC-FIS	20			57.4549
		Sig.		1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

B.43 DUNCAN Multiple Range Test for MFT for VR=L (proposed approaches) (α = 0.05)

MFT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	101.0385	
		MCDRC-PRO	20		120.5446
		MCDRC-FIS	20		126.6643
		Sig.		1.000	.436

Means for groups in homogeneous subsets are displayed.

B.44 DUNCAN Multiple Range Test for MQT for VR=L (proposed approaches) (α = 0.05)

MQT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	9.5212	
		MCDRC-PRO	20	11.7355	11.7355
		MCDRC-FIS	20		13.0899
		Sig.		.167	.395

Means for groups in homogeneous subsets are displayed.

B.45 DUNCAN Multiple Range Test for WIP for VR=L (proposed approaches) (α = 0.05)

WIP

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	21.3250	
		MCDRC-PRO	20		25.7065
		MCDRC-FIS	20		26.4847
		Sig.		1.000	.640

Means for groups in homogeneous subsets are displayed.

B.46 Multiple comparison of proposed approaches with LSD test for MT for VR=L (α = 0.05)

Multiple Comparisons

Dependent Variable: MT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	4.6482	7.73956	.550	-10.8500	20.1464
			MCDRC-FUZZY	17.2747*	7.73956	.030	1.7765	32.7729
	MCDRC-PRO	(J) MTH	MCDRC-FIS	-4.6482	7.73956	.550	-20.1464	10.8500
			MCDRC-PRO					
			MCDRC-FUZZY	12.6265	7.73956	.108	-2.8717	28.1247
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-17.2747*	7.73956	.030	-32.7729	-1.7765
			MCDRC-PRO	-12.6265	7.73956	.108	-28.1247	2.8717
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.47 Multiple comparison of proposed approaches with LSD test for %NTJ for VR=L (α = 0.05)

Multiple Comparisons

Dependent Variable: NTJ
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	4.5681*	2.00973	.027	.5437	8.5925
			MCDRC-FUZZY	12.9407*	2.00973	.000	8.9163	16.9652
	MCDRC-PRO	(J) MTH	MCDRC-FIS	-4.5681*	2.00973	.027	-8.5925	-.5437
			MCDRC-PRO					
			MCDRC-FUZZY	8.3727*	2.00973	.000	4.3482	12.3971
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-12.9407*	2.00973	.000	-16.9652	-8.9163
			MCDRC-PRO	-8.3727*	2.00973	.000	-12.3971	-4.3482
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.48 Multiple comparison of proposed approaches with LSD test for MFT for VR=L (α = 0.05)

Multiple Comparisons

Dependent Variable: MFT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	6.1198	7.79967	.436	-9.4988	21.7383
			MCDRC-FUZZY	25.6259*	7.79967	.002	10.0073	41.2444
	MCDRC-PRO	(J) MTH	MCDRC-FIS	-6.1198	7.79967	.436	-21.7383	9.4988
			MCDRC-PRO					
			MCDRC-FUZZY	19.5061*	7.79967	.015	3.8875	35.1247
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-25.6259*	7.79967	.002	-41.2444	-10.0073
			MCDRC-PRO	-19.5061*	7.79967	.015	-35.1247	-3.8875
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.49 Multiple comparison of proposed approaches with LSD test for MQT for VR=L (α = 0.05)

Multiple Comparisons

Dependent Variable: MQT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	1.3544	1.58125	.395	-1.8120	4.5208
			MCDRC-FUZZY	3.5687*	1.58125	.028	.4023	6.7351
	MCDRC-PRO	(J) MTH	MCDRC-FIS	-1.3544	1.58125	.395	-4.5208	1.8120
			MCDRC-PRO					
			MCDRC-FUZZY	2.2143	1.58125	.167	-.9521	5.3807
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-3.5687*	1.58125	.028	-6.7351	-.4023
			MCDRC-PRO	-2.2143	1.58125	.167	-5.3807	.9521
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.50 Multiple comparison of proposed approaches with LSD test for WIP for VR=L (α = 0.05)

Multiple Comparisons

Dependent Variable: WIP
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	.7782	1.65361	.640	-2.5331	4.0895
			MCDRC-FUZZY	5.1597*	1.65361	.003	1.8484	8.4710
	MCDRC-PRO	(J) MTH	MCDRC-FIS	-.7782	1.65361	.640	-4.0895	2.5331
			MCDRC-PRO					
			MCDRC-FUZZY	4.3815*	1.65361	.010	1.0702	7.6928
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-5.1597*	1.65361	.003	-8.4710	-1.8484
			MCDRC-PRO	-4.3815*	1.65361	.010	-7.6928	-1.0702
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.51 ANOVA for proposed three approaches for VR=M (α = 0.05)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MT	Between Groups	612.793	2	306.397	3.931	.025
	Within Groups	4,442.979	57	77.947		
	Total	5,055.773	59			
NTJ	Between Groups	595.220	2	297.610	6.632	.003
	Within Groups	2,558.034	57	44.878		
	Total	3,153.253	59			
MFT	Between Groups	4,236.021	2	2,118.011	27.089	.000
	Within Groups	4,456.729	57	78.188		
	Total	8,692.751	59			
MQT	Between Groups	34.354	2	17.177	5.139	.009
	Within Groups	190.525	57	3.343		
	Total	224.879	59			
WIP	Between Groups	110.558	2	55.279	18.970	.000
	Within Groups	166.098	57	2.914		
	Total	276.656	59			

B.52 DUNCAN Multiple Range Test for MT for VR=M (proposed approaches) (α = 0.05)

MT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	10.8489	
		MCDRC-FIS	20		17.1056
		MCDRC-PRO	20		18.0515
		Sig.		1.000	.736

Means for groups in homogeneous subsets are displayed.

B.53 DUNCAN Multiple Range Test for %NTJ for VR=M (proposed approaches) (α = 0.05)

NTJ

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	24.5038	
		MCDRC-PRO	20		30.9317
		MCDRC-FIS	20		31.4127
		Sig.		1.000	.821

Means for groups in homogeneous subsets are displayed.

B.54 DUNCAN Multiple Range Test for MFT for VR=M (proposed approaches) (α = 0.05)

MFT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	78.2430	
		MCDRC-FIS	20		95.7527
		MCDRC-PRO	20		96.3658
		Sig.		1.000	.827

Means for groups in homogeneous subsets are displayed.

B.55 DUNCAN Multiple Range Test for MQT for VR=M (proposed approaches) (α = 0.05)

MQT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	4.0304	
		MCDRC-FIS	20		5.6068
		MCDRC-PRO	20		5.6629
		Sig.		1.000	.923

Means for groups in homogeneous subsets are displayed.

B.56 DUNCAN Multiple Range Test for WIP for VR=M (proposed approaches) (α = 0.05)

WIP

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	12.6397	
		MCDRC-FIS	20		15.4677
		MCDRC-PRO	20		15.5683
		Sig.		1.000	.853

Means for groups in homogeneous subsets are displayed.

B.57 Multiple comparison of proposed approaches with LSD test for MT for VR=M (α = 0.05)

Multiple Comparisons

Dependent Variable: MT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-.9459	2.79190	.736	-6.5366	4.6447
			MCDRC-FUZZY	6.2567*	2.79190	.029	.6660	11.8474
	MCDRC-PRO	(J) MTH	MCDRC-FIS	.9459	2.79190	.736	-4.6447	6.5366
			MCDRC-PRO					
			MCDRC-FUZZY	7.2026*	2.79190	.012	1.6120	12.7933
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-6.2567*	2.79190	.029	-11.8474	-.6660
			MCDRC-PRO	-7.2026*	2.79190	.012	-12.7933	-1.6120
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.58 Multiple comparison of proposed approaches with LSD test for %NTJ for VR=M (α = 0.05)

Multiple Comparisons

Dependent Variable: NTJ
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	.4810	2.11844	.821	-3.7611	4.7231
			MCDRC-FUZZY	6.9089*	2.11844	.002	2.6668	11.1510
	MCDRC-PRO	(J) MTH	MCDRC-FIS	-.4810	2.11844	.821	-4.7231	3.7611
			MCDRC-PRO					
			MCDRC-FUZZY	6.4279*	2.11844	.004	2.1858	10.6700
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-6.9089*	2.11844	.002	-11.1510	-2.6668
			MCDRC-PRO	-6.4279*	2.11844	.004	-10.6700	-2.1858
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.59 Multiple comparison of proposed approaches with LSD test for MFT for VR=M (α = 0.05)

Multiple Comparisons

Dependent Variable: MFT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-.6130	2.79622	.827	-6.2123	4.9863
			MCDRC-FUZZY	17.5098*	2.79622	.000	11.9104	23.1091
	MCDRC-PRO	(J) MTH	MCDRC-FIS	.6130	2.79622	.827	-4.9863	6.2123
			MCDRC-PRO					
			MCDRC-FUZZY	18.1228*	2.79622	.000	12.5235	23.7221
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-17.5098*	2.79622	.000	-23.1091	-11.9104
			MCDRC-PRO	-18.1228*	2.79622	.000	-23.7221	-12.5235
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.60 Multiple comparison of proposed approaches with LSD test for MQT for VR=M (α = 0.05)

Multiple Comparisons

Dependent Variable: MQT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-.0561	.57815	.923	-1.2138	1.1016
			MCDRC-FUZZY	1.5764*	.57815	.008	.4186	2.7341
	MCDRC-PRO	(J) MTH	MCDRC-FIS	.0561	.57815	.923	-1.1016	1.2138
			MCDRC-PRO					
			MCDRC-FUZZY	1.6325*	.57815	.007	.4748	2.7902
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-1.5764*	.57815	.008	-2.7341	-.4186
			MCDRC-PRO	-1.6325*	.57815	.007	-2.7902	-.4748
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.61 Multiple comparison of proposed approaches with LSD test for WIP for VR=M (α = 0.05)

Multiple Comparisons

Dependent Variable: WIP
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-.1006	.53981	.853	-1.1815	.9804
			MCDRC-FUZZY	2.8280*	.53981	.000	1.7470	3.9089
	MCDRC-PRO	(J) MTH	MCDRC-FIS	.1006	.53981	.853	-.9804	1.1815
			MCDRC-PRO					
			MCDRC-FUZZY	2.9285*	.53981	.000	1.8476	4.0095
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-2.8280*	.53981	.000	-3.9089	-1.7470
			MCDRC-PRO	-2.9285*	.53981	.000	-4.0095	-1.8476
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.62 ANOVA for proposed three approaches for VR=H (α = 0.05)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MT	Between Groups	5,499.927	2	2,749.963	4.548	.015
	Within Groups	34,465.481	57	604.658		
	Total	39,965.408	59			
NTJ	Between Groups	2,843.211	2	1,421.606	6.902	.002
	Within Groups	11,740.324	57	205.971		
	Total	14,583.535	59			
MFT	Between Groups	10,195.796	2	5,097.898	9.941	.000
	Within Groups	29,229.076	57	512.791		
	Total	39,424.872	59			
MQT	Between Groups	142.608	2	71.304	3.320	.043
	Within Groups	1,224.292	57	21.479		
	Total	1,366.901	59			
WIP	Between Groups	280.192	2	140.096	8.164	.001
	Within Groups	978.075	57	17.159		
	Total	1,258.267	59			

B.63 DUNCAN Multiple Range Test for MT for VR=H (proposed approaches) (α = 0.05)

MT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	39.3006	
		MCDRC-FIS	20		57.6162
		MCDRC-PRO	20		61.1430
		Sig.		1.000	.652

Means for groups in homogeneous subsets are displayed.

B.64 DUNCAN Multiple Range Test for %NTJ for VR=H (proposed approaches) (α = 0.05)

NTJ

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	51.4090	
		MCDRC-PRO	20		65.7446
		MCDRC-FIS	20		66.2649
		Sig.		1.000	.909

Means for groups in homogeneous subsets are displayed.

B.65 DUNCAN Multiple Range Test for MFT for VR=H (proposed approaches) (α = 0.05)

MFT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	87.8019	
		MCDRC-FIS	20		113.5574
		MCDRC-PRO	20		117.0251
		Sig.		1.000	.630

Means for groups in homogeneous subsets are displayed.

B.66 DUNCAN Multiple Range Test for MQT for VR=H (proposed approaches) (α = 0.05)

MQT

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	6.3531	
		MCDRC-FIS	20	9.2196	9.2196
		MCDRC-PRO	20		9.9154
		Sig.		.055	.637

Means for groups in homogeneous subsets are displayed.

B.67 DUNCAN Multiple Range Test for WIP for VR=H (proposed approaches) (α = 0.05)

WIP

			N	Subset for alpha = .05	
				1	2
Duncan	MTH	MCDRC-FUZZY	20	14.7431	
		MCDRC-FIS	20		19.0260
		MCDRC-PRO	20		19.5785
		Sig.		1.000	.675

Means for groups in homogeneous subsets are displayed.

B.68 Multiple comparison of proposed approaches with LSD test for MT for VR=H ($\alpha = 0.05$)

Multiple Comparisons

Dependent Variable: MT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-3.5268	7.77597	.652	-19.0979	12.0443
			MCDRC-FUZZY	18.3156*	7.77597	.022	2.7445	33.8867
	MCDRC-PRO	(J) MTH	MCDRC-FIS	3.5268	7.77597	.652	-12.0443	19.0979
			MCDRC-PRO					
			MCDRC-FUZZY	21.8424*	7.77597	.007	6.2713	37.4135
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-18.3156*	7.77597	.022	-33.8867	-2.7445
			MCDRC-PRO	-21.8424*	7.77597	.007	-37.4135	-6.2713
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.69 Multiple comparison of proposed approaches with LSD test for %NTJ for VR=H ($\alpha = 0.05$)

Multiple Comparisons

Dependent Variable: NTJ
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	.5202	4.53840	.909	-8.5677	9.6082
			MCDRC-FUZZY	14.8559*	4.53840	.002	5.7680	23.9439
	MCDRC-PRO	(J) MTH	MCDRC-FIS	-.5202	4.53840	.909	-9.6082	8.5677
			MCDRC-PRO					
			MCDRC-FUZZY	14.3357*	4.53840	.003	5.2477	23.4237
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-14.8559*	4.53840	.002	-23.9439	-5.7680
			MCDRC-PRO	-14.3357*	4.53840	.003	-23.4237	-5.2477
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.70 Multiple comparison of proposed approaches with LSD test for MFT for VR=H ($\alpha = 0.05$)

Multiple Comparisons

Dependent Variable: MFT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-3.4677	7.16094	.630	-17.8073	10.8718
			MCDRC-FUZZY	25.7555*	7.16094	.001	11.4160	40.0950
	MCDRC-PRO	(J) MTH	MCDRC-FIS	3.4677	7.16094	.630	-10.8718	17.8073
			MCDRC-PRO					
			MCDRC-FUZZY	29.2232*	7.16094	.000	14.8837	43.5628
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-25.7555*	7.16094	.001	-40.0950	-11.4160
			MCDRC-PRO	-29.2232*	7.16094	.000	-43.5628	-14.8837
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.71 Multiple comparison of proposed approaches with LSD test for MQT for VR=H ($\alpha = 0.05$)

Multiple Comparisons

Dependent Variable: MQT
LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-.6958	1.46557	.637	-3.6306	2.2389
			MCDRC-FUZZY	2.8665	1.46557	.055	-.0683	5.8012
	MCDRC-PRO	(J) MTH	MCDRC-FIS	.6958	1.46557	.637	-2.2389	3.6306
			MCDRC-PRO					
			MCDRC-FUZZY	3.5623*	1.46557	.018	.6276	6.4971
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-2.8665	1.46557	.055	-5.8012	.0683
			MCDRC-PRO	-3.5623*	1.46557	.018	-6.4971	-.6276
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.

B.72 Multiple comparison of proposed approaches with LSD test for WIP for VR=H ($\alpha = 0.05$)

Multiple Comparisons

Dependent Variable: WIP

LSD

				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
(I) MTH	MCDRC-FIS	(J) MTH	MCDRC-FIS					
			MCDRC-PRO	-.5525	1.30993	.675	-3.1756	2.0706
			MCDRC-FUZZY	4.2828*	1.30993	.002	1.6597	6.9059
	MCDRC-PRO	(J) MTH	MCDRC-FIS	.5525	1.30993	.675	-2.0706	3.1756
			MCDRC-PRO					
			MCDRC-FUZZY	4.8354*	1.30993	.001	2.2123	7.4585
	MCDRC-FUZZY	(J) MTH	MCDRC-FIS	-4.2828*	1.30993	.002	-6.9059	-1.6597
			MCDRC-PRO	-4.8354*	1.30993	.001	-7.4585	-2.2123
			MCDRC-FUZZY					

*. The mean difference is significant at the .05 level.