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H.G. Wang

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Hong Guang Wang

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prof.dr.ir. J.E. Rooda
en
prof.dr.-ing.dr.-ing. E.h. H.P.Wiendahl

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To Lin
and
our parents

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Summary

Because of the increasing international competition and the increasing complexity of manufacturing systems, production planning and control is becoming more and more important for manufacturers besides the continuous improvement of manufacturing technologies and innovation of products. The economic pressures and the more general commercial issues like demanding for increased product variety, demanding for increased delivery performance (short and reliable delivery times), demanding for reduced inventory (or work-in-process) and demanding for increased quality are drives that have led to the current development in manufacturing technology and approaches to manufacturing control. These current control approaches are more or less developed on the basis of experts' knowledge and operators' experience and are subjected to further development in the course of time when the manufacturing systems and their environment change.

In recent years, the desire to make controllers more autonomous and intelligent led to much attention being paid to artificial intelligence methods, such as fuzzy control, neural network and genetic algorithm, that are expected to be successful. In this thesis manufacturing system control problems are addressed using a non-classical approach, namely fuzzy control, supported by the fuzzy theory. Fuzzy theory (fuzzy set and logic theory) is a relative new theory with a history of 30 years. It was introduced by Zadeh in 1965 by the publication of his seminal work Fuzzy Sets [Zad65]. Such a theory intends to deal with vague and fuzzy concepts. It provides a way to represent linguistic knowledge and support for approximate reasoning. Fuzzy control theory which is based on the fuzzy theory is supposed to have the ability to imitate the human reason-

ing and thinking in control. Fuzzy control provides an effective way to model operators' or experts' controlling behavior and experience which may enable a computer to perform a good and flexible control instead of human beings. Thus it might be a useful technique for manufacturing system control.

In the literature much attention is given towards the use of fuzzy control concept based methodologies in various fields of application, especially continuous control systems. The application of fuzzy control concepts in discrete event dynamic systems has not been paid much attention until recent years, mainly in the field of scheduling. In this thesis a broad investigation has been carried out in order to provide an insight into the applicability of this control concept for control applications in discrete event dynamic systems. The studies on fuzzy control design related topics in Chapter 3 provide some useful preferences for a fuzzy controller design.

The feasibility of applying the fuzzy control concept in discrete event dynamic systems is studied by means of a simple single-machine model. This study has shown that fuzzy control is a practical and effective way to control such a system. The results obtained are employed in controlling a job shop system, which is one of the most complex discrete event dynamic systems. Simulation studies on the job shop performance, in terms of a high production and constant short lead times, under resource failures and demand variations, are carried out. The total work-in-process in a job shop consists of two parts, namely the real work-in-process and the potential work-in-process. Real work-in-process is more important than the potential work-in-process in the sense that a zero real work-in-process may cause machine idleness. By making the distinction between real work-in-process and potential work-in-process and using both of them as the input variables it is possible for the fuzzy controller to make a more accurate control decision.

Scheduling is to properly allocate resources over time to perform a collection of tasks. For manufacturing systems that are responsible for manufacturing and transporting products, there are unavoidable waiting queues in front of machines because of the limited capacity of the machines and other factors, like technology and social conditions. The lead time of an order is often several times the processing time. The control of the waiting queue or the waiting time by means of scheduling to meet various criteria is an important aspect of production control. Because it is normally difficult to solve these problems directly, scheduling heuristics, like dispatching rules, are often employed to simplify the problem. In order to achieve multi-criteria, the so-called aggregated rules are employed. The suggested fuzzy scheduling approach presented in Chapter 6 illustrates how fuzzy control concepts make the compromise between different dispatching rules possible in a pragmatic and direct manner. Scheduling knowledge can then be accumulated and stored in a rule base. The balance of the elementary dispatching rules via the fuzzy decision rule base adjustment can be achieved intuitively when the systems' environment changes.

Fuzzy control can be an appropriate alternative for controlling discrete event dynamic systems. At the end of this thesis the application of the fuzzy control concept in practice is illustrated. The modelling and the implementation of a fuzzy control system in Philips' new wafer factory, MOS4YOU, has been presented. The MOS4YOU factory has a job shop layout. The job shop characters can be seen from the often repeated process steps on one and the same type of machine, the big number of various process steps and the varying operation times. The control performance of the designed fuzzy controller is evaluated by means of a simulation study.

Samenvatting

Vanwege de groeiende internationale concurrentie en de toenemende complexiteit van productiesystemen, worden planning en besturing van de productie steeds belangrijker voor de producenten, nog afgezien van de voortdurende verbetering van productietechnologieën en de innovatie van producten. De economische druk en de meer algemene commerciële aspecten zoals de vraag naar verhoogde productverscheidenheid, de vraag naar verhoogde leveringsprestaties (korte en betrouwbare leveringstijden) en de vraag naar verminderde voorraden (of onderhanden werk), zijn de drijvende krachten die geleid hebben tot de huidige ontwikkelingen in de productietechnologie en de aanpak van productiebesturingen. Deze aanpak van productiebesturingen is tegenwoordig min of meer ontwikkeld op grond van de kennis van experts en de ervaring van operators en wordt in de loop van de tijd verder ontwikkeld, omdat de productiesystemen en hun omgeving veranderen.

In de afgelopen jaren heeft de wens om regelaars zelfstandiger en intelligenter te maken ertoe geleid dat er veel aandacht is besteed aan methoden uit de kunstmatige intelligentie, zoals vage regeling ('fuzzy control'), neurale netwerken en genetische algoritmen, waarvan men succes verwacht. In dit proefschrift worden de regelingsproblemen voor productiesystemen benaderd met een niet-klassieke aanpak, namelijk vage regeling, ondersteund door de vage theorie. Vage theorie (de theorie van vage verzamelingen en vage logica) is een betrekkelijk nieuwe theorie met een geschiedenis van dertig jaar. De theorie werd geïntroduceerd door Zadeh in 1965 door middel van de publicatie van zijn veelgeciteerde werk Fuzzy Sets [Zad65]. Zo'n theorie heeft de bedoeling om de omgang mogelijk te maken met vage begrippen. De theorie levert een manier om in taal uitgedrukte kennis weer te geven en geeft steun aan onzeker redeneren. Vage regeltheorie die gebaseerd is op de vage theorie, wordt verondersteld het vermogen te hebben om menselijk redeneren en denken te imiteren in productiebesturing. Vage regeling geeft een effectieve manier om het gedrag en de ervaring van operators of experts op het gebied van productiebesturing te modelleren, wat de mogelijkheid biedt dat een goede en flexibele besturing door een computer wordt uitgevoerd, in plaats van door een mens. Daarom zou dit een nuttige techniek kunnen zijn voor de besturing van productiesystemen.

In de literatuur wordt veel aandacht geschonken aan het gebruik van methodogieën gebaseerd op het begrip vage regeling in verscheidene toepassingsgebieden, in het bijzonder op continue besturingsystemen. Er is tot voor kort niet veel aandacht besteed aan de toepassing van het begrip vage besturing op dynamische systemen voor discrete gebeurtenissen en dan nog vooral op het gebied van scheduling. In dit proefschrift is een breed onderzoek uitgevoerd met het doel om inzicht te krijgen in de toepasbaarheid van dit regelbegrip voor toepassingen van productieregeling in dynamische systemen voor discrete gebeurtenissen. De bestudering van onderwerpen verband houdend met het ontwerp van vage regelaars die in Hoofdstuk 3 zijn beschreven, geven een aantal nuttige aanbevelingen voor het ontwerp van een vage regelaar.

De uitvoerbaarheid van het gebruik van het begrip vage regelaar in dynamische systemen voor discrete gebeurtenissen wordt bestudeerd aan de hand van een eenvoudig enkele-machine-model. Dit onderzoek heeft aangetoond dat vage regeling een praktische en effectieve manier is om zo'n systeem te regelen. De verkregen resultaten worden gebruikt in de regeling van een job shop systeem, wat een van de meest complexe dynamische systemen voor discrete gebeurtenissen is. Simulatiestudies worden uitgevoerd over de prestaties van de job shop, in termen van een hoge productie en constante korte levertijd, rekening houdend met storingen van de aanvoer en variaties in de vraag. Het totale onderhanden werk in een job shop bestaat uit twee delen, namelijk het werkelijke onderhanden werk en het potentiële onderhanden werk. Het werkelijke onderhanden werk is belangrijker dan het potentiële onderhanden werk, in de zin dat een nulwaarde voor het werkelijke onderhanden werk tot inactiviteit van de machine kan leiden. Door verschil te maken tussen werkelijk en potentieel onderhanden werk en door beide als invoervariabelen te gebruiken, is het voor de vage regelaar mogelijk om een nauwkeuriger regelbeslissing te nemen.

Het maken van een scheduling dient om de grondstoffen tijdens het verloop van de tijd op een goede manier toe te wijzen, met het doel om een hoeveelheid taken uit te kunnen voeren. Voor productiesystemen die verantwoordelijk zijn voor de productie en het transport van producten, zijn er onvermijdelijk wachtrijen vóór de machines, wegens de beperkte capaciteit van de machines en andere factoren, zoals de technologie en sociale voorwaarden. De levertijd van een order is vaak vele malen de verwerktijd. De regeling van de wachtrij en de wachttijd door middel van scheduling, om aan verschillende criteria te voldoen, is een belangrijk aspect van productiebesturing. Omdat het normaliter moeilijk is om deze problemen direct op te lossen, gebruikt men vaak scheduling heuristieken, zoals verzendregels, om het probleem te vereenvoudigen. Om aan meervoudige criteria te voldoen, gebruikt men vaak zogenaamde geaggregeerde regels. De gesuggereerde aanpak van vage scheduling zoals beschreven in Hoofdstuk 6, laat zien hoe begrippen uit de vage regeling het mogelijk maken om op een pragmatische en directe manier een compromis te bereiken tussen verschillende verzendregels. Kennis over scheduling kan dan verzameld worden en opgeslagen in een regelbestand. De afweging van de elementaire verzendregels door een aanpassing van het regelbestand voor de vage beslissingen, kan op intuïtieve basis bereikt worden, in het geval dat de omgeving van de systemen verandert.

Vage regeling kan een geschikt alternatief zijn voor de regeling van dynamische systemen voor discrete gebeurtenissen. Aan het eind van dit proefschrift illustreren we de toepassing van het begrip vage regeling met een voorbeeld uit de praktijk. We presenteren de modellering en de implementatie van een vaag regelsysteem in de nieuwe chipwafelfabriek van Philips, MOS4YOU. De MOS4YOU-fabriek heeft de structuur van een job shop. De job shop-karakteristieken blijken uit de vaak herhaalde processtappen en hetzelfde type van machine, het grote aantal van de afzonderlijke processtappen en de variërende werkingstijden. De regelprestaties van de ontworpen vage regelaar worden geëvalueerd door middel van een simulatiestudie.

摘要

随着国际间经济竞争日益加剧以及生产系统日趋复杂，生产厂家在不断改进生产技术及革新产品的同时，也将注意力越来越多地转向生产计划和控制方面。此外，快速及可靠提供高质量，多样化产品及减少库存货物等经济及商业原因，也是导致现代生产技术及控制方法发展的动因。目前的控制方法多多少少都是建立在专家的控制知识及操作员的控制经验上的，当生产系统及其环境变化时，这些方法也不可避免地做相应改进。

近年来，由于对控制器自动化和智能化要求不断提高，使得人们对人工智能方法，如模糊控制，神经网络等的应用给予重新认识，并寄予极大期望。本论文中，我们也将运用模糊控制这一非经典方法来控制生产系统。模糊控制理论是奠基在模糊理论基础上的。模糊理论是模糊集合理论及模糊逻辑理论的简称。这个理论是1965年由美国学者扎德首次提出的，迄今仅有三十余年的历史。模糊理论是针对模糊概念的，它提供了一种表述语言知识的方法，从而支持近似推理。模糊控制理论可用来模拟人对系统进行控制时的推理及决策行为，从而使计算机代替人进行更好，更灵活的控制成为可能。从这点来看，模糊控制应该可以成为一种有效的生产系统控制技术。

有关模糊控制概念在不同领域运用的文献层出不穷，然而模糊控制理论在动态离散事件系统中的应用却仅在近几年才得到重视，而且也仅限于生产调度领域。本论文将在较广的范围内对模糊控制理论在动态离散事件系统中应用的可行性进行研究。本论文第三章中有关模糊控制器设计的实验研究，为实际设计控制器提供了一套合理的设计准则。

模糊控制概念在动态离散事件系统中应用可行性的研究首先借助于一个简单的单机器模型。仿真实验表明，模糊控制可成为一种切实可行的方法用来控制这类系统。进而将研究结果运用到工作作业车间

系统(最复杂的动态离散事件系统)进行控制，也得到很好的控制特性。在工作作业车间系统中，总的在线工作量由两部分组成：实际在线工作量和潜在在线工作量。实际在线工作量为零将导致机器空闲。从这方面来讲，实际在线工作量要比潜在在线工作量重要。对这两个变量加以区分定义，并选它们作为模糊控制器的输入变量，可使模糊控制器作出更准确的控制决策，从而达到更好的控制特性。

生产调度是适时地合理地分配机器，人力及原材料，由于机器容量和其它技术及社会因素的限制，不可避免地会在生产机器前产生等待队列。产品在生产系统中的滞留时间通常为实际生产时间的数倍。因此，如何来控制这样的等待队列或等待时间以满足特定的要求是生产控制的一个重要方面。由于通常直接解决这个问题很难，故实际中多用启发式的方法，如分配调度规则。为满足多种要求，几个不同的分配调度规则可以用不同方式进行组合。本论文第六章中提出的模糊调度方法可以灵活地协调各种分配调度规则，为满足多种要求寻找最佳折中方案。生产调度知识可储存于一个调度规则决策库中。这个库可以随着生产系统及其环境的改变而不断加以扩充完善。

本论文最后给出了一个实际系统模糊控制范例，模拟并实现了一个模糊控制及调度系统，用于控制菲利浦的新芯片厂。仿真实验进一步证明模糊控制可以作为一个合适的技术来控制动态离散事件系统。

Contents

Chapter 1

Introduction

The economic pressures and the more general commercial issues like *demanding for increased product variety, demanding for increased delivery performance (short and reliable delivery times), demanding for reduced inventory (or work-in-process) and demanding for increased quality* are drives that have led to the current development in manufacturing technology and approaches to manufacturing control. It has more and more been realized by many companies that to be competitive, improved production management must become a strategic objective equal in priority to product innovation. It is essential for companies to innovate in manufacturing in order to survive in the increasingly competitive world marketplace. This challenge also coupled with the increasing application of computers which has led to significant changes in the techniques applied in manufacturing.

Previously, utilization of both machinery and manpower were the most important objectives of a company. Besides, the company desires the lowest possible inventories of raw materials, semi-completed and completed products. However, the increased emphasis on fast and punctual delivery has changed the weighing of these objectives. Nowadays, to achieve short delivery times, punctual delivery, high throughput and low inventories all at once are the most important objectives [Wie95].

Advanced technologies like *Flexible Manufacturing Systems* (*FMS*), *Computer Integrated Manufacturing* (*CIM*) and *Computer Aided Design and Manufacturing* (*CAD/CAM*), and advanced manufacturing control approaches like *Just-In-Time* (*JIT*), *Kanban pull system*, *Total Quality Control* (*TOC*), *Manufacturing Resource Planning* (*MRP II*) and *Load-Oriented Order Release* (*LOOR*) are commonly used today in manufacturing systems. These current control approaches are more or less developed on the basis of experts' knowledge and operators' experience and are subjected to further development in the course of time when the manufacturing systems and their environment change.

In recent years, the desire to make controllers more autonomous and intelligent led to much attention being paid to artificial intelligence methods, such as fuzzy control and neural network, that are expected to be successful. Fuzzy control is supposed to have the ability to imitate the human reasoning and thinking in control, it provides an effective way to model operators' or experts' controlling behavior and experience which may enable a computer to perform a good and flexible control instead of human beings. Thus it might be a useful technique for manufacturing system control. In this thesis the manufacturing system control is addressed by using fuzzy control concepts, which is supported by the fuzzy theory (fuzzy set theory and fuzzy logic theory).

Fuzzy control concepts have been applied to a wide variety of systems, especially continuous control systems [Mam74, Lar80, Yam89]. The application of fuzzy control concepts in *Discrete Event Dynamic Systems* (*DEDS*) has not received much attention until recent years [Cha84, Hin89, Gra94a, Gra94b]. The validation of the fuzzy control approach as an interesting alternative to controlling manufacturing systems will be the main contribution of the work reported in this thesis.

In Chapter 2 the subjects of manufacturing systems and their control are discussed. Many relevant terms like systems and industrial systems are defined and explained. Manufacturing systems are viewed as subsystems of industrial systems. The reasons why we need good control of manufacturing systems are given after the objectives and characteristics of such systems are presented. The set of the most often encountered control methods is briefly mentioned and summarized in Section 2.2. The fuzzy control structure is then illustrated. Since the *LOOR* is chosen as the basis for deriving the fuzzy control knowledge-base in our study, it is explained in detail at the end of the chapter.

The field of fuzzy theory and the fuzzy control theory based on it are the topics of Chapter 3. We start with a general description in Section 3.1 of the history of fuzzy theory. A detailed explanation of the fuzzy theory follows in Section 3.2. Section 3.3, 3.4 and 3.5 present respectively the detailed studies on three different, but closely related processes concerning a fuzzy controller design. The preference concerning a fuzzy controller design has been outlined there.

In Chapter 4 the feasibility of applying the fuzzy control concept in *DEDS* is studied by means of a simple *single-machine* model. Two other control approaches, namely the proportional control (*P-control*) and the *LOOR-control*, are employed to be compared with the fuzzy control approach. These studies have shown that fuzzy control is a practical and effective way to control such a system. The results obtained are employed in controlling a *job shop* system in Chapter 5. The *LOOR* control approach is employed as a reference to be compared with the fuzzy control approach. Simulation studies on the *job shop* performance, in terms of a high production and constant short lead times, under resource failures and demand variations, are carried out.

Solving *scheduling* problems with the proposed fuzzy approach is the concern of Chapter 6. After a brief introduction of the scheduling by means of dispatching rules in Section 6.1, the proposed fuzzy scheduling approach is illustrated in Section 6.2. The trading off each elementary dispatching rule can be realized by modifying the fuzzy decision rule base. The scheduling performance is also examined via simulation studies.

Chapter 7 is devoted to the application of the fuzzy control concept in practice by applying it to a real system, Philips new wafer factory named *MOS4YOU*. All the results obtained from the studies in the previous chapters are employed. The control performance will be evaluated by means of a simulation study. After a brief introduction to *MOS4YOU*, the factory layout and the wafer processing will be illustrated in Section 7.2. Some assumptions are made for modeling and controlling. The factory with its control model is described in Section 7.3. The simulation study on the fuzzy control performance of the *MOS4YOU* factory will be presented in Section 7.4.

Finally, the general conclusions and recommendations concerning the whole Ph.D. study are presented in Chapter 8.

Chapter 2

Manufacturing Systems and Their Control

Before we can give a clear definition of manufacturing systems and their control, the terms '*system*' and '*industrial system*' are explained first in Section 2.1. Manufacturing systems are viewed as sub-systems of industrial systems. The objectives and characteristics of manufacturing systems are also presented in Section 2.1. The reasons why we need good control of such systems are given in Section 2.2. There the bulk of the most often encountered control methods are also briefly mentioned and summarized. The control method applied in this thesis, *fuzzy control*, is then introduced. The detailed study of fuzzy control will be continued in Chapter 3. A fuzzy control system is a kind of knowledge-based system or expert system. The control knowledge employed in our study is based on the *Load-Oriented Order Release* (*LOOR*). The *LOOR* is thus explained in detail at the end of this chapter.

2.1 Manufacturing systems

We first look at what is a system. *System* is a very broad term and thus has many different definitions. By referring to [Roo96], a system is defined as: a collection of different objects arranged in an ordered form to serve certain pre-defined purposes. What constitutes a system depends on the point of view of the observer. Anything not belonging to the system is part of the environment. The objects within the system have relations with each other (internal relations) and also have relations with the environment (external relations).

There are also quite a number of definitions of industrial systems. *Industrial systems* are systems like machines, production-lines, production-cells and factories. Such a system can be large and complex, so it is normally difficult to keep an overview of the total industrial system. An industrial system is viewed as a collection of products and a production system. The production system is further decomposed into three sub-systems, namely the *manufacturing system*, the *information system* and the *financial system*. The basic sub-systems in an industrial system, which have been identified as described in [Bra93], are redrawn in Figure 2.1.

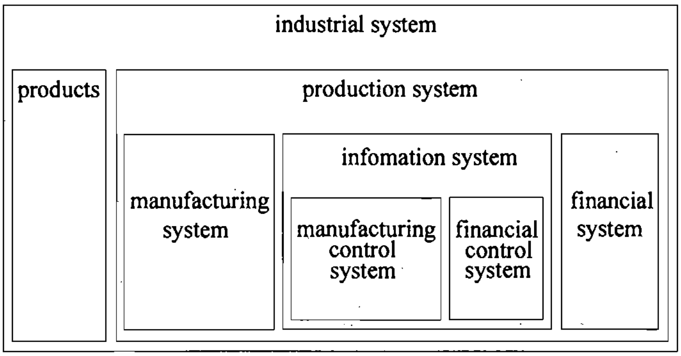

Figure 2.1: The basic sub-systems of an industrial system

The manufacturing system and the information system are also called the *primary* system and the *secondary* system respectively, while the financial system or economical system is called the *tertiary* system [Roo96].

A *manufacturing system*, sometimes also being called a *productive system*, is a transformation system in which the actual manufacturing of products takes place. In this sense the manufacturing systems are defined as the means for transforming or converting raw material inputs into useful product outputs. "*The input-conversion-output sequence is a* *useful way to conceptualize productive systems, beginning with the smallest unit of production activity, which we commonly refer to as an operation*" [Buf87]. An *operation* is the smallest production step in the overall process of producing a product that leads to the final output. A *resource* is necessary for the execution of an operation. A *process* is a set of consecutive operations which complete a significant stage in the manufacturing of a product. *Material* is the operand that undergoes the process. The materials used as input to a manufacturing system are called *raw materials*, while the outputs of a manufacturing system are *products*. Products are created by different operations on one or more raw materials. The way these operations are performed is defined by a *recipe*. "*A recipe can be considered as a list of operations that have to be executed. A recipe indicates which operations have to be performed, what type of material is involved and in which sequence these operations have to be executed*" [Roo96]. The recipes are used by the control system to navigate the products through the manufacturing system. The *control system* involves controlling the conversion process and all the variables that affect its performance. The financial system or economical system is the energy stream of the production system. In this thesis we only concentrate on the manufacturing control system and the manufacturing system.

A rough classification of manufacturing systems is made by considering the *universality* of the resources and the *route flexibility* inside the system; this results in the classes *flow shop* and *job shop*. A flow shop is characterized by dedicated resources and a fixed route. Flow shops are *product-oriented* manufacturing systems. In a job shop there are universal resources which can be used for many different operations and many possible routes. Job shops are *process-oriented* manufacturing systems. The producing of high-volume standardized products in a flow shop results in continuous use of the facilities. Also the material flow is usually continuous. In contrast the producing of small-batch variant products in a job shop results in intermittent demand for the system's facilities, and the material flows from one process to the next intermittently. Job shop systems are the main concern in this thesis.

Since every manufacturing system is unique, it is very difficult to define a standard control system. The findings from the studies in the Institut

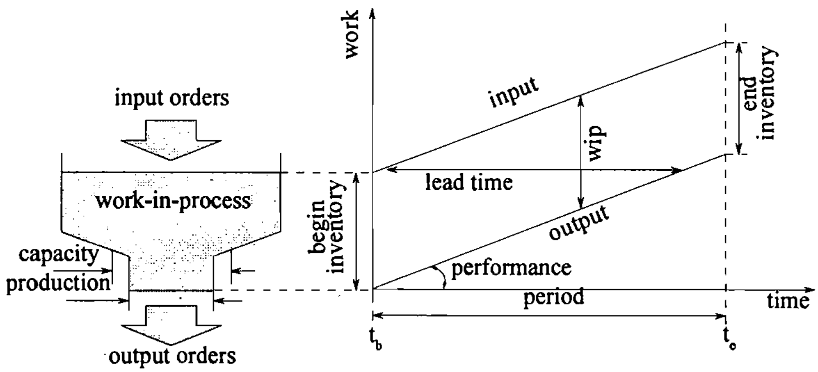

Figure 2.2: The funnel model and the throughput diagram

Für Fabrikanlagen at the Universität Hannover lead to a universal model of the production process of manufacturing systems. The model, which is based on the idea that every work center or system can be seen as a *funnel* (the left part of Figure 2.2), is mathematically represented in what is known as the *throughput diagram* (the right part of Figure 2.2). The funnel model is very important for understanding the manufacturing process. All the input orders want to pass the funnel, but they cannot get through at once because of the capacity limit. The output orders corresponds to the capacity. Thus part of the input orders form the inventory of waiting orders, which is depicted as work-in-process in Figure 2.2. The mean lead time of an order is proportional to the work-in-process, and it is reverse proportional to the capacity. The throughput diagram graphically and numerically represents the work input and output at the work center or the system over a period of time. At the starting observation time t_b, one has to determine the *begin inventory* in order to draw the input trend curve. The input curve is obtained by adding up the input order work contents over time within the period. The output curve is plotted by adding up the completed order work contents over time within the period. At the end of the observation time t_e there is also certain inventory, *end inventory* in Figure 2.2, which can be seen as the *begin inventory* for the next observation period. Further, the throughput diagram shows how the key values of work-in-process, lead time and performance (production rate or utilization) can be calculated from the diagram and represented graphically (refer to [Wie95]). The *lead time* here is defined as the time period between the time when an order arrives at the funnel and the time when it leaves the funnel. The *mean lead time* is determined by calculating the arithmetic mean of the individual lead times. When the orders are with very different processing times, it is more interesting to look at the work of orders instead of the number of orders through the funnel. It is thus better to use the term weighted lead time instead of lead time. *Weighted lead time* is determined by the lead time multiplies the work contents of the order. The *mean weighted lead time* (*mwlt*) is defined as the total weighted lead time divided by the total work of the concerned orders. The *funnel model* can be described by the so-called *funnel formula* [Lit61, Wie95]:

$$mwlt = mwip \;/\; mpe$$

Each time when an order comes in or goes out of the funnel, a work-in-process value is registered. The *mean work-in-process* (*mwip*) is the arithmetic mean of the individual work-in-process values. The performance is defined as work per time unit, and *mean performance* (*mpe*) in the period is output/period. This formula cannot only be used for analytical purpose but also for control purpose.

The problem that we are interested in is how to meet the demands of the customers meanwhile keeping a high profit for the company. One of the measures is to have a reliable short delivery time of orders with a high production rate (or utilization) of the manufacturing system. Having a reliable short delivery time for customer orders is quite important for manufacturers in the competitive industrial world as mentioned in Chapter 1. Reliable short delivery times can be ensured by reliable short lead times. The production rate can be measured by the throughput of the system, defined as standard hours per time unit. The control objectives of a manufacturing system are thus to obtain short mean lead times (*mlt*) of orders and reasonable high throughput (*tp*) of the system. Both *mlt* and *tp* can be adjusted by the mean work-in-process (*wip*). A high *wip* generally means a high rate of production, but leads to long lead times. Low *wip* may guarantee short lead time, but it results in a low rate of production. Obviously, *tp* and *mlt* have a conflicting relation. A good knowledge of the three parameters, namely *mlt*, *tp* and *wip*, is helpful in making the compromise between the two controlled parameters. The graphical representation of the relation between these three main parameters is given in Figure 2.3 (after Wiendahl in [Wie95]). The *mlt* and the *tp* are given separately as a function of the *wip*. The *mlt* and the *tp* curves representing these two functions are defined as the *characteristic curves* of the system.

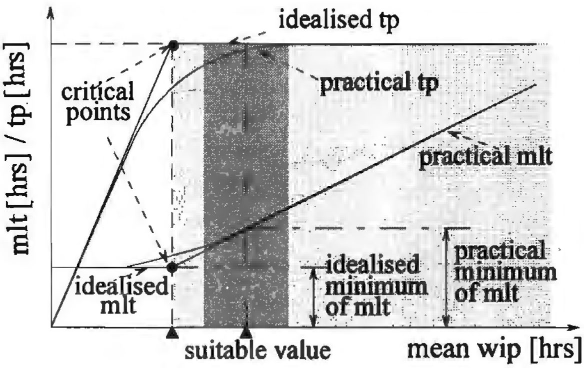

Figure 2.3: The characteristic curves

If the *wip* is varied within a wide range, a corresponding variation of the *mlt* will result (see Figure 2.3). The so-called *critical points* on the idealized *mlt* and *tp* curves correspond to a *wip* at which the system works on its whole capacity, whereas the lead time attains its minimum value which is equal to the mean operation time. By increasing the *wip* from this point the production rate does not change and equals the system capacity, but the lead time increases proportionally to the *wip*. Since the performance remains constant the work center obeys the funnel formula. The lead time will remain constant and equal to the operation time if the *wip* decreases from this point, with an abrupt proportional decreasing of the production rate. The characteristic curves in Figure 2.3 are thus divided into two parts. The unshadowed part implies that the machine is idle or waiting for orders from time to time. The shadowed part represents the cases in which the system is always busy. The critical points are obviously the desired stable work points. The practical critical points are expected somewhat different from the theoretical ones and are more shifted to the right. The dark shadowed part gives out a suggested control region, while the suitable value is the desired set-point. Obviously it is only interesting to apply control to the shadowed part in Figure 2.3. The goal of the control is to solve the conflict by making a good compromise between *tp* and *mlt*. This goal can be achieved by keeping a proper constant *wip*, which ensures that on the one hand, idle time is avoided, but on the other hand, a short lead time is achieved. In the next section we illustrate how this goal can be achieved.

2.2 Control of manufacturing systems

Because of the increasing international competition and the increasing complexity of manufacturing systems as aforementioned, production planning and control (*PPC*) is becoming more and more important for manufacturers besides the continuous improvement of manufacturing technologies. The advanced manufacturing technologies like *NC* (*Numerically Controlled*) *machines*, *Flexible Manufacturing System* (*FMS*), *Computer Aided Design and Manufacturing Systems* (*CAD/CAM*), *Computer Integrated Manufacturing* (*CIM*) and *Group Technology* (*GT*), as described in [Buf87, Cha92 and Wie95], facilitate the development of advanced production planning and control approaches. There are now existing many such approaches like *Just-In-Time* (*JIT*), *Kanban pull system*, *Total Quality Control* (*TQC*), *Material Requirements Planning* (*MRP*), *Manufacturing Resource Planning* (*MRP II*), *Queueing Models* and *Load-Oriented Order Release* (*LOOR*).

The application of *MRP* to production control is considered as the big breakthrough in the 1970s within the manufacturing society. "*This approach ties together in a computer program all the parts that go into complicated products. This program thus enables production planners to quickly adjust production schedules and inventory purchases to meet changing demands for final products*" [Cha92]. As soon as *MRP* considered resources as well as materials, it was extended as *MRP II*. *JIT* production is clearly the major breakthrough in manufacturing philosophy in the 1980s. *JIT* is an integrated set of activities designed to achieve high-volume production using minimal inventories of parts that arrive at the workplace *"just-in-time"*. The *Kanban pull system* is simple and self-regulating, which provides good management visibility. This system is designed to produce only the number of parts needed by a *"pull"*. The *Kanban pull system* of inventory control works particularly well in situations where standardized parts and products are cycled in the manufacturing systems, as for example in an assembly environment. From the late 80s, concepts in the field of *artificial intelligence*, such as *fuzzy control* and *neural networks*, are increasingly being introduced into the manufacturing societies.

In this thesis manufacturing system control problems are addressed using a non-classical approach, namely *fuzzy control*, supported by the fuzzy theory. Fuzzy control provides an effective way to model operators' and experts' controlling behavior and experience which may enable a computer to perform a good and flexible control instead of human beings. Thus it might be a useful technique for manufacturing system control. Starting with a linguistic model of human beings' control behavior rather than a precise mathematical model of the system itself is one of the advantages of fuzzy control over conventional control. Before we present the general structure of fuzzy control, a number of control related terms should first be defined clearly, which we do below.

The *control system* regulates the actions of the *controlled system.* To do this the control system has to have some conception of the goal (objectives) that has to be reached. In order to control, there have to be interactions between the control system and the controlled system. The control system influences the controlled system with stimuli and it needs to know the status of the controlled system and the response of the controlled system to a stimulus. By comparing the response and the status of the controlled system with the goal, the control system determines the stimuli for the controlled system. These stimuli are also influenced by the stimuli the control system receives from the outside world, called the environment [Sim92].

There are generally two types of control structures, namely the *feedforward control* and the *feedback control* structure. With feedforward control a deviation of the actual stimuli from the norm stimuli is measured. The stimuli can be adjusted to compensate for the deviation. The advantage of using feedforward control is the fact that there is no significant delay between the monitor and the control action, since the control action takes place before the process. A disadvantage is the fact that it can only deal with measurable disturbances. In many situations, the disturbances consist of a part which is measurable, and a part which is not. To compensate for the part which is not measurable, an extra feedback loop is needed. With feedback control a deviation of the response from the norm (or the goal) will require a control action on the stimuli side. The advantage of feedback control is that all disturbances are taken into account. A disadvantage is the delay between measure and control action.

Manufacturing systems concerned in this thesis are discrete event dynamic systems. This kind of systems have inherent uncertainty and are stochastic, there are non-avoidable existence of non-measurable disturbances. Thus the feedback control structure is used in this thesis.

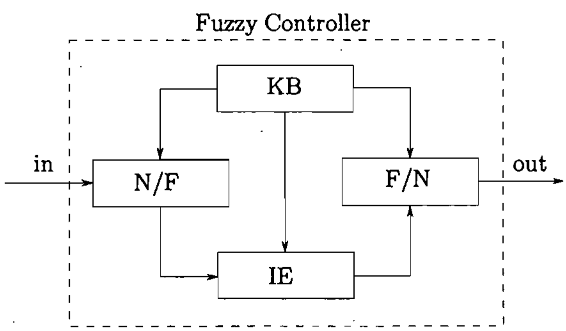

Figure 2.4: The fuzzy control structure

The general structure of a fuzzy controller is usually that of Figure 2.4. A fuzzy controller consists of four main elements, namely the *Fuzzification* (*N/F*), the *Inference Engine* (*IE*), the *Defuzzification* (*F/N*) and the *KnowledgeBase* (*KB*). *N* stands for numerical value, and *F* stands for fuzzy value. The system input and output variables are represented symbolically in the fuzzy controller. These symbolic variables are associated with fuzzy sets (also called *membership functions*). Once the observation of the system output variables is sent to the fuzzy controller, the *N/F* element will transform the received observation into fuzzy values via a mapping process. These fuzzy values represent to what degree the observed value belongs to each set associated with this variable. The reasoning process then evaluates the control action rules with the fuzzy values obtained. The reasoning process is carried out by the *IE*. This reasoning process results in fuzzy values which are used as control signals after the defuzzification process. The defuzzification process translates the fuzzy values into crisp (or numerical) values. The defuzzification process is performed by the *F/N* element. Fuzzy control is a knowledge-based control scheme in which membership functions for physical variables are used to cope with uncertainty in process dynamics or the control environment [Isa92]. The membership functions which are needed for the fuzzification and the defuzzification processes are pre-stored in the *KB*, so do the control action rules.

The *Fuzzification*, the *Inference Engine* and the *Defuzzification* are studied and discussed in detail in the next chapter after the introduction to fuzzy theory. The *KnowledgeBase* contains two kinds of information, one is related to the individual variables, represented by membership functions; another deals with the relations between variables, represented by control action rules. The control knowledge is mainly based on and derived from the *LOOR* strategy. Thus, it is necessary for us to give a brief and general introduction to the *LOOR*. For interested readers, we refer to [Wie95].

The *LOOR* control concept was developed at the Institut für Fabrikanlagen, Universität Hannover. It is a product of many years of experts experience and efforts. "*Since 1979, the manufacturing control method has seen numerous commercial software versions, and has been put into practice successfully in over 100 plants in Germany and throughout Europe. It is mainly directed towards manufacturers with high-variant job-shop production. It is a new, self-contained, logical approach to manufacturing control. It also contributes to a flexible, simple and error-tolerant manufacturing control*" [Wie95]. The idea of *LOOR* is to limit and balance work-in-process inventory on a level as low as possible in order to accomplish a high work-centre utilization as well as a rapid and in-time flow of orders [Bec94]. Figure 2.5 (after Wiendahl in [Wie95]) shows the situation at the end of a plan period, and by that time a new plan period should be considered. The left part of Figure 2.5 is the throughput diagram in planning period P, the right part of Figure 2.5 depicted the terms that are needed for introducing the *load-oriented order release* method.

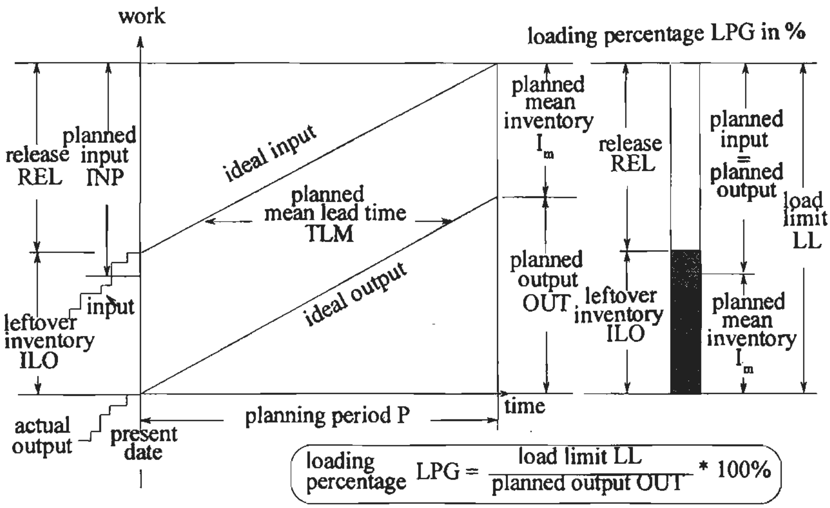

Figure 2.5: The load-oriented order release for one work center.

The real initial inventory (also called the '*leftover inventory*', ILO) usually deviates from the *planned mean inventory* (I_m). In Figure 2.5 there holds $ILO > I_m$. Thus, the work to be released is not the *planned input* (*INP*) but rather *load limit* (*LL*) minus *ILO*. The sum of the planned mean inventory and the planned output is called the load limit; the difference between the load limit and the leftover inventory is called the *release* (*REL*). "*The method developed from this is called load-oriented order release. Unlike conventional capacity scheduling methods, this method does not try to schedule single orders along the scheduled output curve with an accuracy to the day or the hour, but performs a period-by-period balance on the basis of the expected inputs and outputs*" [Wie95].

To avoid having to redetermine the load limit for every change in the planned performance, it should be related to the planned output (OUT). The value calculated in this way is called the *loading percentage* (LPG), and is defined as:

$$LPG = (1 + I_m/OUT) \times 100\%$$

This value is, however, not only related to the inventory values OUT and I_m, but also to the time values mean lead time (TLM) and planning period (P):

$$LPG = (1 + TLM/P) \times 100\%$$

In mechanical engineering shops, the length of one plan period is usually one week; thus, with the usual mean lead times of one to two weeks per operation, loading percentages of 200 to 300 result, we refer to [Wie95]. The *LOOR* follows a step-by-step procedure, which is explained below. A *load account* registers the work contents in the shop. The inputs planned for the subsequent period are released onto the account up to the load limit. During the plan period, orders enter and leave so that at the end of the period we get a new balance with a new leftover inventory. The amount of work released to the system in the next plan period is decided according to the load limit of the system. The released work is then dispatched to the work floor in a way which maintains the desired *wip* of the system.The step-by-step procedure is as follows:

- Step 1: Appoint the lead time for all issued orders, which have not yet been released, via backward scheduling. Backward scheduling results in a list of orders arranged in the sequence of planned start dates. The start dates of the first orders can even lie in the past. In the list, the orders that must start before a time limit are classified as *urgent orders.* The time difference between this time limit and the time when planning is carried out is called the *anticipation horizon*, and should be measured in numbers of *plan periods.* Two or three plan periods have been found to be a practical value for the anticipation horizon because normally the orders that must start in the next plan period cannot reach the load limit yet. This step results in two list, namely an *urgent orders* list and a *non-urgent orders* list. The list of urgent orders with their planned start dates, the operations sequences with standard times and work centers, and the planned exit dates are arranged according to the planned starting dates. The list of non-urgent orders are deferred and left in the inventory of un-released orders until, in the next planning cycle, they are again subjected to the release process, together with the other issued but not yet released orders (including new ones) [Wie95].

- Step 2: Evaluate whether the urgent orders will actually meet the planned inventory conditions at the individual work centers after their release. This means that a check is made as to whether the load limit of any work center passed by the released order is expected to be exceeded as a result of the release. The operation time of the first operation of the most urgent order is added up to the work center where this operation has to take place. Normally, the load limit of the work center cannot be reached yet. The second operation can go to the next work center in the same plan period. There is a chance (or probability) for such a possibility. If this probability is known, the load value of the second operation can be multiplied by this *probability factor*, and the resulting load value (or called converted load) can be added to the load account in the next plan period. This calculation is called conversion of order times. "*It is probably the most important idea behind the whole concept of load-oriented order release*" [Wie95]. If this conversion is carried out for each operation, one can be sure that the load account is, on average, loaded correctly. All the orders are tested in the same way. As soon as the load limit of an account is exceeded for the first time, this account is blocked. The next operation arriving at this blocked account is refused together with all the other operations of the same order, and the entire order is entered into the list of *non-feasible orders.* Together with the *non-urgent orders* and the *rescheduled orders* it is re-entered into lead time scheduling in the next planning cycle, and probably released, since the work center in question had some output in the meantime and can therefore take new input [Wie95].

The *LOOR* is employed as the basis for deriving the fuzzy control knowledge. In the next chapter, fuzzy theory is discussed and fuzzy control is studied in detail.

Chapter 3

Fuzzy Control Theory

Before going into detail about the possible applications in control of discrete event industrial systems, we describe fuzzy control theory as much as needed. Fuzzy control theory is based on fuzzy theory. We start with a general overview in Section 3.1 of the history of fuzzy theory. A detailed description of the fuzzy theory follows in Section 3.2. Section 3.3, 3.4 and 3.5 present detailed studies on three different, but related processes concerning a fuzzy controller design. We focus on the feasibility of applying this theory to the control of discrete event industrial systems.

3.1 History of fuzzy theory

Fuzzy theory is a relatively new theory with a history of 30 years. It was introduced by Zadeh in 1965 by the publication of his seminal work Fuzzy Sets [Zad65]. In that publication the mathematics of fuzzy theory (fuzzy set theory and fuzzy logic theory) was presented. This theory was intended to deal with uncertainty and imprecise concepts. It proposed that the truth values can take any real number within the interval $[0.0, 1.0]$, thus smooth and gradual transitions can be dealt with. New operations for the logic calculus were proposed and showed to be in principle at least a generalization of the classic logic. Fuzzy theory does have its origin in the ancient Greek philosophy. As it is pointed out by Gaines [Gai77], fuzzy theory has its technical roots in philosophical and mathematical studies of multi-valued logics and vague reasoning. Fuzzy theory is a natural product on the way of classical set and logic theory development.

The concise theory of bi-valued logic was devised by Aristotle and the other earlier philosophers around 400 B.C. The "Law of the Excluded Middle " states that every proposition must either be True or False. But there were strong and immediate objections: things could be simultaneously True and not True. In Plato's theory of Knowledge, he argues that knowledge requires thinking, that thought with the statements of them can be false as well as true [Kor67]. It was Plato who laid the foundation for what would become fuzzy theory, indicating that there was a third region beyond True and False. Other, more modern philosophers echoed his sentiments, notably Russell. In [Rus23], Russell pointed out that: "*All traditional logic habitually assumes that precise symbols are being employed. It is therefore not applicable to this terrestrial life but only to an imagined celestial existence.*"

But it was Łukasiewicz who first proposed a systematic alternative to the bi-valued logic of Aristotle [Lej67]. In the early 1900s, Lukasiewicz described a three-valued logic, along with the mathematics to accompany it. The third value he proposed can best be translated as the term *possible*, and he assigned it a numeric value between True and False. Eventually, he proposed an entire notation and axiomatic system from which he hoped to derive modern mathematics. Later, he also explored four- and five-valued logic. He declared that in principle there was nothing to prevent the derivation of an infinite-valued logic. Łukasiewicz felt that three- and infinite-valued logic were the most intriguing, but he ultimately settled on a four-valued logic, because the four-valued logic seemed to be the most easily adaptable to Aristotelian logic. It was not until recently that the notion of an infinite-valued logic took hold [Bru85].

Fuzzy theory has not received much attention for almost 20 years since its inception. A pioneering application of the fuzzy theory to control was made in 1974 by Mamdani [Mam74]. It was not until the late 80s, however, when the appearance of the fuzzy controlled Sendai subway system and fuzzy consumer products in Japan became a landmark which convinced the whole world to pay more attention to the fuzzy theory. Since then, fuzzy theory has advanced in a wide variety of disciplines, e.g., control engineering, decision theory, expert systems, operations research and data grouping and analysis. Various fuzzy research organizations, like IFSA (International Fuzzy Systems Association), LIFE (Laboratory for International Fuzzy Engineering), NAFIPS (North American Fuzzy Information Processing Society), ELITE (European Laboratory for Intelligent Techniques Engineering) and BISC (Berkeley Initiative for Software Computing), were founded. Many international fuzzy conferences have taken place all over the world. This phenomenon has been baptized the "Fuzzy Boom". Now let us take a look at the fuzzy theory itself.

3.2 Fuzzy theory

Fuzziness, in the sense of impreciseness and uncertainty, can be found in almost all areas of our daily life. "*As a matter of fact, fuzziness seems to pervade most human perception and thinking processes.*"[Dub80]. It is not difficult for one to encounter the fuzzy or vague terms like: *young, tall, beautiful, warm* and *cold.* Imagine that you have to park your car precisely in one place with certain angle and coordinates. It would be extremely difficult if not impossible. But it is fairly easy a task if you don't keep these precise data in mind.

Fuzzy theory is a short name for *fuzzy set and fuzzy logic theory.* Fuzzy sets and fuzzy logic are used for modelling the imprecise modes of reasoning. This reasoning plays an essential role in the remarkable human ability to make rational decisions in an environment of uncertainty and imprecision.

One should notice that fuzzy theory is well defined and mathematically sound, which will be shown below within this section. What's crucial to realize is that fuzzy theory is a theory of fuzziness, not a theory which is itself fuzzy. Just as the laws of probability are not random, so the laws of fuzziness are not vague. The fuzziness lays in the linguistic concepts which are intrinsic vague. Fuzzy theory distincts itself from the probability theory as was described in [Zad65]: it provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria of class membership rather than the presence of random variables. We will not treat these subjects further in this thesis. We refer interested readers to [Zad65, Hir81].

One of the most powerful insights of Zadeh is the observation that the linguistic terms can be represented by functions whose values are numerical degrees of membership in the membership domain, say $[0, 1]$. Such a representation is fundamental to the modelling of approximate reasoning, "*the process or processes by which a possible imprecise conclusion is deduced from a collection of imprecise premises.*" [Tur91].

We cite: "... *the notion of a fuzzy set provides a convenient point of departure for the construction of a conceptual framework which parallels in many respects the framework used in the case of ordinary sets, but is more general than the latter* ..." as written in [Zad65]. Fuzzy theory does have its origin and basis in classical set and logic theory as aforementioned. A brief review of the classical set and logic theory is helpful to have a better understanding of the fuzzy theory.

Classical set and logic theory

A *set* is a well-defined collection of objects or elements with certain features or properties in common. In classical set theory it is said that an element x of the *universe* $\mathcal{U}$ can either belong to, or not belong to a set C, but nothing in between. All elements belonging to C have a common feature which is represented by the so-called *characteristic function* $\mu_C(x)$. $\mu_C(x)$ equals one for all elements in C and zero for the other elements in $\mathcal{U}$. Mathematically this relation is presented as follows:

$$\mu_C(x) = \begin{cases} 1 & x \in C \\ 0 & x \notin C \end{cases} \qquad \forall x \in \mathcal{U} \tag{3.1}$$

It can also be interpreted as a mapping from $\mathcal{U}$ to $\{0, 1\}$ or $\mu_C(x) : \mathcal{U} \rightarrow \{0, 1\}$. Such a set $\{0, 1\}$ is featured with a very sharp boundary.

A classical set can be *finite, countable* or *uncountable.* Logical operations like complement, intersection, union etc. can be performed on sets. Let C_1 and C_2 be two sets being part of the *universe* $\mathcal{U}$, then these operations can be defined as:

- *intersection:* $C_1 \cap C_2 = \{x \mid x \in C_1 \textit{ and } x \in C_2\}$
- *union:* $C_1 \cup C_2 = \{x \mid x \in C_1 \textit{ or } x \in C_2\}$
- *complement:* $\neg C_1 = \{x \mid x \notin C_1\}$

These operations are clearly defined with well defined meaning here. But we shall see that their interpretation is not so simple in the fuzzy case because graded concepts are used. There are many different notations and terminologies in fuzzy theory due to the many different areas that fuzzy theory is applied to. We shall try our best to use the conventional notations and terminologies as proposed in [Zad65, Hel90, Zim92, Dri93].

Fuzzy set and fuzzy logic theory

An element x of the universe $\mathcal{U}$ can partially belong to a set F. The universe $\mathcal{U}$ is a set that all other sets in concern exist in it. This F is defined as a *fuzzy set*. The characteristic function $\mu_C(x)$ mentioned above is extended to *membership function* $\mu_F(x)$ which can take values from $[0,1]$ instead of $\{0,1\}$. A fuzzy set F is written as a set of pairs (*member*, *membership degree*):

$$F = \{(x, \mu_F(x)) \mid x \in \mathcal{U}\}, \;\; \mu_F(x) \in [0,1] \tag{3.2}$$

Here $\mu_F(x)$ represents the mapping from $\mathcal{U}$ to $[0,1]$ or $\mu_F(x) : \mathcal{U} \rightarrow [0,1]$. The value zero is used to represent complete non-membership, the value one is used to represent complete membership, and a value in between is used to represent an intermediate degree of membership. Note that in practice, the terms "membership function" and "fuzzy set" are used interchangeably.

Note that a classical set C can always be seen as a particular case of a fuzzy set, by putting:

$$F_c = \{(x, \mu_{F_c}(x)) \mid x \in \mathcal{C}\} = \{(x,1) \mid x \in \mathcal{C}\} \cup \{(x,0) \mid x \notin \mathcal{C}\} \tag{3.3}$$

On the other hand, most fuzzy sets can only be *approximated* by a classical set (see the example below).

As an example, a fuzzy set of *all real numbers close to* 10, see (3.4), is illustrated in Figure 3.1. A classical approximation, (3.5), is shown in Figure 3.2.

$$F = \{(x, \mu_F(x)) \mid x \in \mathcal{R}\} \quad \text{where} \quad \mu_F(x) = (1 + (x - 10)^2)^{-1} \tag{3.4}$$

$$C = \{x \in \mathcal{R} \mid 9.8 \leq x \leq 10.2\} \tag{3.5}$$

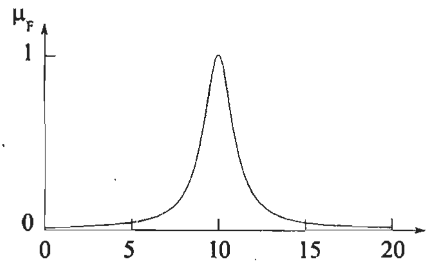

Figure 3.1: Fuzzy set of all real numbers close to 10.

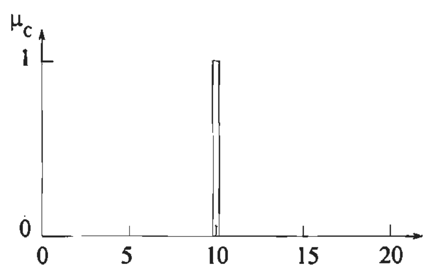

Figure 3.2: Classical set of all real numbers close to 10.

Intersection, union and complement, etc. can be extended to apply to fuzzy sets. Let F_1 and F_2 be two fuzzy sets, then according to the definition in [Zad65]:

- *intersection*

$$\begin{aligned} F_1 \cap F_2 &= \{(x, \mu_{F_1 \cap F_2}(x)) | x \in \mathcal{U}\} \\ \text{where} \quad \forall x \in \mathcal{U}: \ \mu_{F_1 \cap F_2}(x) &= \min\{\mu_{F_1}(x), \mu_{F_2}(x)\} \end{aligned}$$

- *union:*

$$\begin{aligned} F_1 \cup F_2 &= \{(x, \mu_{F_1 \cup F_2}(x)) | x \in \mathcal{U}\} \\ \text{where} \quad \forall x \in \mathcal{U}: \mu_{F_1 \cup F_2}(x) &= \max\{\mu_{F_1}(x), \mu_{F_2}(x)\} \end{aligned}$$

- *complement:*

$$\begin{aligned} &F_1' = \{(x, \mu_{F_1'}(x)) \mid x \in \mathcal{U}\} \\ &\text{where} \quad \mu_{F_1'}(x) = 1 - \mu_{F_1}(x) \end{aligned}$$

Here the min and the max operators are used for $\cap$ and $\cup$, the logical *and* and *or* operations. But in principle any t-norms and s-norms can be applied instead of the min and the max operators. A *triangular norm* or *t-norm* denotes a class of binary functions that can represent the intersection operation. A *triangular co-norm* or *s-norm* denotes a class of binary functions that can represent the union operation. Similarly, a *c-norm* represents the complement operation. But it is always very difficult to make the right choice. Some often encountered t-norms, s-norms and c-norms can be found in [Kli88, Zim92].

Next, we give some notions and definitions which are needed for our study. Whoever wants to have a systematic study of the fuzzy theory may turn to [Dub80, Kli88, Zim92, Dri93].

The *support*, $S(A)$, of a fuzzy set A is the classical set that contains all elements of A with non-zero membership degree. $S(A)$ is defined as:

$$S(A) = \{x \in \mathcal{U} \mid \mu_A(x) > 0\} \tag{3.6}$$

The *nucleus*, $N(A)$, of a fuzzy set A is the classical set that contains all elements of A with membership degree 1. $N(A)$ is defined as:

$$N(A) = \{x \in \mathcal{U} \mid \mu_A(x) = 1\} \tag{3.7}$$

A more general notion of support and nucleus is the so-called *α-level-set*. The *α-level-set* of a fuzzy set A, A_α, is a classical set that contains all elements of A with membership degree greater than or equal to α. Formally A_α is defined as:

$$A_\alpha = \{x \in \mathcal{U} \mid \mu_A(x) \geq \alpha) \tag{3.8}$$

The *strong α-level-set* of a fuzzy set A, $A_{\bar{\alpha}}$, is defined by:

$$A_{\bar{\alpha}} = \{x \in \mathcal{U} \mid \mu_A(x) > \alpha) \tag{3.9}$$

It is obvious that: $S(A) = A_{\bar{0}}$, and $N(A) = A_1$.

The *height* of a fuzzy set A, $\text{hgt}(A)$, is equal to the largest membership degree. $\text{hgt}(A)$ is defined as:

$$\text{hgt}(A) = \sup_{x \in \mathcal{U}} \mu_A(x). \tag{3.10}$$

A fuzzy set A is *normal*, if $\text{hgt}(A) = 1$, and *subnormal*, if $\text{hgt}(A) < 1$.

Convex is an important notion which one often encounters in the fuzzy control context. We use the definition given by [Hel90b]. A fuzzy set is convex if its membership function does not contain 'dips'. This means that the membership function is, for instance, increasing, decreasing or bell-shaped. A fuzzy set A is convex if and only if (note that $\lambda x_1 + (1-\lambda)x_2$ is "between" x_1 and x_2 for $x_1 \neq x_2$ and $\lambda \in (0,1)$):

$$\forall x_1, x_2 \in \mathcal{U} \quad \forall \lambda \in [0,1] : \mu_A(\lambda x_1 + (1-\lambda)x_2) \geq \min(\mu_A(x_1), \mu_A(x_2)). \tag{3.11}$$

Convex sets are useful for the representation of linguistic concepts. Actually we only use convex fuzzy sets in our study.

Two other important notions are projection and cylindrical extension, see Figure 3.3. A general definition of this two notions concerning the *n-dimensional* case can be found in [Dri93]. Here we only give the most simple, but most applicable definition concerning the 2-dimensional case. The notion fuzzy relation is used to define these two notions. A *fuzzy relation* is a simple extension of a fuzzy set. In contrast to ordinary fuzzy sets A and B, defined respectively on $\mathcal{X}$ and $\mathcal{Y}$, a function $R(x,y)$ on $\mathcal{X} \times \mathcal{Y}$ can be seen as a fuzzy set on $\mathcal{X} \times \mathcal{Y}$. Such a set is called a fuzzy relation. $\mu_R(x,y)$ is the membership function of $R(x,y)$.

The *projection* of R onto $\mathcal{Y}$ is defined as:

$$\text{proj } R \;\; on \;\; \mathcal{Y} = \{(y, \sup_x \mu_R(x,y)) \mid y \in \mathcal{Y}\} \tag{3.12}$$

This projection is also written as $\int_{\mathcal{Y}} \sup_x \mu_R(x,y)/y$ in the case that $\mathcal{Y}$ is uncountable. The $\sum$-*sign* is used instead of the $\int$-*sign* if $\mathcal{Y}$ is countable. $\sup_x \mu_R(x,y)/y$ is an alternative notation for $(y, \sup_x \mu_R(x,y))$, where $/$ denotes a tuple.

The projection of $R(x,y)$ on $\mathcal{X}$ is defined similarly.

The cylindrical extension is more or less the opposite of the projection, refer to Figure 3.3. The *cylindrical extension* of A on $\mathcal{X} \times \mathcal{Y}$, ce($A$), is the set of all tuples $(x,y) \in \mathcal{X} \times \mathcal{Y}$ with membership degree equal to $\mu_A(x)$. We have:

$$\text{ce}(A) = \{((x,y), \mu_A(x)) \mid x \in \mathcal{X}, y \in \mathcal{Y}\} \tag{3.13}$$

This cylindrical extension is also written as $\int_{\mathcal{X}\times\mathcal{Y}} \mu_A(x)/(x,y)$ in the case that $\mathcal{X}$ and $\mathcal{Y}$ are uncountable. The $\sum$-*sign* is used instead of the $\int$-*sign* if $\mathcal{X}$ and $\mathcal{Y}$ are countable. $\mu_A(x)/(x,y)$ is an alternative notation for $((x,y), \mu_A(x))$.

The cylindrical extension of B on $\mathcal{X} \times \mathcal{Y}$ is defined similarly.

One should notice that proj ce(A) *on* $\mathcal{X} = A$, but in general ce(proj R *on* $\mathcal{Y}) \neq R$.

With these basic knowledge about fuzzy theory, we can go on with the introduction and study of the fuzzy control theory. *A fuzzy controller* is a knowledge-based controller. Design of a fuzzy controller requires specification of both membership functions and control rules. Besides, the decision making or reasoning process should also be specified. Most fuzzy controllers are similar in their basic structure, but a large number of parameters must be specified in the design of a given controller. Although

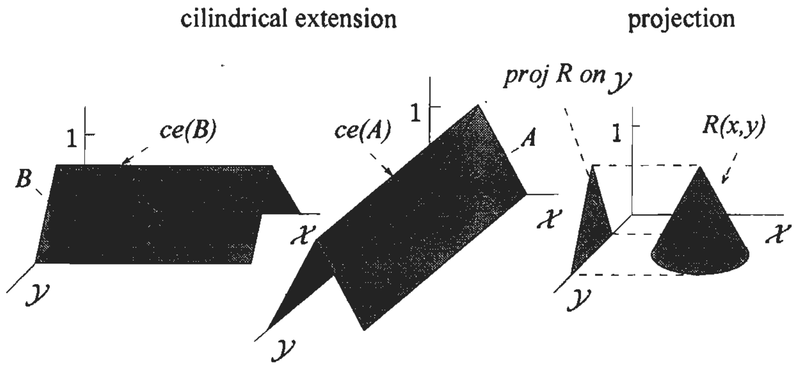

Figure 3.3: Cylindrical extention and projection

exploitation of experts knowledge or operators experience in control decision is the most advantageous aspect of fuzzy control approach, the lack of effective and systematic design techniques is a limiting factor. Evaluation and tuning of the controller parameters are typically done in a *trial-and-error* manner through simulations or actual implementations.

"*An important subject in fuzzy control theory is tuning of a fuzzy controller. If one wants to tune a fuzzy controller, one can focus on the choice of rules, membership functions, number of input and output fuzzy sets and their degree of overlapping, implication, and connection operations, and defuzzification method. All these choices are closely related and in no way independent of each other.*" [Hel93]. Anyone who tries to apply fuzzy theory in control faces with these choice problems and must make his decisions in one way or another. We focus ourselves on three different, but closely inter-related subjects, namely membership functions, inference and defuzzification in the following sections.

3.3 Membership functions

The fuzzy sets should represent linguistic concepts in a way close to the human beings' interpretation. This is the first step to use fuzzy theory, and it is also one of the most important and basic steps. Fuzzy sets are characterized by the so-called *membership functions* (*MFs*). Thus the study on *MFs* is presented first.

A *Membership Function* (*MF*) is a relationship between a quantity and its grade. It assigns a membership grade to each element x of the universe $\mathcal{U}$. *Membership Functions* (*MFs*) are used to represent fuzzy sets that are associated with linguistic concepts. The name for a specific fuzzy set is its *label.*

In principle any real value from $[0, +\infty)$ can be chosen as the membership grade. But for sake of simplicity the range for the membership grade is normally taken from $[0, 1]$. The membership function $\mu_F(x)$ of a fuzzy set F is a function:

$$\mu_F(x) : \mathcal{U} \rightarrow [0, 1] \tag{3.14}$$

MFs come in various kinds, depending on the linguistic terms they have to represent. The linguistic concepts can be classified in three different sorts, namely *increasing*, *decreasing*, and *approximating* concepts. Thus three different types of *MFs*, see Figure 3.4, are used to represent these three different concepts respectively.

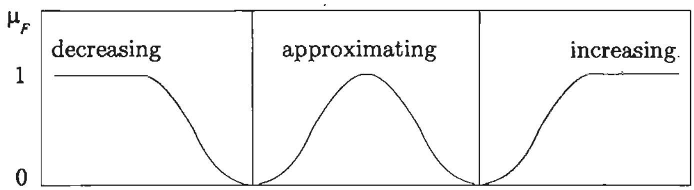

Figure 3.4: Three kinds of membership functions

A fuzzy set F is completely determined by the set of tuples:

$$F = \{(x, \mu_F(x)) \, | x \in \mathcal{U}\} \tag{3.15}$$

The three frequently encountered *MFs* shapes are ***triangular***, ***trapezoidal*** and ***bell-shaped***; see Figure 3.5 (All these are examples of convex functions). Due to its greater simplicity advantage, the triangular shaped *MFs* are widely used.

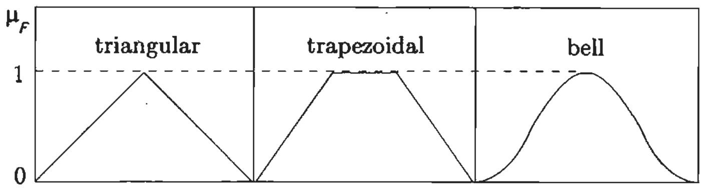

Figure 3.5: Three different shape of membership functions

Membership functions generally are supposed "*to be given*" [Zim92]. Obviously this should not be the case. One always needs to specify certain *MFs* for his own applications. Precise membership values do not exist by themselves, they are tendency indices that are subjectively assigned by an individual or a group. Moreover, they are context-dependent. The grades of membership reflect an "ordering" of the objects in the universe, induced by the predicate associated with F; this "ordering" when it exists, is more important than the membership values themselves [Dub80].

There are many ways for generating membership functions. We list five of them below in order to get some more insights into membership functions.

1. Subjective evaluation and elicitation. Interested readers can consult the work done by Hisdal [His88a, His88b].

2. Ad-hoc forms. Used quite often in fuzzy control applications.

3. Converted frequencies or probabilities.

4. Physical measurement.

5. Learning and adaptation.

According to Mamdani [Mam77], you should not tune the membership functions because they are chosen on the basis of knowledge from an expert. However, this is true only when the knowledge is exact. Otherwise there is always some free space for tuning. By membership function tuning we mean to change the parameters of membership functions.

In our study, the steps of the fuzzy control process are inevitably dependent on the *MFs* chosen. The performance of a fuzzy controller can be improved by improving the quality of the membership functions. In most cases the membership functions are chosen in an *ad-hoc* manner. In that case a large number of *trial-and-error* evaluations are necessary.

A triangular membership function is completely determined by giving the *peak point*, *height*, *left-width* and *right-width*. The relation with another membership function is determined by the *overlap*, *cross point*, *cross point height*. Some of these aspects are interdependent. The definitions of these terms are illustrated in Figure 3.6. Empirical studies on the membership function shape have been presented in [Bok95, Cha91], but the influence of the membership function shape to the control performance of the single machine system isn't so obvious there. The following guidelines are proposed for membership functions chosen in fuzzy control on the basis of our knowledge and literature:

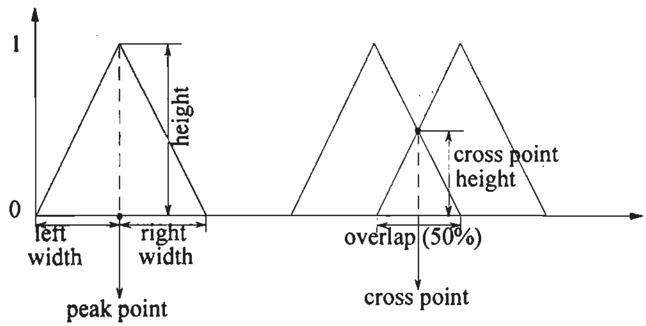

Figure 3.6: Terms or parameters of membership functions

- The membership functions are composed so that the supports overlap. This provides for a reliable reading. The overlap percentage is preferred to be 50%, see Figure 3.6.

- The symmetrical triangular membership functions will be used throughout the rest part of our studies. Since most of the linguistic terms or concepts are symmetrical, we prefer to choose symmetrical membership functions. Triangular membership functions are chosen because of their simplicity.

- The number of labels for both the input and output variables are limited to 5 (e.g., '*very low*', '*low*','*normal*','*high*','*very high*', refer to [Haa95, Wan96b]). The membership functions or fuzzy sets used to define a variable are all with the same width.

3.4 Inference mechanisms

Fuzzy logic differs from conventional logic in that it aims at providing a model for approximate rather than precise reasoning. It covers a variety of inference rules whose premises contain fuzzy propositions. Inference in approximate reasoning is computation with fuzzy sets that represent the meaning of a certain set of fuzzy propositions. The process of fuzzy inference can be defined by three context independent entities [Zim91]. The most important characteristic of fuzzy logic is the infinite number of possible *truth values* (*membership degrees*) on the continuous interval $[0, 1]$, see the previous section. With this, the first context independent entity is laid down. The *set of operators or connectives* (negation, disjunction, implication, conjunction and equivalence) is the second entity. Concerning this set, a large number of possibilities is available. The third context independent entity of fuzzy inference is the *inference scheme*. Before we start a survey of the inference rules or schemes in approximate reasoning, the fundamental notions and definitions should be explained first.

The first notion is the so-called *linguistic variable*. "*By a linguistic variable we mean a variable whose values are words or sentences in a natural or artificial language. For example: age is a linguistic variable if its values are linguistic rather than numerical, i.e., young, not young, very young, quite young, old, not very old and not very young, etc., rather than 20, 21, 22, 23....*" [Zad75]. A linguistic variable is the fundamental knowledge representation unit in approximate reasoning.

The framework associated with the notion of a linguistic variable is: $\langle X$, **L**X, $\mathcal{X}$, $M_X\rangle$ in [Dri93]. X denotes the symbolic name of a linguistic variable. **L**X, being called the term-set of X, is the set of *linguistic values* that X can take. An arbitrary element of **L**X is denoted as LX. A linguistic value denotes a symbol for a particular property of X. $\mathcal{X}$ is the actual physical domain over which the linguistic variable X takes its quantitative values. $\mathcal{X}$ can be discrete or continuous. M_X is a semantic function which gives a 'meaning' (interpretation) of a linguistic value in terms of the quantitative elements of X, i.e., $M_X : LX \rightarrow F_{LX}$. F_{LX} is a fuzzy set defined over $\mathcal{X}$. M_X takes a symbol for a linguistic value as its argument and returns the 'meaning' of the symbol in terms of a fuzzy set.

Example: $X = Age$, $\mathbf{L}X = \{young,\ middle\text{-}aged,\ old\}$, $\mathcal{X} = [0, 120]$, $M_X = young \rightarrow F_{young},\ middle\text{-}aged \rightarrow F_{middle-aged},\ old \rightarrow F_{old}$. For F_{LX}, see Figure 3.7.

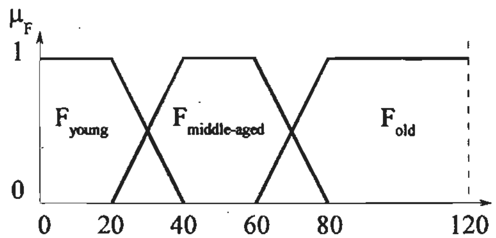

Figure 3.7: Fuzzy sets associated with linguistic variable Age

"*Approximate reasoning is used to represent and reason with knowledge expressed in atomic primitives, which are expressed in a natural language form, ...*" as stated in [Dri93]. An example of an atomic primitive is: 'work-in-process has the value high'. The formal symbolic translation of this natural language expression in terms of linguistic variable and linguistic value is: '*wip* is *H*', such an expression is called an *atomic fuzzy proposition*, where *wip* is the symbol chosen to denote the variable work-in-process and H is the symbol chosen to denote the term high. The meaning of the atomic fuzzy proposition is defined by the fuzzy set F_H or membership function μ_{F_H}, defined as the *predicate* of the proposition.

Based on the notion of atomic fuzzy propositions and linguistic connectives such as '*and*', '*or*' and '*not*' one can form more complex fuzzy propositions called compound fuzzy propositions, e.g., $\langle X$ is A *and* X is $B\rangle$, $\langle X$ is A *or* X is $B\rangle$ and $\langle X$ is *not* $A\rangle$. The meaning of these compound fuzzy propositions is given by interpreting the connectives '*and*', '*or*' and '*not*' as '*conjunction*', '*disjunction*' and '*negation*' respectively. We assume that A and B are defined on the same universe of discourse $\mathcal{U}$. Conjunction is represented by the intersection operation which can be implemented via any *t-norm*. Disjunction is realized by the union operation which can be implemented via any *s-norm*. The complement operation, which can be implemented by any *c-norm*, is used to realized the negation. The *t-norm*, the *s-norm* and the *c-norm* have been defined in the Section 3.2. When A and B are defined on *different* domains, e.g. A on $\mathcal{X}$ and B on $\mathcal{Y}$, then one needs a fuzzy *relation* for interpreting the operations such as the '*and*' and '*or*' connectives. For instance, $\langle X$ is A *and* Y is $B\rangle$ and $\langle X$ is A *or* Y is $B\rangle$.

With the notion of proposition we can look at the fuzzy conditional or fuzzy *if-then* production rules. A fuzzy conditional or a fuzzy if-then production rule is represented as:

$$\textit{if} \;\; \langle \textit{fuzzy proposition} \rangle \;\; \textit{then} \;\; \langle \textit{fuzzy proposition} \rangle \tag{3.16}$$

where *fuzzy proposition* is either an atomic or compound fuzzy proposition. The fuzzy proposition following *if* is called the rule *antecedent*, while the fuzzy proposition following *then* is named as *consequent*. Such a rule describes the causal relationship between process state and control output variables in fuzzy control. This relationship may be definitional, or heuristic. The meaning of such a rule can be interpreted in many different ways. All these interpretations are intended to imitate the human beings' interpretation of this rule within the contents of approximate reasoning. The symbolical expression of a fuzzy *if-then* rule is as follows:

$$\textit{if} \;\; \langle X \textit{ is } A \rangle \;\;\; \textit{then} \;\; \langle Y \textit{ is } B \rangle \tag{3.17}$$

The meaning of such a rule can be represented as a fuzzy relation defined on $\mathcal{X} \times \mathcal{Y}$, where $\mathcal{X}$ and $\mathcal{Y}$ are the domains of linguistic variables X and Y. A and B are linguistic values. Different implications are devised to try to interpret this causal relation properly. The Gödel and the Mamdani implications which will be explained in the following are two of these implications.

Implication is defined as a connective in logic that indicates that if the antecedent is true, the consequent is also true. This connective has already been represented by many different mathematical formulas. From this side of view an *if-then* rule is also a kind of compound proposition. Although the implications derived from many-valued logic are claimed to be useful in control, it is a surprise that only the application of the Mamdani implication has been observed. Why haven't the others been applied? Is it possible to apply them in control? Comparisons and analysis of two different groups of implications and the inferences will be carried out in order to determine the proper implication and inference rule for control.

An intuitive interpretation of the rule in (3.17) is as follows:

$$\begin{aligned}
&Y \textit{ is maximally } B \quad \textit{if} \quad X \textit{ is maximally } A; \\
&Y \textit{ is unknown} \quad \textit{if} \quad X \textit{ is not } A; \\
&Y \textit{ changes between these two extremes} \\
&\quad \textit{when } X \textit{ changes from } A \textit{ to not } A.
\end{aligned} \tag{3.18}$$

The *Gödel implication* is one of the best-known implications in *many-valued logic*. So it is chosen here as a representation of all other implications derived from many-valued logic in order to compare it with the *Mamdani implication*. The relation obtained by the Gödel implication is *unidirectional* from A to B. The *unknown* here is interpreted as that every element of Y in $\mathcal{Y}$ is possible, so the membership degree of Y in $\mathcal{Y}$ is always 1. The meaning of the rule by applying the Gödel implication is shown in Figure 3.8 a.

With respect to fuzzy control, the *Mamdani implication* is the most important and widely used implication known in the literature. Its definition is based on the *intersection* operation. The relation obtained by the Mamdani implication is a *bi-directional* relation. This differs from all other implications derived from many-valued logic, like the Gödel implication just described. The *unknown* here is interpreted as that no conclusion can be drawn, so the membership degree of Y in $\mathcal{Y}$ is always 0. Figure 3.8 b illustrates the meaning representation by means of the Mamdani implication. With the notions of fuzzy proposition and implication, we can now look at the kernel part of approximate reasoning, the *inference*.

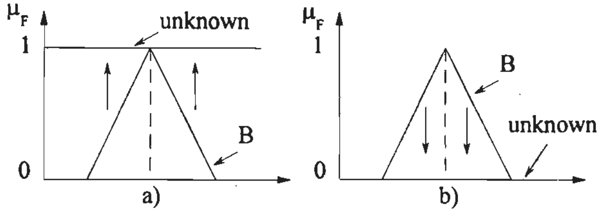

Figure 3.8: The Godel and the Mamdani implication

Inference is defined as the process of reaching a conclusion based on an initial set of propositions, the truths of which are known or assumed. Two inference rules, namely the *generalized modus ponens* and the *compositional rule of inference*, are the most often encountered ones in fuzzy logic. The *generalized modus ponens* inference scheme is deducted from the Boolean *modus ponens*:

$$\begin{array}{lll} A & & Premise: X\ is\ A \\ \underline{A \Rightarrow B} & or: & \underline{Implication:\ If\ X\ is\ A\ then\ Y\ is\ B} \\ B & & Conclusion: Y\ is\ B \end{array} \tag{3.19}$$

There is a nice example to illustrate this inference scheme:

$$\begin{array}{l} Premise: This\ tomato\ is\ red \\ \underline{Implication:\ If\ a\ tomato\ is\ red\ then\ the\ tomato\ is\ ripe} \\ Conclusion: This\ tomato\ is\ ripe \end{array} \tag{3.20}$$

The deduction of the *modus ponens* to the *generalized modus ponens* is indicated as a generalization that can be described in two steps [Ter87]:

- The *predicates* (red and ripe) in the propositions of the *modus ponens* may be represented by fuzzy sets. After this generalization the inference scheme is also referred to as '*approximate reasoning*'.

- A slight variation on the identity of the *predicates* in the premise and the conclusion is possible. Now this inference is indicated as '*plausible reasoning*' [Zim91].

The inference scheme of the *generalized modus ponens* can then be presented as follows:

$$\begin{array}{l} Premise : X\ is\ A' \\ \underline{Implication:\ If\ X\ is\ A\ then\ Y\ is\ B} \\ Conclusion : Y\ is\ B' \end{array} \tag{3.21}$$

Here X and Y are symbolic names for objects, and A, A', B and B' are object properties. The intention is to obtain B' from the given A' and $A \Rightarrow B$. This B' has a pre-defined meaning which may be somewhat stronger or weaker than B. Some criteria for a desired B' are established and practical calculation methods are provided. The tomato example with this scheme is [Miz82]:

$$\begin{array}{l} Premise : This\ tomato\ is\ very\ red \\ \underline{Implication:\ If\ a\ tomato\ is\ red\ then\ the\ tomato\ is\ ripe} \\ Conclusion : This\ tomato\ is\ very\ ripe \end{array} \tag{3.22}$$

The *generalized modus ponens* alone is not sufficient for drawing any conclusions automatically from *un-identical* predicates in the premise and the implication (like '*very red*' and '*red*'). This means that an algorithm is needed that implements the reasoning process according to this inference scheme. Based on the fuzzy set A' and the implication, this algorithm has to specify the fuzzy set B'. This specification involves the definition of the shape, the place in the universe of discourse of Y and the support of the fuzzy set B'. Important in this matter is the type of rule which is being modelled. In the above example the decision rule is similar to the gradual rule as it is defined in [Dub91]. This type of rule is characterized by the fact that the overall meaning of the predicates in the antecedent and the consequent of the implication does not change. The predicates can only be strengthened or weakened.

To model this conditional inference scheme, Zadeh [Zad75] proposed the '*compositional rule of inference*' for the case that the implication is essentially a *relation* (this is a case which occurs often). This formalization makes it possible to draw conclusions automatically. The definition of the *compositional rule of inference* is [Zim91]:

$A(x)$ and $B(y)$, $x \in \mathcal{X}$, $y \in \mathcal{Y}$, are fuzzy sets in $\mathcal{X}$ and $\mathcal{Y}$. $R(x, y)$ is a fuzzy relation in $\mathcal{X} \times \mathcal{Y}$. For $B(y)$ it holds that: $B(y) = A(x) \circ R(x, y)$.

This definition is based on a mathematical principle, *composition of relations.* It can be deducted from [Dri93] and rewritten in a form which we dealt with above, using *projection* (proj) and *cylindrical extension* (ce):

$$B(y) = A(x) \circ R(x, y) = \text{proj}(\text{ce}(A(x)) \wedge R(x, y)) \ on \ \mathcal{Y} \tag{3.23}$$

In most common applications the intersection is implemented by means of the minimum operator and the projection by means of the maximum operator, thus indicated as min − max *composition.* In that case the compositional rule of inference is defined as:

$$\mu_B(y) = \max_x \min(\mu_A(x), \mu_R(x, y)) \tag{3.24}$$

The *Compositional rule of inference* is characterized by the following inference scheme [Zim91]:

$$\begin{array}{l} Premise : x \ is \ A \\ \underline{Relation : \ y \ is \ R(x)} \\ Conclusion : y \ is \ B \end{array} \tag{3.25}$$

$$\begin{array}{l} Premise : \ John \ is \ tall \\ \underline{Relation : \ Paul \ is \ almost \ as \ tall \ as \ John} \\ Conclusion : Paul \ is \ fairly \ tall \end{array} \tag{3.26}$$

This inference scheme provides a way to compute the individual set which composes the total control signal set. This inference scheme is based on the availability of an *explicit relationship* between the predicates of the variables X and Y. Note that the *relation* in the example above is a special case of an *implication*: 'Paul is almost as tall as John' may be rewritten as: '*If* Paul has length l, *then* John has a length which is slightly smaller than l'.

In below the functionality of the compositional rule of inference combined with the Gödel and the Mamdani implications will be analyzed. Both implications are a formalized way to find the *relation* $R(x, y)$, given the fuzzy sets $A(x)$ and $B(y)$. For the Mamdani implication, the formula is:

$$\mu_{R_m}(x, y) = \min(\mu_A(x), \mu_B(y)),$$

and for the Gödel implication:

$$\mu_{R_g}(x, y) = \begin{cases} 1 \;\; \textit{if} \;\; \mu_A(x) \leq \mu_B(y) \\ \hline \mu_B(y) \;\; \textit{else} \end{cases}$$

(See the graphical representations of both implications in Figure 3.9, first step.)

The compositional rule of inference is combined with the Gödel or Mamdani implication in the process of finding the conclusion 'y *is* B'', given the premise 'x *is* A'' and the *relation* R connected with the implication '*If* x *is* A *then* y *is* B'. The strengthening or weakening of the predicate A, otherwise said: the transformation from A to A', is based on the so-called shifted hedging method [Hel88], i.e. A' results from a shift of the triangular fuzzy set A along the $\mathcal{X}$ axis.

An inference scheme can be verified if the fuzzy set B' relates to the semantics of the original fuzzy set B. The derivation of the fuzzy set B' is displayed in four steps in Figure 3.9. Step one describes the graphical representation of the implication. Step two displays the fuzzy set A' as a strengthening (or a weakening) of fuzzy set A according to the shifted hedging method. This step also involves the determination of the intersection of the cylindrical extension of A' and the implication R. This intersection is displayed as a three dimensional entity. This three dimensional entity is isolated in step three. Finally the projection of this entity

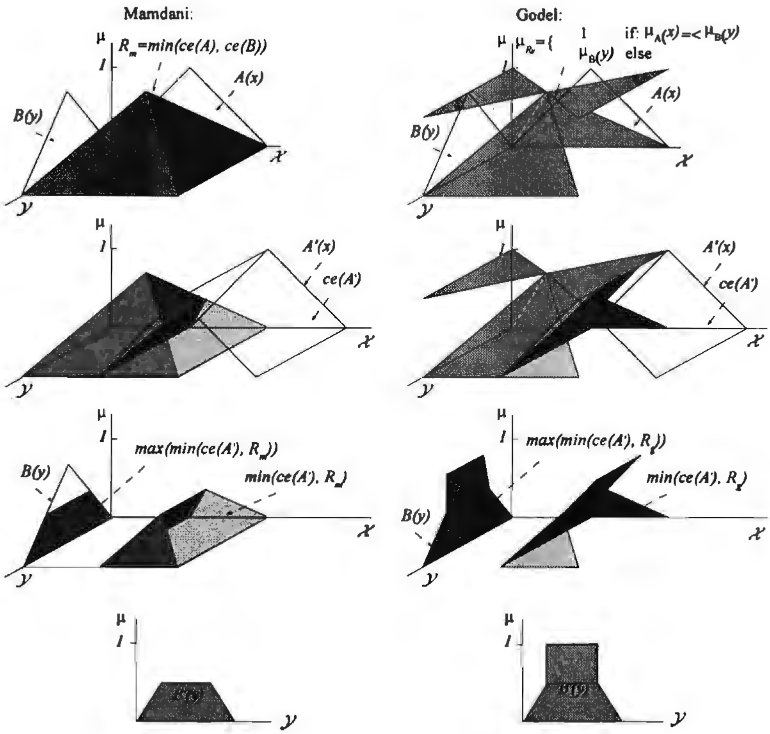

Figure 3.9: Graphical analysis of the semantics of the compositional rule of inference in combination with the Mamdani and Godel implication

on $\mathcal{Y}$ is exhibited in step four. This projection represents the fuzzy set B' from the inference scheme. The B' obtained by employed *Mamdani implication* in combination with the *compositional rule of inference* is called *clipped set.* It can be seen as that the consequent set is limited or clipped by the *truth value* of the antecedent part. From Figure 3.9 the following observations can be drawn:

- The semantics of the two fuzzy sets that represent the predicate B' are very unclear. The fuzzy set B' is virtually not explainable as a strengthening or weakening of the predicate B.
- Both a strengthening and a weakening of fuzzy set A in the same

amount, according to the shifted hedging method, will result in an identical fuzzy set B'. This is due to the symmetrical feature of the implications.

- The support of fuzzy set B' is fixed. B' can not be shifted from the fuzzy set B. This is related to the truth functional character of the implication R. This means that R is determined completely by the fuzzy sets A and B [Swa92].
- As soon as the intersection of A and A' gets empty, the fuzzy set B' is a dichotomous (crisp) set that adds a membership value of one (Gödel implication) or zero (Mamdani implication) to all the elements of the support of the fuzzy set B . The semantics of this fuzzy set is defined as *unknown* [Hel88].

Based on these observations, the fuzzy set B' that resulted from the compositional rule of inference and the Mamdani and Gödel implication does not represent the semantics of the predicate in the inference scheme. The same analysis for the implications according to Łuckasiewicz, Sharp, Kleene-Dienes and Zadeh are described in [The94, The95]. Because of this meagre result, which does not allow a verification of the semantics of the inference scheme of the generalized modus ponens, one can try to search for a more appropriate relationship or implication. This implication should, combined with min-max composition, deliver a fuzzy set B' that fits the semantics of the predicate B' in the inference scheme.

In order to characterize the *generalized modus ponens* inference scheme, a number of criteria can be defined. We should keep in mind that a weakening or strengthening of a fuzzy set in both antecedent and consequent should be implemented according to the shifted hedging method. [Hel90a] describes some criteria that however do not focus on the semantics of the conclusion. Therefore, in this study, we suggest the following intuitive criteria:

- If A' equals A, then B' is identical to B [Hel90a].
- If the intersection of A and A' is empty ($A \wedge A' = \emptyset$), then the only valid conclusion based on this type of rule can be whether B' is stronger or weaker than B.

- As the intersection of A' and A gets smaller, it gets more and more difficult to draw a shaded conclusion B'. In other words, the fuzzy set B' gets more and more imprecise, or the support of B' gets wider.

- The conclusion B' may never be more precise then the fuzzy set B. According to this criterion, the support of B', $S(B')$, is supposed to be larger than the support of B, $S(B)$, $S(B') \geq S(B)$.

The analyzed implications combined with the compositional rule of inference appear to satisfy only the first (trivial) criterion. Therefore, an alternative approach is presented to initiate a process to find a more suitable relationship or implication that in combination with the min-max composition can model the inference scheme of the generalized modus ponens. In Figure 3.10, a relationship that resulted from this approach is outlined (The idea originates from R.P. Nederpelt).

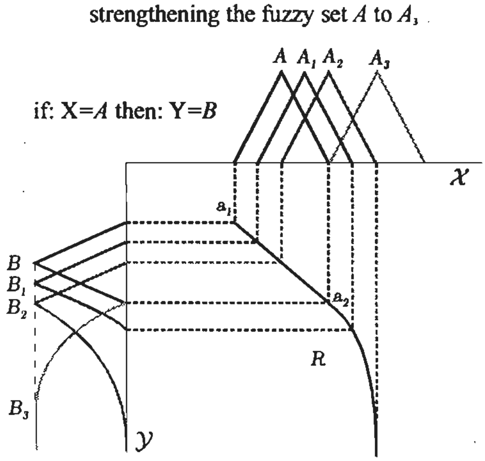

Figure 3.10: An alternative implication

By strengthening the fuzzy set that represents the predicate A in three steps, refer to Figure 3.10, the accompanying fuzzy sets representing the shift of predicate B can be checked according to the criteria mentioned above:

- The straight line between points a_1 and a_2 takes care of the first criterion. The intersection of relationship R and the cylindrical extension of the original fuzzy set A, (ce(A)), projected on $\mathcal{Y}$ results in the original fuzzy set B.

- This criterion is met by the asymptotic part of relationship R. For example: a strengthening of predicate A to A_3 should result in a conclusion that only indicates whether the predicate is stronger or weaker then predicate B. This conclusion can be represented by fuzzy set B_3. In this fuzzy set there exists only very little differentiation between the membership values of the elements of B_3.

- This asymptotic part of R also takes care of the third criterion. With the reduction of the intersection of A to A_n $(n = 1, 2, 3)$, the base of the conclusion gets wider: base$(B_3) >$ base$(B_2) >$ base(B_1).

- The straight line between a_1 and a_2 in Figure 3.10 is determined by the fuzzy sets that represents the predicates A and B of the original inference scheme. Combined with the asymptotic part this straight part of relationship R prevents that the base of a conclusion can become smaller than the reference conclusion B.

The relationship proposed in Figure 3.10 seems a good alternative implication according to the aforementioned criteria. The relationship is illustrated very clearly by means of the graphical approach. But we should notice that it's fairly a difficult job to represent this relationship analytically, which is needed to combine with the *compositional rule of inference* to model the *generalized modus ponens.* It's thus not practical for us to use it in the further study in this thesis. We shall look back to the Gödel and the Mamdani implications below. The meaning of B' is not important in fuzzy control and only its contribution to the total resulting fuzzy set is interesting. The latter one can be called a suggested control signal for obvious reasons.

All the individual results are combined by a *union* operation if the Mamdani implication is applied. An *intersection* operation will be used to combine all the individual results in the case of employing the Gödel implication. Whether a *union* or an *intersection* should be used to combine all the individual rules is depending on the feature of the employed implications. With Mamdani implication an empty fuzzy set of control is resulted if an empty information is provided, see Figure 3.8, the *unknown* is interpreted as the membership degree of Y in $\mathcal{Y}$ is always 0. So a union operation should be used when we look at the contribution of each individual rule to the total control set. The Gödel implication on the converse interprets the *unknown* as the membership degree of Y in $\mathcal{Y}$ is always 1, in another word it implies that every Y is a possible value for control. Thus an intersection operation should be used when we try to find the common control set in which the common suggested control signal can be found (also see Chapter 6 in [Ped93]).

A *non-convex* suggested control signal set (see [Dri93]) may be resulted in if more than two rules are activated at the same time by using the Gödel implication. It is obviously not desired in control. The results obtained by applying the Mamdani and the Gödel implication combined with the compositional rule of inference are shown in Figure 3.11. The combined set by using Gödel inference is *non-convex*. The resulting crisp value y_{god} shouldn't be considered as a good control signal because it corresponds to a very small membership degree (see Section 3.5). This might be one of the reasons that *Gödel-like* implications haven't been found in fuzzy control applications, and only the *Mamdani* implication is being used. The implications derived from multi-valued logic are not suited to be applied in control. As far as fuzzy control is involved the Mamdani implication combined with the compositional rule of inference will be employed for interpreting the rules.

Because there are essential differences between Mamdani implication and the other implications derived from many-valued logic (like the Gödel implication), it is better to make a distinction between *fuzzy control* and *fuzzy logic control*. The controller using the Mamdani implication will be named as *fuzzy controller*, while reserving the name of *fuzzy logic controller* for one that actually uses other implications from many-valued logic.

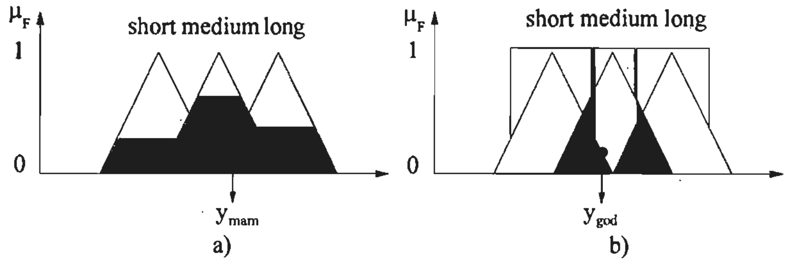

Figure 3.11: Results of combined fuzzy set for three active rules with Mamdani and Godel implication.

3.5 Different defuzzification methods

Since a fuzzy control system consists of two parts, namely a fuzzy controller and a non-fuzzy process, a defuzzification step is always needed in a fuzzy control procedure. There are many defuzzification methods available, we give the four best-known ones from the literature. Their respective merits and shortcomings are described, dependent on the inference scheme, rules, domains, etc. The four defuzzification methods are: *center-of-area/gravity*, *center-of-sums*, *height* and *middle-of-maxima*.

A *clipped set* (see Section 3.4) results by using Mamdani implication in combination with the compositional rule of inference. The individual clipped set is denoted as $CLU^{(k)}$[Dri93]. We denote the union of these sets as CLU with $CLU = \bigcup_{k=1}^{n} CLU^{(k)}$.

Center-of-area/gravity

The *center-of-area* or *center-of-gravity* method is the best well-known and the most widely used defuzzification method. This method determines the center of the area below the combined fuzzy set, Figure 3.12. It doesn't count the overlap between two individual sets twice.

$$y^*_{\text{cog}} = \frac{\int_{\mathcal{Y}} y \cdot \max_k \mu_{CLU^{(k)}}(y)dy}{\int_{\mathcal{Y}} \max_k \mu_{CLU^{(k)}}(y)dy} \tag{3.27}$$

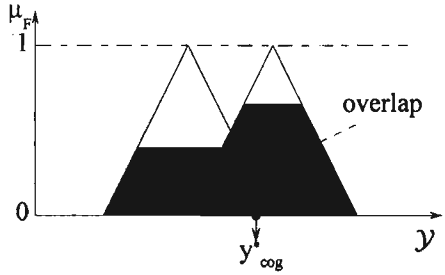

Figure 3.12: Center-of-gravity

Center-of-sums

A similar but faster defuzzification method is *center-of-sums*. It considers the contribution of the area of each clipped fuzzy set individually. Thus overlapping areas, if such exist, are reflected more than once by this method (see Figure 3.13).

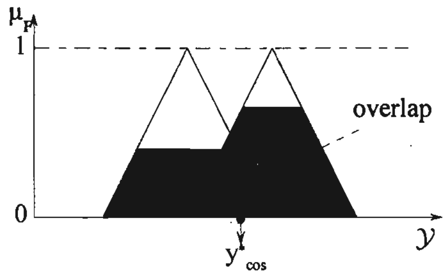

Figure 3.13: Center-of-sums

$$y^*_{\cos} = \frac{\int_{\mathcal{Y}} y \cdot \sum_{k=1}^{n} \mu_{CLU^{(k)}}(y)dy}{\int_{\mathcal{Y}} \sum_{k=1}^{n} \mu_{CLU^{(k)}}(y)dy} \tag{3.28}$$

Height

Height defuzzification method is also using the individual sets instead of their union. It takes the *peak point* of each individual clipped set, then builds up the weighted sum of these peak points using their corresponding heights (Figure 3.14). Thus neither the support nor the shape of $CLU^{(k)}$ play a role in the computation of y^*_{hgt}. If we denote the peak point of $CLU^{(k)}$ as p_k and its height as h_k, then:

$$y^*_{\mathrm{hgt}} = \frac{\sum_{k=1}^{n} p_k \cdot h_k}{\sum_{k=1}^{n} h_k} \tag{3.29}$$

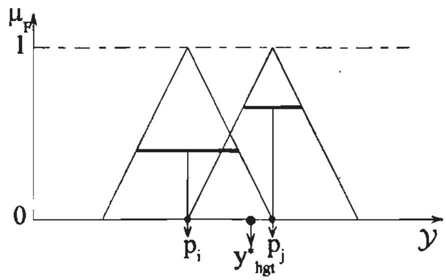

Figure 3.14: Height

Middle-of-maxima

Middle-of-maxima is a mean or average of the so-called first-of-maxima and last-of-maxima. *First-of-maxima* method uses the union and takes the smallest value of the domain $\mathcal{Y}$ with maximal membership degree in the union set, see y^*_{fom} in Figure 3.15.

$$y^*_{\mathrm{fom}} = \inf_{y \in \mathcal{Y}} \{y \in \mathcal{Y} \mid \mu_{CLU}(y = \mathrm{hgt}(CLU)\} \tag{3.30}$$

Where $\mathrm{hgt}(CLU) = \sup_{y \in \mathcal{Y}} \mu_{CLU}(y)$ is the highest membership degree of CLU, and $\{y \in \mathcal{Y} \mid \mu_{CLU}(y) = \mathrm{hgt}(CLU)\}$ is the set of domain elements with degree of membership equal to $\mathrm{hgt}(CLU)$.

The alternative of this method is called the last-of-maxima, Figure 3.15, and y^*_{lom} is given as:

$$y^*_{\text{lom}} = \sup_{y \in \mathcal{Y}} \{y \in \mathcal{Y} \mid \mu_{CLU}(y) = \text{hgt}(CLU)\} \tag{3.31}$$

The *Middle-of-maxima* defuzzification method is illustrated in Figure 3.15, and y^*_{mom} is given by:

$$\begin{aligned} y^*_{\text{mom}} &= \frac{y^*_{\text{fom}} + y^*_{\text{lom}}}{2} \qquad (3.32)\\ &= \frac{\inf_{y \in \mathcal{Y}} \{y \in \mathcal{Y} \mid \mu_Y(y) = \text{hgt}(Y)\} + \sup_{y \in \mathcal{Y}} \{y \in \mathcal{Y} \mid \mu_Y(y) = \text{hgt}(Y)\}}{2} \end{aligned}$$

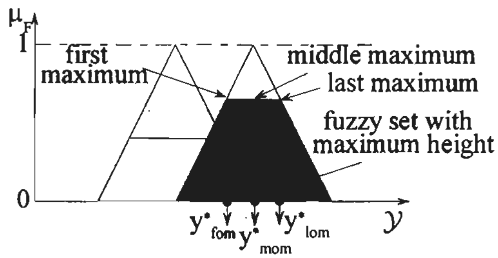

Figure 3.15: Middle-of-maximum

There are some criteria that an ideal defuzzification method should satisfy. None of the defuzzification methods described above satisfies all criteria listed below. One has to weigh these criteria for the application under concern to be able to make the right choice of a defuzzification method. The output domain is assumed symmetrical in our discussion of defuzzification. For other situations one can consult [Hel93].

- Continuity: A small change in the input of the fuzzy controller should not result in a large change in the output. While the methods like *first-of-maxima*, *last-of-maxima* and *middle-of-maxima* lead to discontinuity which in most of the control cases is not expected. Figure 3.16 shows an example of using the *middle-of-maxima* defuzzification method. When there is a small change in the input,

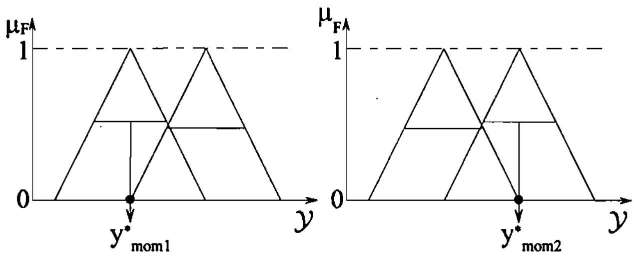

Figure 3.16: An example of discontinuity by using the middle-of-maximum defuzzification method

which causes a slightly change of the relative importance of the two activated rules. But a very abrupt change of the output crisp values may result by using *middle-of-maxima*, from y_{mom_1} to y_{mom_2}.

- Disambiguity: A defuzzification method is disambiguous if the algorithm to find y^* is well defined. All the defuzzification methods discussed above satisfy this criterion. There is one method, named *center-of-the largest area*, which does not satisfy this criterion (e.g. when there are two largest areas that are equal large).

- Plausibility: Every defuzzified control output has a horizontal component $y^* \in \mathcal{Y}$ and a vertical component $\mu_{CLU}(y^*) \in [0,1]$. The y^* is defined to be plausible if it lies approximately in the middle of the support of the union set and has a high degree of membership in the union set. *First-of-maxima*, *last-of-maxima* and *middle-of-maxima* hardly satisfy this criterion, especially the first two of them. They guarantee that y^* with the maximum $\mu_{CLU}(y^*)$, but most of the time y^* is not lies in the middle of the support. *Center-of-gravity*, *center-of-sum* and *height* methods are better concerning this criterion.

- Computational complexity: The *height*, together with the *first-of-maxima, last-of-maxima* and *middle-of-maxima* are fast methods. *Center-of-sum* is faster than *center-of-gravity.* This criterion will be less and less restrictive due to the fast development of the computers.

- Weight counting: A defuzzification method is weight counting if each of the overlapping parts is counted in the formula calculating the overall output or union fuzzy set. None of the methods being discussed satisfies this criterion. It deserves a further study to investigate this subject.

As follows from these criteria, the *height* defuzzification method is the best method. The *center-of-sum* defuzzification method comes next. An empirical study on different defuzzification methods has been carried out in [The94]. The results obtained there are very close to the expectation, the *height* and the *center-of-sum* are the two best ones and the *center-of-gravity* comes second.

With the knowledge of fuzzy controller design, we shall apply the fuzzy control concept to control *Discrete Event Dynamic Systems* (*DEDS*) in the next chapters.

Chapter 4

Fuzzy Control in a Single Machine System

In this chapter the fuzzy control of a single machine system is presented. Simulation studies have been performed on the basis of a descriptive model for investigating the control performance. Two other control approaches, namely the proportional control (*P-control*) and the Load-Oriented Order Release control (*LOOR-control*), are employed to compare with the fuzzy control approach. After presenting a descriptive model of the single machine system and its control system in Section 4.1, the fuzzy control process for controlling the single machine system is given out in Section 4.2. Section 4.3 deals with the simulation study and analysis of the fuzzy control performance in comparing it with the other two control strategies. The aim of this study is to investigate the feasibility of applying the fuzzy control concept for the control of Discrete Event Dynamic Systems (*DEDS*).

4.1 Single machine system model

A system model is needed here to conduct control. Because of the features of *DEDS*, it is not possible to have a mathematical model of such a system. A descriptive model of a system is illustrated graphically below.

An industrial system is described by a collection of *systems*, *processes* and *communication channels*. [Roo96]. A system is depicted by a shaded circle. A system usually contains more than one process. A normal circle denotes a process. Processes are connected via channels. Channels are depicted by arrows. The direction of the communication corresponds with direction of the arrow.

The top layer of the model is shown in Figure 4.1. The orders generated by generator G are sent to system S. The order generating time is modelled by an Erlang-distribution with $k = 2$ and $mean = 2.5$ (hrs). Each order is modelled with a fixed order processing time of 10 hrs. So there in average four times more orders generated than the capacity can handle. The intention is to avoid machine starvation. S can accept or reject orders according to the system load status. If an order cannot be accepted by S for further processing, it is delivered to the sub-contractor Sc. Orders which have been processed by S are placed on the material pile P. The material needed for the production is supplied by the supplier Su.

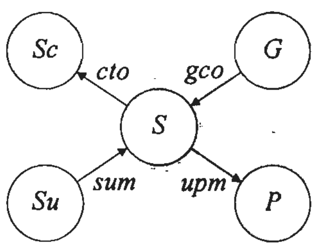

Figure 4.1: One machine system model

S consists of system controller C and production unit U (see Figure 4.2). U sends system state information, for instance *work-in-process* and *lead time*, to C. These informations are sent on the request of C and C is also responsible for sending the control signal to U. Different control strategies can be employed here to perform the control function.

Production unit U (see Figure 4.3) consists of buffer B and machine M. The orders accepted are stored in B waiting to be processed. M can break down during processing and repair is necessary. This situation is modelled by introducing two statistic variables, namely the "Mean

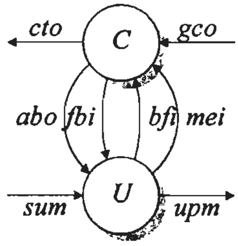

Figure 4.2: System S

Time To Failure" ($MTTF$) and the "Mean Time To Repair" ($MTTR$). Exponential distributions are used to define these two parameters, $MTTF$ is with mean 32 hrs and $MTTR$ is with mean 8 hrs. After a period of $MTTF$, a failure will occur and the recovery from the failure will take $MTTR$. The unfinished process is continued after the recovery from the machine break down. This is known as the *resume policy*.

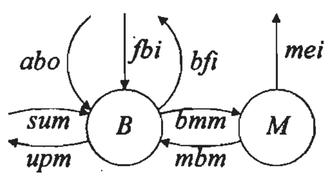

Figure 4.3: Production unit U

In the stable and desired situation, the input rate should be equal to the output rate and the mean lead time should be constant and equal to a desired mean lead time. It is the inevitable disturbance of the system that makes the stable situation impossible, and this is why a controller is always necessary to adjust the system to overcome the disturbance.

C consists of three processes (see Figure 4.4). Order acceptor A accepts or rejects orders and passes on accepted orders to U. This order acceptance can be controlled by fuzzy controller F. This is also the place where the other different control concepts and techniques are implemented for control. The pre-calculation for the controller and some statistical calculation are performed in evaluator E.

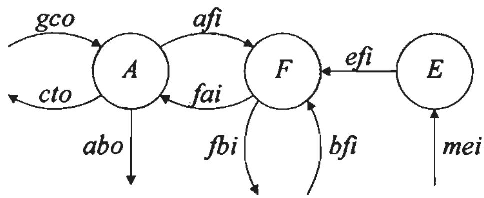

Figure 4.4: System controller C

The problem that we are interested in is how to meet the demands of the customers meanwhile keeping a high profit for the system. One of the measures is to have a reliable short delivery time of orders with a high production rate of the system. Reliable short delivery times can be ensured by reliable short lead times. The control objective is thus to obtain short mean lead times at a reasonable high rate of production (throughput) of the system. The relationship among the three parameters, namely *lead time*, *throughput*, and work-*in-process*, has been illustrated in Chapter 2. By adjusting work-in-process, the control objectives can be reached. In the next section we shall illustrate how to achieve the objective by applying the fuzzy control concept.

4.2 Fuzzy control process

The fuzzy controller follows the structure as described in Chapter 2. The output variables of the system are the *lead time (lt)* and the *work-in-process* (*wip*). The deviation of the lead time from the norm mean lead time is denoted by *dlt* and is equal to (lead time - norm mean lead time). The *dlt* and the *wip* are the two input variables to the fuzzy controller. The control signal is the arrival rate of orders to the system which is realized by an acceptance interval (*ain*). The *ain* is a time interval within which only one order can be accepted. The smaller the acceptance interval, the higher the arrival rate.

dlt\wip	low	ok	high
small	short	short	medium
ok	short	medium	long
large	medium	long	long

Table 4.1: The rule base for the single machine system control

The *dlt* and the *wip* are represented by fuzzy sets as shown in Figure 4.5 a) and b). Each variable is associated with three fuzzy sets which are in 50% overlapped with each other. The widths of all sets for one variable are equal. For reasons of simplicity triangular membership functions (*mfs*) are chosen in our application to represent all the fuzzy sets as aforementioned in Chapter 3. The *ain* is also associated with three fuzzy sets as illustrated in Figure 4.5 c).

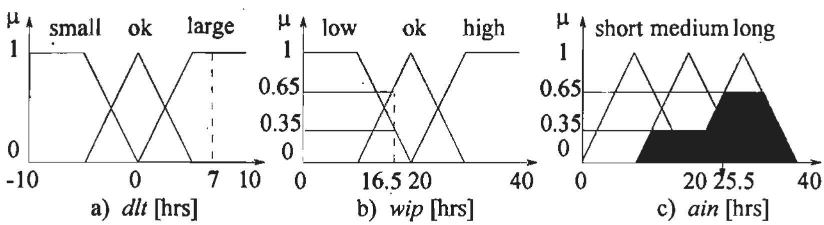

Figure 4.5: Fuzzy control process

With the observation 7 for *dlt* (Figure 4.5 a)), its fuzzy value is 1 in the *large* set. While with the observation 16.5 for *wip* (Figure 4.5 b)), the corresponding fuzzy values are 0.35 and 0.65 in the *low* and *ok* set respectively. The shadowed area of *ain* (Figure 4.5 c)) is the combined fuzzy set obtained by evaluating two relevant rules in the rule base (Table 4.1).

This rule base is a representation of the linguistic control protocol derived on basis of the experts knowledge. The first row gives the three sets associated with *wip*, while the first column shows the three sets associated with *dlt*. The other elements in the matrix represent the control decision value for *ain*. In the table form of the rule base, the last row and the second-last column, for example, define one of the active rules: *If dlt* is

large and wip is ***ok then ain*** is ***long.*** Interpreting the intersection ***and*** with a minimum operation, min (1, 0.65), the resulting fuzzy value for the rule antecedent is thus 0.65. This value will be used to limiting the fuzzy set *long* for *acceptance interval* (*ain*) according to Mamdani implication. All relevant rules are evaluated separately and these individual results will then be combined by an union action following Mamdani inference.

The centre-of-gravity defuzzification method is used to get a crisp value from the combined fuzzy set. This crisp value, 25.5 in Figure 4.5 c), is sent to the system to implement the control. Depending on the observation of the lead time and the work-in-process, more rules can be evaluated at the same time to obtain the control results. This control process is implemented to conduct the simulation study in the next section.

4.3 Comparison between p-, LOOR- and fuzzy-control

A series of simulation experiments have been performed to verify the feasibility of fuzzy control of *DEDS*. Two other control methods, the *P-control* and the *LOOR-control*, are employed in this study for comparison. It is assumed that more orders are generated than the system can handle, so certain orders should be sent to the sub-contractor in order to avoid high *wip* which may cause long lead time (see Section 4.1). What orders should be sent to the sub-contractor is a decision from the controller. Such a controller is capable of regulating the system under disturbance, like a machine failure.

The performance of the system without any control function can be expected to be very poor because all generated orders will be waiting on the work floor of the system. This appears from the extremely long and unstable *mean lead time* due to the high *work-in-process*, refer to Table 4.2 and Figure 4.6. The mean lead time during a simulation run is scattered across a very large time-scale and the mean lead time of different simulation runs are quite diverse. The symbols used in the following tables are: *mlt* (mean lead time (hrs)), *sdlt* (standard deviation lead time (hrs)), *tp* (throughput).

run	mlt	sdlt	tp
1	3942.02	2305.67	799
2	4147.39	2325.76	797
3	4051.82	2361.25	802
4	3919.60	2326.01	794
5	3974.36	2301.61	804
6	3928.13	2250.64	795
average	3993.89	2311.82	799

Table 4.2: No control

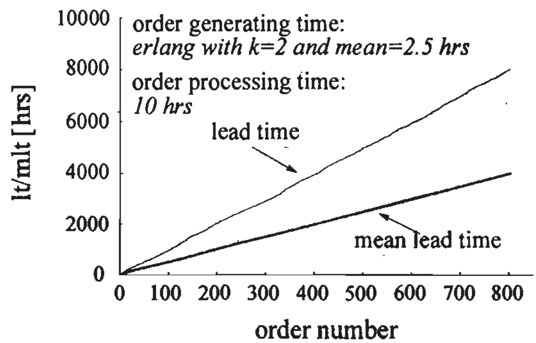

Figure 4.6: No control

By applying different control strategies reasonable good results can be obtained as described in the following. Each simulation run produces a set of results, and the results from different simulation runs are expected different because of the stochastic behavior of the model. So normally it is not fair to draw conclusions from only one simulation run. A widely used method for determine the number of simulation runs is the relative precision method. It uses a *student-test.* In this study each simulation experiment is performed in 6 runs which is sufficient for a relative precision of 0.1 with 95% of confidence. All control approaches are implemented by using the feedback control structure as shown in Figure 4.7.

The *P-controller* results from the study on the relationship between continuous systems control and *DEDS* control [Mom90]. The lead time observed from the system is compared with the norm mean lead time. Their difference, denoted by *dlt*, is taken as the input variable to the *P-*

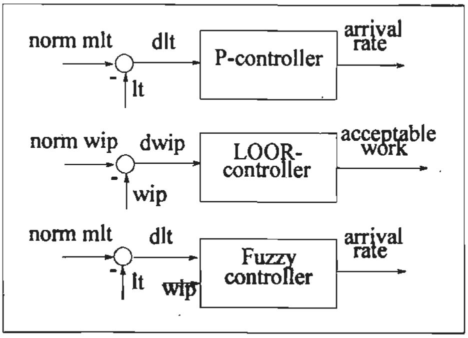

Figure 4.7: Three different controllers

run	mlt	sdlt	tp
1	26.87	15.30	766
2	28.69	18.47	764
3	26.99	16.49	764
4	27.82	17.82	767
5	26.42	16.45	777
6	28.47	17.44	762
average	27.54	17.00	767

Table 4.3: P-control

controller. Depending on the *dlt* the arrival rate of orders to the system can be adjusted in order to maintain a constant *wip*. The arrival rate adjustment is realized by variating the *acceptance interval* (*ain*) as defined in the last section. The control algorithm is:

$$ain = constant - p * dlt$$

where *constant* is the offset value and p is the proportional parameter which can be tuned to improve the control performance. The offset value is set to 12.5 *hrs* (idealized minimum lead time at a 20% capacity disturbance). The p value in this control is 0.5, see [Mom90]. The simulation results are obtained as shown in Table 4.3 and Figure 4.8.

The throughput is reasonable high, while the mean lead time (*mlt*) becomes much shorter and more constant compared to the uncontrolled

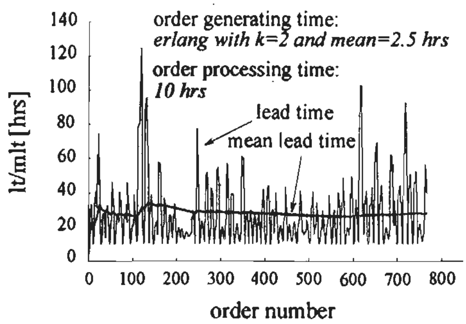

Figure 4.8: P-control

case, looking to the smooth and stable line of *mlt* in Figure 4.8. The *mlt* is about 150 times shorter than that of the uncontrolled system. The reason is that all generated orders will come in the system and wait on the work floor for production if there is no control of the orders acceptance and rejection. Thus the *mlt* will keep on increasing due to the increasing *wip*. By sending some orders to the sub-contractor the increasing high *wip* can be avoid. A much short and stable lead time can be obtained with the reasonable low and constant *wip*. The scatter of *mlt* becomes smaller. The average standard deviation of *mlt* is 17.00, much smaller than 2311.82 under the uncontrolled case. The system's performance is considerably improved.

The *LOOR* controller is also shown in Figure 4.7. In this study the plan period is assumed to be 25 hrs, so the expected mean lead time is also 25 hrs. The load limit is 40 hrs with a load percentage of 200% at 20% capacity disturbance, and the capacity is $0.8 \times 25\ hrs = 20\ hrs$. The desired or the norm *wip* is thus 20 hrs, see Chapter 2.

The simulation results by applying *LOOR-control* can be found in Table 4.4 and Figure 4.9. The lead time scatter is over an even smaller timescale when compared to the *P-control* case. The *mlt* is a little bit closer to the norm *mlt* (25 hrs), while the throughput is higher.

The fuzzy control process described in section 4.2 is implemented here to control the one machine system. The simulation results are obtained as in Table 4.5 and Figure 4.10. The small average standard deviation,

run	mlt	sdlt	tp
1	27.50	14.61	788
2	27.28	12.60	797
3	27.15	12.83	795
4	27.55	14.91	792
5	26.87	13.90	801
6	26.94	14.20	799
average	27.22	13.84	796

Table 4.4: LOOR control

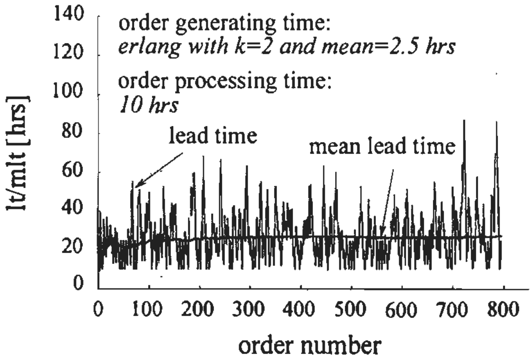

Figure 4.9: LOOR-control

12.16 in Table 4.5, implies the small scatter of *mlt*. The *mlt* is close to the norm *mlt* with a reasonably high throughput.

run	mlt	sdlt	tp
1	26.56	11.63	804
2	26.64	11.68	799
3	27.29	12.63	795
4	26.79	12.19	803
5	27.04	12.80	811
6	27.15	12.00	807
average	26.91	12.16	803

Table 4.5: Fuzzy control

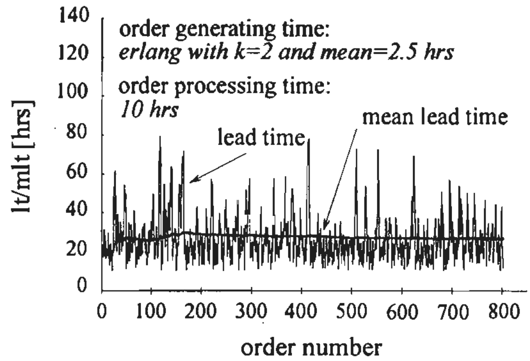

Figure 4.10: Fuzzy-control

In order to further investigate the control performance, another series of simulation experiments have been carried out to obtain the characteristic curves. The characteristic curves, presented in Figure 4.11 and Figure 4.12, are intended to have a good comparison of different control methods. These curves are obtained by variating the work-in-process values. In the *P-control* case, the desired *wip* is set with the proportional related desired *lt* value. The throughput as a function of the work-in-process for each control method is depicted separately in Figure 4.11. The mean lead times in relation with the work-in-process are illustrated in Figure 4.12.

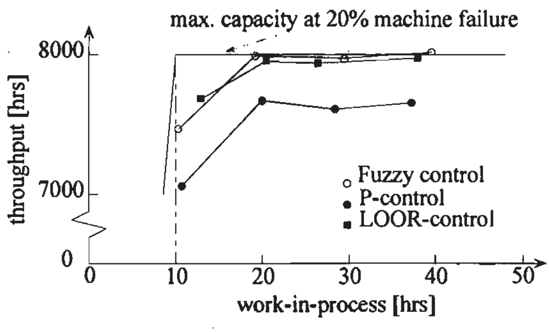

Figure 4.11: Throughput versus work-in-process

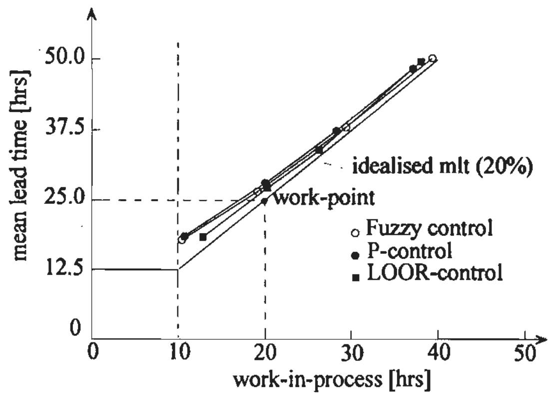

Figure 4.12: Mean lead time versus work-in-process

Each point on the curves indicates one simulation run at a certain work-in-process. While each simulation runs over 10000 *hrs* which is long enough to neglect the transition period (about one tenth of the simulation time). With the assumptions that each order needs 10 *hrs* to be processed and the mean repair time for machine failures is around one fifth of the processing time, the mean maximum throughput of the system comes to 8000 (10000 − 2000) *hrs*. The constant horizontal line (tp = 8000 *hrs*) in Figure 4.11 represents the idealized tp or *maximum capacity* line at 20% machine failures. If the desired mean lead time is assumed to be 25 *hrs*, the theoretic work-in-process corresponding to this desired mean lead time should be around 20 *hrs*, as illustrated in Figure 4.12. The line which connects the critical point and the (20, 25) point and extends to the right is the idealized *mlt* line at 20% of machine failures. The theoretical mean maximum throughput can be reached with the minimum mean lead time if there is always one and only one order (10 *hrs* work) in the system, refer to Figure 4.11 and 4.12.

The *P-control* produces the poorest results concerning the throughput and the mean lead time as shown in the figures. The characteristic curves obtained are both comparably far from the idealized curves. Due to the delay feature of such a *P-controller* (the control action is based on the status from the history), the control performance is expected poor. The machine is with 3% of idle time because of the inappropriate control, and it's why the *tp* line obtained by applying *P-control* is always lower than the idealize maximum capacity line in Figure 4.12. We should also notice that it is rather time consuming to tune the p parameter. Besides, because there is no mathematical model of the system available, to conceive a precise *P-controller* for such a system control is extremely difficult. It is not a preference for such systems control.

The *LOOR-control* method gives very good results concerning the mean lead time and the throughput as depicted in the figures. The characteristic curves are closer to the idealized curves, compared to the *P-control.* The *LOOR-control,* which is developed by many years of experts effort, is indeed a good control method.

The characteristic curves obtained by applying fuzzy control are also quite close to the idealized curves. Fuzzy control provides quite good results concerning the compromise between mean lead time and throughput. The standard deviation of the mean lead time under fuzzy control is the smallest one. From this study at least we can say that it is feasible to apply the fuzzy control concept in *DEDS* control. The results obtained lend support to the possible application of fuzzy control in *job shop* like systems. By properly applying experts knowledge, for instance *LOOR* control concept, a promising fuzzy controller should be expected. In the next chapter research on the control of complex job shop systems using the fuzzy control concept in combination with the *LOOR* control concept will be presented.

Chapter 5

Fuzzy Control in a Job Shop System

Job shops are generally classified as high-variety, low-volume manufacturers. Job shop systems are the most complex *Discrete Event Dynamic Systems* (*DEDS*), consisting of a network of machines that produce in the course of time a big variety of products that are in demand. Flexibility is important in a job shop. Such a job shop system is featured by orders which may vary in series numbers and kinds, processing sequence (route) and processing time, etc. Besides, job shop systems have inherent uncertainty and are stochastic. The responsibility to control such a job shop system is conventionally given to the experienced operator. It is difficult to establish a mathematical model for a job shop system on the one side, and on the other side it is reasonably easy for a trained operator to conduct a reasonable control. An operator often needs to take decisions to balance a job shop system in order to make a good compromise among systems' multi-criteria, like short lead time and high utilization.

Because of the increasing international competition among companies and the increasing complexities of job shop systems a good automatic control of job shop systems becomes more and more important. The fast development of computers provides such a possibility. The classical approach when seeking a higher degree of automatic control of a system has been to establish a mathematical model of the system, and is hardly applicable here. Applying the methodology of fuzzy control the operational experience of manual control can be used as the basis for implementing automatic control.

On the basis of the research on fuzzy control of a single machine system which has been presented in [Wan96] and the previous chapter, this chapter deals with the application of fuzzy concepts to the computer control of a simplified job shop system. The control knowledge is also based on the *Load-Oriented Order Release* (*LOOR*) strategy. The *LOOR* control approach is employed as a reference to be compared with the fuzzy control approach. In the next section the descriptive model of a simple job shop system together with its control module will be given. In Section 5.2, the proposed fuzzy control methodology is presented. A comparative analysis of the LOOR and the fuzzy control performances on the basis of simulation study is provided in Section 5.3.

5.1 The descriptive model of a simple job shop system

A descriptive model of a simple *job shop* system is illustrated graphically in below. A shaded circle, a normal circle and a arrow depict a system, a process and a communication channel respectively as explained in Chapter 4. Simulation studies of the control performances are carried out on the basis of the descriptive model which is implemented on a personal computer.

Job shop *JS* together with its environment, namely customers *Cu* and suppliers *Su*, is shown in Figure 5.1. Customers ask for various products from job shop by means of orders. Each order follows a given process plan or a recipe that specifies the sequence of machines it must visit and the operations performed by these machines. Suppliers are responsible for supplying the required material to the job shop. The manufacturing process takes place in the job shop.

Sufficient amount (120) of orders are put in the system when the simulation starts, which intends to shorten the system's warm up period.

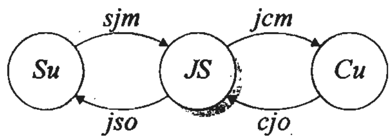

Figure 5.1: Job shop with its environment

Customers Cu then continuous generate orders after each fixed time interval (2.5 hrs). The assumption here is that there are more orders are generated than the job shop capacity can handle in order to avoid job shop starvation. In another words the job shop is overloaded.

Job shop consists of job shop controller JSC, store JSS, transporter JST and three different workstations WS_1, WS_2, and WS_3 as shown in Figure 5.2. JSC is not only responsible for the good communication with customers and suppliers, but also takes care of the monitoring and the controlling of the real production process. Different control strategies can be implemented here to conduct this control function. In this study two control strategies, namely the $LOOR$ control and the fuzzy control, are employed. Our attention is paid to the application of fuzzy control. The $LOOR$ control is only used as a reference for the comparison with the fuzzy control approach.

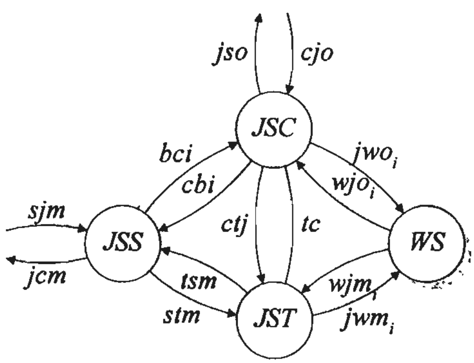

Figure 5.2: The simple job shop model

Raw materials from suppliers and (half-) finished products from workstations are stored in *JSS*. The transportation of raw materials and (half-) finished products among *JSS* and the workstations is performed by transporter *JST*. In this study each move of *JST* is assumed to be 0.5 *hrs*. The actual material transformations are carried out in workstations.

Each workstation consists of four elements as illustrated in Figure 5.3. For the sake of simplicity each workstation contains only one machine M in this study. Local transporter WST is responsible for transporting materials and (half-) finished products between local store WSS and machine M. The time for each move of the WST is assumed to be 0.1 *hrs*. Machine M can break down during processing and repair is necessary, refer to Chapter 4. This situation can be modelled as: after a period of "Mean Time To Failure" ($MTTF$), a failure will occur and the recovery from the failure will take "Mean Time To Repair" ($MTTR$). Exponential distributions are used to define these two parameters, $MTTF$ is with mean 16 *hrs* and $MTTR$ is with mean 4 *hrs*. The unfinished process is continued after the recovery from the machine break down. Operation time can be modelled by a constant (5 *hrs*) or by a distribution (exponential with mean 5 *hrs*), see Section 5.3.

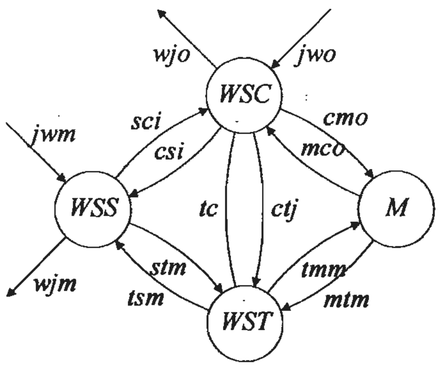

Figure 5.3: The workstation model

5.2 The fuzzy control approach

The control objective is to obtain short mean lead times (*mlt*) at a reasonable high rate of production of the system. The work-in-process (*wip*) plays an important role in realizing this control. Both the *LOOR* and the fuzzy control approaches are implemented using the feedback control structure as shown in Figure 5.4. The output (or controlled) variable of both controllers are the same, namely the acceptable work load (*awl*) to the system. The input variable of the LOOR controller is *dwip*, the deviation of the actual *wip* from the *norm* or *desired wip*. The input variables of the fuzzy controller are the real wip $rWip$ and the potential wip $pWip$. We have:

$$wip = rWip + pWip$$

The LOOR strategy follows the description in Chapter 2. The fuzzy control approach is presented below.

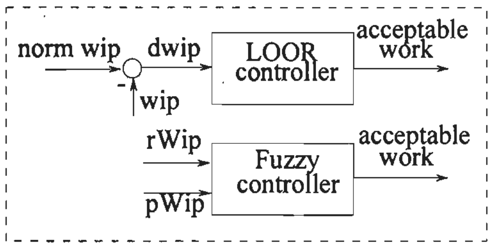

Figure 5.4: Feedback control structure

The real wip $rWip$ and the potential wip $pWip$ of each workstation are used as input variables to the fuzzy controller. The sum of work needed to be performed on a workstation, which is calculated from all orders directly queuing in front of the workstation is defined as the *real wip* of this workstation. The *potential wip* of a workstation is the sum of the work needed to be done in the workstation, which is calculated from all other orders not directly queuing in front of the workstation. The *acceptable work load* for each workstation is decided on the basis of its *wip* information. Controller *JSC* controls the three workstations in the same

$pWip_1 \backslash rWip_1$	XL	L	M	H	XH
XL	XB	B	M	S	XS
L	B	M	S	XS	XS
M	B	M	S	XS	XS
H	M	S	XS	XS	XS
XH	M	S	XS	XS	XS

Table 5.1: The rule base for controlling workstation WS_1

way. The control of workstation WS_1, as an example, will be illustrated in more detail in the following.

The real wip and the potential wip of workstation WS_1 are represented symbolically as $rWip_1$ and $pWip_1$ respectively. These two input variables cannot be treated equally because of the different degrees of influence they have on the system. This will lead to the asymmetrical control rule base as presented in Table 5.1. The general guide line for the design of a control rule base can be found in [Dri93, Ped93]. In the table form of the rule base, the last row and the last column, for example, define a rule: if $rWip_1$ is XH and $pWip_1$ is XH then awl_1 is XS.

The acceptable work load to workstation WS_1 is awl_1. Each variable is associated with five sets (or labels). VeryLow *XL*, Low *L*, Medium *M*, High *H* and VeryHigh *XH* are the five fuzzy sets for $rWip_1$ and $pWip_1$, while the five sets for awl_1 are VerySmall *XS*, Small *S*, Medium *M*, Big *B* and VeryBig *XB*, refer to Figure 5.5.

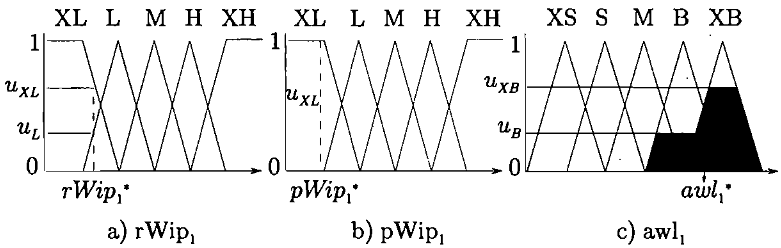

Figure 5.5: Fuzzy control process

With the observation $rWip_1$* and $pWip_1$*, for example, the fuzzy values are XL and L for $rWip_1$ and XL for $pWip_1$ respectively. The two activated

$pWip_1 \backslash rWip_1$	XL	L	M	H	XH
XL	XB	B	M	S	XS
L	XB	B	M	S	XS
M	XB	B	M	S	XS
H	XB	B	M	S	XS
XH	XB	B	M	S	XS

Table 5.2: The rule base which only counts the influence of $rWip_1$

$pWip_1 \backslash rWip_1$	XL	L	M	H	XH
XL	XB	XB	XB	XB	XB
L	B	B	B	B	B
M	M	M	M	M	M
H	S	S	S	S	S
XH	XS	XS	XS	XS	XS

Table 5.3: The rule base which only counts the influence of $pWip_1$

action rules are: if $rWip_1$ is XL and $pWip_1$ is XL then awl_1 is XB and if $rWip_1$ is L and $pWip_1$ is XL then awl_1 is B. Two clipped fuzzy sets of awl_1 are obtained by applying the Mamdani implication. These two clipped fuzzy sets will then be combined by an union action following from the Mamdani inference. The centre-of-gravity defuzzification method is used to get a crisp value from the combined fuzzy set, see Figure 5.5. This crisp value will be sent to the system to implement the control. Depending on the status of $rWip_1$ and $pWip_1$, more rules can be evaluated at the same time to obtain the control results. This control process will be implemented to conduct the simulation study in the next section.

Table 5.2 presents the rule bases which only the influence of $rWip_1$ counts, while Table 5.3 shows the rule bases which only the influence of $pWip_1$ counts. The symmetrical rule base in Table 5.4 obtained by equally treating the influence of $rWip_1$ and $pWip_1$ on the control action. If unequal influence of $rWip_1$ and $pWip_1$ on the control action should be taken into account, we can obtained the asymmetrical rule base from the adjustment of Table 5.2 or Table 5.3. Table 5.1, for instance, can be viewed as developed from Table 5.2 by shifting some elements along the *top-left* to *bottom-right* diagonal.

$pWip_1 \backslash rWip_1$	XL	L	M	H	XH
XL	XB	XB	B	B	M
L	XB	B	B	M	S
M	B	B	M	S	S
H	B	M	S	S	XS
XH	M	S	S	XS	XS

Table 5.4: The symmetrical rule base

5.3 Comparison between LOOR- and fuzzy-control

A series of simulation experiments have been performed to investigate the control performances. It is assumed that there are two kinds of uncertainties, namely the machine failures and the demand variation. Orders differ in product type and processing time. The product type is modelled by a discrete distribution like (*a*, *b*, *c*, *ab*, *ac*, *ba*, *bc*, *ca*, *cb*, *abc*, *acb*, *bac*, *bca*, *cab*, *cba*). A processing time consists of one or more operation times that can be modelled either by a constant (5 *hrs*) or by a distribution (exponential with mean 5 *hrs*). The simulation time for each run is assumed to be a half year with 7 days a week and 24 hours a day. This simulation time is long enough so that a sufficiently large sample is gathered for purpose of analysis and testing. The start values for a simulation is set in a way which tries to minimize the warm up period. As we shall see in the figures below the warm up period is around one week.

In order to investigate the control performance under different system situations four simulation experiments, namely *constant operation time with no machine failures* (*c-no-d*), *exponential distribution operation time with no machine failures* (*e-no-d*), *constant operation time with 20% machine failures* (*c-w-d20*) and *exponential distribution operation time with 20% machine failures* (*e-w-d20*), have been carried out. Each simulation run produces a set of results, and the results from different simulation runs are expected different because of the stochastic behavior of the model. It is not fair to draw conclusions from only one simulation run. A widely used method for determine the number of simulation runs is the relative precision method. It uses a *student-test.* In this study each simulation experiment is performed in 6 runs which is sufficient for a relative precision of 0.1 with 95% of confidence. Besides, the procedure of using the same stream of random numbers, as has been done in this study is a good approach in that it sharpens the differences between alternatives.

The simulation results obtained are shown below. All variables and parameters connected with *LOOR* control will be indicated with a subscript l, while those with fuzzy control will be indicated with a subscript f. These indications are introduced only for the convenience of explaining the results. For instance $m\text{-}wlt_l$ and $m\text{-}wlt_f$ are representing the mean weighted lead time under *LOOR* control and under fuzzy control respectively. The standard deviation of lead times is abbreviated as *sd-wlt*. The symbols *ut* and *nr.o* stand for utilization of the system and the number of orders respectively. The mean and the standard deviation of *wip* are indicated as *m-wip* and *sd-wip* separately, while *c-in* and *c-out* are the cumulative input and cumulative output of the system. The *units* for *m-wlt*, *sd-wlt*, *m-wip*, *sd-wip*, *c-in* and *c-out* are all *hrs*.

Constant operation time with no machine failures

The simulation results obtained with constant operation time and no machine failures are presented in Table 5.5, Table 5.6, Figure 5.6 and Figure 5.7. The fuzzy control results in this case are much better than that of the *LOOR* control. The lead times and the deviation of lead times are much smaller with even a little bit higher utilization by applying fuzzy control. The $m\text{-}wlt_f$ is 256 hrs which is 31 hrs (11%) shorter than $m\text{-}wlt_l$ that is 287 hrs. The $m\text{-}wlt_f$ is also more stable than $m\text{-}wlt_l$ because of the smaller $sd\text{-}wlt_f$.

Comparing Table 5.5 with Table 5.6 one can easily find that a high output is achieved with a relative low input to the system when applying fuzzy control. The characteristic curves described in Chapter 2 can be shifted vertically when using different control methods. Because the small $sd\text{-}wip_f$, the input and output curves in Figure 5.6 is much more similar in form than that in Figure 5.7. The $m\text{-}wip_f$ line is smooth with small momentary wip_f waving around it.

Run	m-wlt$_l$	sd-wlt$_l$	ut$_l$	nr.o$_l$	m-wip$_l$	sd-wip$_l$	c-in$_l$	c-out$_l$
1	284	84	93	1183	829	134	13250	12290
2	290	82	94	1161	840	125	13295	12330
3	286	84	93	1164	830	135	13255	12275
4	288	85	94	1160	834	133	13265	12330
5	285	82	93	1138	829	131	13235	12265
6	288	85	93	1163	841	131	13230	12205
Ave.	287	84	93	1162	834	132	13255	12283

Table 5.5: LOOR (c-no-d)

Run	m-wlt$_f$	sd-wlt$_f$	ut$_f$	nr.o$_f$	m-wip$_f$	sd-wip$_f$	c-in$_f$	c-out$_f$
1	254	76	94	1193	730	90	13120	12395
2	256	73	94	1170	735	85	13195	12380
3	259	77	95	1180	743	94	13170	12435
4	259	78	94	1165	745	90	13180	12365
5	255	73	95	1151	732	87	13155	12450
6	255	76	94	1179	733	88	13145	12355
Ave.	256	76	94	1173	736	89	13161	12397

Table 5.6: Fuzzy (c-no-d)

Run	m-wlt$_l$	sd-wlt$_l$	ut$_l$	nr.o$_l$	m-wip$_l$	sd-wip$_l$	c-in$_l$	c-out$_l$
1	276	85	76	968	644	123	10755	10005
2	280	85	77	947	651	127	10820	10050
3	276	86	76	967	646	116	10690	10000
4	278	86	74	914	638	128	10515	9705
5	270	81	76	961	634	124	10840	10020
6	276	81	77	956	648	123	10900	10115
Ave.	276	84	76	952	644	124	10753	9983

Table 5.7: LOOR (c-w-d20)

Run	m-wlt$_f$	sd-wlt$_f$	ut$_f$	nr.o$_f$	m-wip$_f$	sd-wip$_f$	c-in$_f$	c-out$_f$
1	254	81	77	975	591	76	10640	10070
2	254	83	77	965	594	74	10680	10080
3	253	82	76	976	590	72	10610	10025
4	261	81	75	922	596	73	10485	9890
5	249	80	77	970	586	75	10745	10095
6	258	77	78	955	604	76	10780	10185
Ave.	255	81	77	961	594	74	10657	10058

Table 5.8: Fuzzy (c-w-d20)

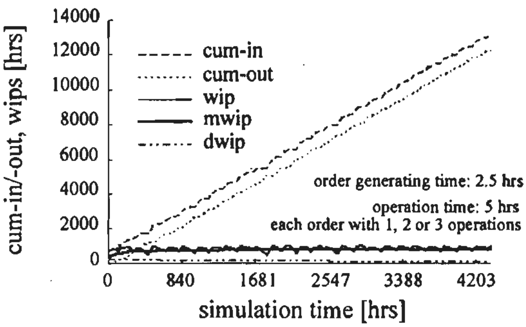

Figure 5.6: LOOR(c-no-d)

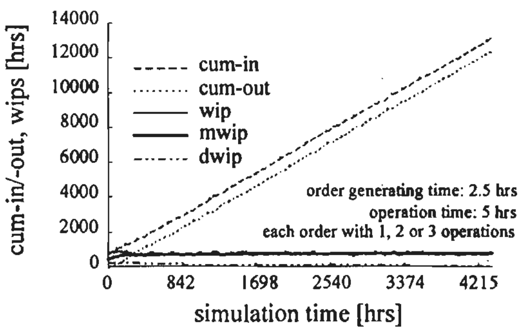

Figure 5.7: Fuzzy(c-no-d)

Constant operation time with 20% machine failures

The $m\text{-}wlt_f$ is still much smaller than the $m\text{-}wlt_l$ in the constant operation time with 20% machine failures case, refer to Table 5.7, Table 5.8, Figure 5.8 and Figure 5.9. The $sd\text{-}wip_f$ is only around the half of the $sd\text{-}wip_l$. The input and the output curves in Figure 5.8 are more similar in form than that in Figure 5.9. The momentary wip_f shows even smaller waving around the $m\text{-}wip_f$ in this case. Other conclusions obtained from the above case can also be observed in this case.

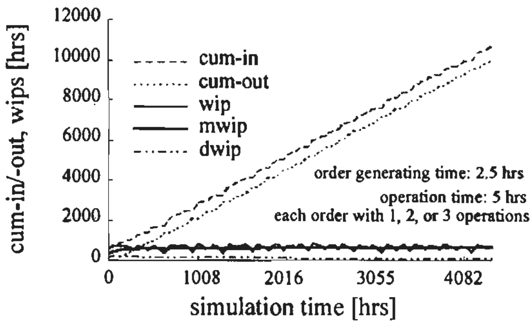

Figure 5.8: LOOR(c-w-d20)

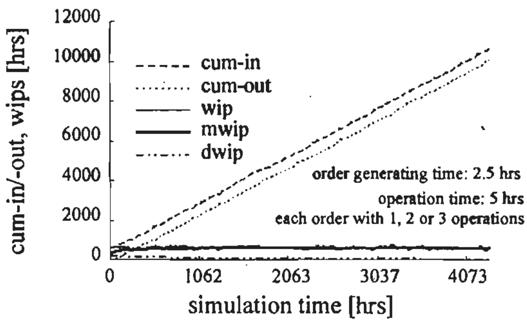

Figure 5.9: Fuzzy(c-w-d20)

Exponential distribution operation time with no machine failures

One can find the results from exponential distribution operation time with no machine failures experiment in Table 5.9, Table 5.10, Figure 5.10 and Figure 5.11. The $m\text{-}wlt_f$ and $d\text{-}wlt_f$ are still quite small compared with $m\text{-}wlt_l$ and $sd\text{-}wlt_l$. The $sd\text{-}wip_f$ is also remaining smaller than the $sd\text{-}wip_l$.

Run	m-wlt$_l$	sd-wlt$_l$	ut$_l$	nr.o$_l$	m-wip$_l$	sd-wip$_l$	c-in$_l$	c-out$_l$
1	280	88	93	1179	802	145	13190	12240
2	284	81	92	1175	814	150	13210	12173
3	280	84	93	1162	801	166	13274	12264
4	276	82	94	1154	783	162	13282	12288
5	275	83	94	1162	788	167	13261	12284
6	280	85	94	1194	795	156	13248	12346
Ave.	279	84	93	1171	797	158	13244	12266

Table 5.9: LOOR (e-no-d)

Run	m-wlt$_f$	sd-wlt$_f$	ut$_f$	nr.o$_f$	m-wip$_f$	sd-wip$_f$	c-in$_f$	c-out$_f$
1	257	85	94	1187	732	112	13082	12318
2	257	77	95	1187	737	109	13114	12427
3	264	87	95	1170	751	133	13170	12414
4	258	81	94	1150	735	129	13106	12307
5	260	79	94	1170	741	123	13246	12323
6	258	86	94	1199	740	133	13307	12387
Ave.	259	83	94	1177	739	123	13171	12363

Table 5.10: Fuzzy (e-no-d)

Exponential distribution operation time with 20% machine failures

The $m\text{-}wlt_f$ is rather smaller than the $m\text{-}wlt_l$. The $m\text{-}wip_f$ line is more stable with a relative high output. It is expected that performances of

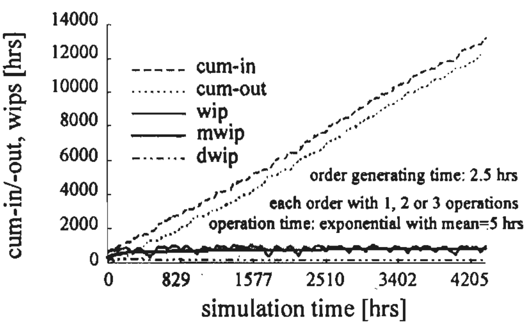

Figure 5.10: LOOR(e-no-d)

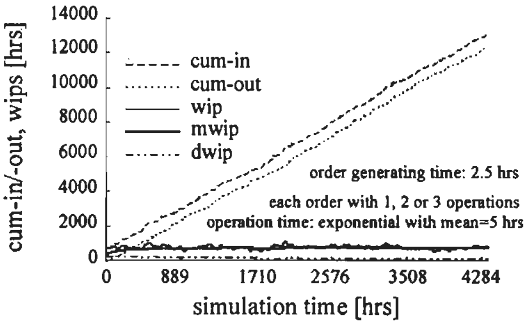

Figure 5.11: Fuzzy(e-no-d)

Run	m-wlt$_l$	sd-wlt$_l$	ut$_l$	nr.o$_l$	m-wip$_l$	sd-wip$_l$	c-in$_l$	c-out$_l$
1	269	87	75	980	625	139	10541	9913
2	280	90	75	942	644	117	10660	9822
3	276	90	74	1017	627	131	10541	9760
4	275	85	77	893	629	148	10812	10098
5	275	92	75	996	623	130	10569	9819
6	278	85	76	901	645	120	10703	9927
Ave.	276	88	75	955	632	131	10638	9890

Table 5.11: LOOR (e-w-d20)

the static fuzzy controller will be worse when the system is associated with more statistic dynamic variations. It still is the better one when comparing with the pure *LOOR* control, but the better performances shown in previous cases is not so obvious in the exponential distribution operation time with 20% machine failures case, see Table 5.11, Table 5.12, Figure 5.12 and Figure 5.13.

One of the major advantages of fuzzy control is the capability by which process conditions and control actions can be described directly from the experience of human operators. The job shop control example presented in this chapter illustrates how fuzzy concepts in a pragmatic and direct manner make it possible to apply practical operational experience and knowledge in the computerised automatic control of multi-variable processes.

Run	m-wlt$_f$	sd-wlt$_f$	ut$_f$	nr.o$_f$	m-wip$_f$	sd-wip$_f$	c-in$_f$	c-out$_f$
1	258	89	76	983	595	123	10708	10038
2	258	93	76	949	586	95	10531	9949
3	255	95	74	999	573	107	10436	9775
4	271	99	77	906	618	115	10622	10124
5	249	91	75	993	563	97	10398	9857
6	275	100	75	893	622	110	10533	9876
Ave.	261	95	76	954	593	108	10538	9937

Table 5.12: Fuzzy (c-w-d20)

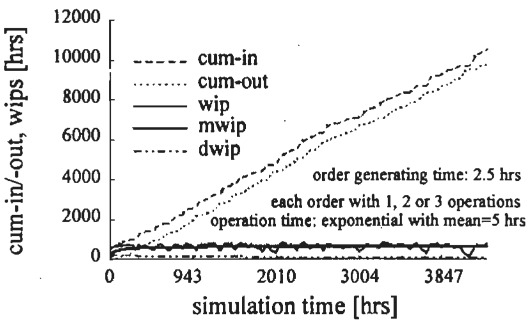

Figure 5.12: LOOR(e-w-d20)

Fuzzy control shows obviously better performance compared with the load-oriented order release control itself, which is not the case for the single machine system control. This is because the work-in-process (*wip*) is just the real work-in-process (*rWip*) in the single machine system case, there is no such concept like potential work-in-process (*pWip*). The control process is simply following a linear relation between the input variable (*wip*) and the output variable (acceptable work load, *awl*), thus the effective coordinative feature of the fuzzy controller could not be shown there.

The total *wip* in a job shop consists of two parts, namely the *rWip* and the *pWip*. The *rWip* is more important than the *pWip* in the sense that a zero *rWip* may cause machine to become idleness. By making the distinction between *rWip* and *pWip* and using both of them as the input variables

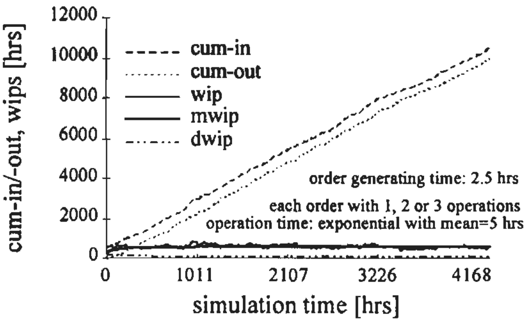

Figure 5.13: Fuzzy(e-w-d20)

it is possible for the fuzzy controller to make a more accurate control decision. Load-oriented order release control process is still following more or less a linear relation between *wip* and *awl*. Compared with the study on the single machine system control this study of fuzzy control in a simple job shop control is quite satisfactory. Simulation results reveal that the proposed fuzzy control system exhibits good performance, in terms of a high production and constant short lead times, under resource failures and demand variations.

Chapter 6

Fuzzy Scheduling

Scheduling is to properly allocate resources over time to perform a collection of tasks. The practical problem of scheduling arises in a variety of situations. For manufacturing systems that are responsible for manufacturing and transporting products, there are unavoidable *waiting queues* in front of machines because of the limited capacity of the machines and other factors, like technology and social conditions. The lead time of an order is often several times the processing time. The control of the waiting queue or the waiting time by means of scheduling to meet various criteria is an important aspect of production control.

The scheduling problem is known to be NP-complete [Bla82], by giving n jobs queued at a work station there are $n!$ ways to sequence those jobs. In most systems this problem is greatly complicated by having several interacting workstations. Because of the difficultly of solving these problems directly, scheduling heuristics are often employed to simplify the problem. One of the most common classes of scheduling heuristics is *dispatching rules*. In practice there are plenty of dispatching or priority rules being used for ordering the jobs in a queue in front of a machine. Each rule intends to satisfy a single performance criterion. The often encountered criteria are, for instance, lateness or tardiness minimization and lead time minimization.

Since a manufacturing system is always a multi-objectives or multi-criteria system, it is important to have a way to easily make compromises among individual criteria. A lot of work has been done to achieve such a compromise by means of the so-called *aggregated rules* which can provide intermediate result of the elementary rules of which they are composed [War92, Yan94, Gra94a]. A classical aggregated rule is a linear combination of decision factors, each of which is initially assigned a relative weighting. But it is always a difficult task to decide the relative weighting, especially when the requirements are changed with the evolution of the production environment. For a recent survey of dispatching and aggregated rules we refer to [Mon90].

Work has been carried out to make the scheduler more flexible and adaptable by means of advanced technologies, like fuzzy control and neural networks [Hin89, Cus94, Gra94a, Gra94b, Wan96b]. In this chapter we present a new approach to make a compromise by using fuzzy control theory. The trading off each elementary dispatching rule can be realized by modifying the fuzzy decision rule base. After a brief introduction of the scheduling by means of dispatching rules in the next section, the proposed fuzzy scheduling approach is illustrated in Section 6.2. The model which will be employed for our simulation study is the same as the one used in the previous chapter. The workstation controller *WSC* will take responsibility for scheduling. The simulation results will be presented and analyzed in Section 6.3.

6.1 Dispatching rules

A *dispatching rule* is used to select the next job to be processed from a set of jobs awaiting service. Dispatching rules are often dedicated to the satisfaction of a single performance criterion, and are used whatever the characteristics of the system or the type of jobs [Gra94a], though scheduling is a multi-criteria problem. One solution to this problem is by using the so-called aggregated rules. A *classical aggregated rule* is a linear combination of decision factors, each of which is initially assigned a relative weighting.

In [Her75] seven combined or aggregated rules are tested, selecting the job with the smallest ratio of slack time to the number of remaining operations (*slack-per-operation* or *SLK/RO*) performs better than other due-date based rules. The *SLK/RO* was also chosen for a scheduling study in [Dar82] and [Bal84]. It's concluded in [Bal84] that the *SLK/RO* consistently outperforms other due-date rules. But the scheduling result by applying the *SLK/RO* rule is not so promising in [Mcc81]. The aggregated rule does perform better than the individual rules in the sense of performance compromise in our study of fuzzy scheduling [Wan96b].

The dispatching rules' chosen depend on the criteria being looked at, the system itself, and the due-date assignment rules chosen. Baker and Bertrand examine the use of different kinds of information in setting due-dates, compare of due-date selection rules, and investigate the relationship between the due-date assignment rules and the priority dispatching rules [Bak81a, Bak81b, Bak82]. [Udo93, Udo94] also present ways of due-dates assignment. A useful model might be one in which due-dates are produced by a balance of production control considerations and market pressures. It can be the result of negotiation between a "scheduler" and "customer". There are broadly two ways to assign due-dates:

1. *due-dates* can be externally imposed parameters, represented as "given" information in the statement of a scheduling problem.

2. *due-dates* can be internally selected parameters, determined within the control system itself.

In our study the production control system completely determines the due-dates for all jobs to be scheduled according to the slack information for the sake of simplicity.

A big list of dispatching rules, over 100 rules, can be found in [Pan77]. For a survey of dispatching and aggregated rules we refer to [Mon90], there literature reviews of the dispatching rules can also be found. The purpose is to illustrate the fact that general results are hardly available. The literature review reveals very few general results, *i.e.* the performance of scheduling rules depends very heavily on the criteria chosen as well as the configuration of the production system at hand. Literature results often appear to be contradictory precisely because researchers fail to provide sufficient details and the peculiarities of their experimental environment. A list of dispatching rules presented with classifications is given in [Cas96], namely *local static*, *local dynamic*, and *global dynamic*.

1. Local static: *FIFO*, *SPT*, *EDD*
2. Local dynamic: *SLK/RO*
3. Global dynamic: *WINQ*

We have no intention to present an exhaustive list of all dispatching rules considered in current research. The above rules are some often encountered rules according to our knowledge and literature.

Work has been carried out to make the scheduler more flexible and adaptable by means of advanced technologies, like fuzzy control and neural networks. In the next section we present a new approach to make a compromise by using fuzzy control theory only. The ability to deal with multi-variables makes fuzzy control a good alternative for the scheduling problems because it can easily make compromises among multi-criteria by properly combining elementary dispatching rules. These compromises can easily be adjusted in accordance with the objectives of the system and the characteristics of the jobs. The trading off each elementary dispatching rule can be realized by modifying the fuzzy decision rule base.

6.2 Fuzzy approach

It is stated in [Wir96] that "*In spite of the vast literature about scheduling, almost no insight into the decision behavior of human schedulers in practice exists. In practice, formal techniques are rarely used straightforwardly, and schedulers mostly still use their own 'rules of thumb' especially in dynamic, uncertain and complex scheduling environments*". Fuzzy control concepts start with the modelling of operators experience and experts knowledge, and it is introduced to deal with the linguistic terms that human beings use in their daily life. So it seems an appropriate approach in solving scheduling problems in this sense. Besides, the fuzzy scheduling approach provides a way to combine different dispatching rules with potential adapting ability. The approach doesn't depend on what rules will be chosen.

A heuristic approach to n/m (n jobs, m machines) job shop scheduling by using fuzzy dynamic scheduling algorithms is studied in [Roy96]. There the concept of new membership functions is discussed in the algorithm as a link to connect several priority rules. The concept of fuzzy logic has been applied as a link to combine those priority rules to form an aggregated heuristic rule. They show that Fuzzy Dynamic Scheduling Algorithms perform better than traditional single priority rule techniques in their simulation results. While we think this comparison is not fair, further research should be carried out on the comparison of fuzzy aggregated rules with their classical counterparts.

There are generally two kinds of major requirements of a manufacturing system: the customers' satisfaction and the resources utilization's optimization. The often encountered criteria are, for instance, lead time minimization and lateness or tardiness minimization. In this chapter we shall also emphasize these criteria and study on the *SPT&SLK/RO* (combined Shortest Processing Time and SLacK per Remaining Operation) and *SPT&WINQ* (combined Shortest Processing Time and Work In Next Queue) rules. The extended study of other rules like *SLK/RO&WINQ* (combined SLacK per Remaining Operation and Work In Next Queue), *RW&SLK/RO* (combined Remaining Work and SLacK per Remaining Operation) and the *SPT&EDD* (combined Shortest Processing Time and Earliest Due Date) are carried out in [Ber97]. The detailed study of the *SPT&EDD* rule can also be found in [Haa95, Wan96b]. In the following the *FPFS* (fuzzy *SPT&SLK/RO*) in scheduling will be illustrated in detail. The other rules follow exactly the same methodology.

For the *FPFS* rule, the input variables sent to the fuzzy controller are processing time (p) and slack per remaining operation (s) respectively. The first step is to represent these two variables symbolically, and to associate fuzzy sets or membership functions with them as shown in Figure 6.1. XS, S, N, L, XL means very short, short, normal, long, very long; XS, S, N, B, XB means very small, small, normal, big, very big; and XL, L, M, H, XH means very low, low, medium, high, very high.

p \ s	XS	S	N	B	XB
XS	XH	XH	H	H	M
S	XH	H	H	M	L
N	H	H	M	L	L
L	H	M	L	L	XL
XL	M	L	L	XL	XL

Table 6.1: Fuzzy decision rule basel

With observation p_0 for processing time (Figure 6.1 a)), the corresponding fuzzy values are μ_s and μ_n in the S set and the N set, respectively. With the observation s_0 for slack per remaining operation (Figure 6.1 b)), its fuzzy value is μ_{xs} in the XS set. These fuzzy values represent to what degree the observed value belongs to each set associated with the variable. The *reasoning* process then evaluates the decision rules with the fuzzy values obtained. The hatched area of priority (Figure 6.1 c)) is the combined fuzzy set obtained by evaluating the two relevant rules in the fuzzy decision rule base (Table 6.1). The first row gives the five sets associated with slack per remaining operation s and the first column gives the five sets associated with processing time p. The two relevant rules are: *if p is S and s is XS then pr is XH* and *if p is N and s is XS then pr is H*. The fuzzy values obtained by the reasoning process will be used as ordering priority after the defuzzification process. The *defuzzification* process translates the fuzzy values into crisp or numerical values, pr_0.

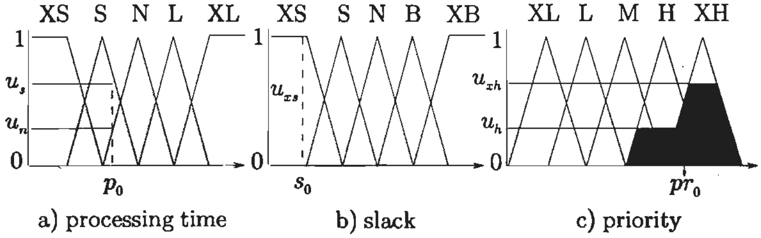

Figure 6.1: The fuzzy control process

The method suggested in [Gra94a] to balance different elementary dispatching rules is to assign a weighting factor for each elementary rule

p \ s	XS	S	N	B	XB
XS	XH	H	H	M	L
S	XH	H	M	L	L
N	XH	H	M	L	XL
L	H	H	M	L	XL
XL	H	M	L	L	XL

Table 6.2: Fuzzy decision rule base2

p \ s	XS	S	N	B	XB
XS	XH	XH	XH	H	H
S	H	H	H	H	M
N	H	M	M	M	L
L	M	L	L	L	L
XL	L	L	XL	XL	XL

Table 6.3: Fuzzy decision rule base3

and to specify the weighting factors according to the importance of each rule in the aggregated rule. The balance can be more intuitively and easily realized in the rule base itself. Take the diagonal from the *right-top* to the *left-bottom* as reference. If we rotate this diagonal *clockwise* or *anti-clockwise*, the relative importance of each elementary dispatching rule in the aggregated rule will be changed. In Table 6.2, the slack rule becomes more important compared with that in Table 6.1 by rotating the diagonal *anti-clockwise*. Thus the processing time rule becomes relatively less important in the aggregated rule. The processing rule becomes more important compared with that in Table 6.1 by rotating the diagonal *clockwise*, see Table 6.3. Thus the slack rule becomes relatively less important in the aggregated rule. This rotating rule base adjustment is equivelent in effect to the shifting rule base adjustment described in Chapter 5. Interested readers can found a detailed description of the rotating rule adjustment in [Ber97]. In principle we can modify each item in the rule base to balance the two elementary dispatching rules with different importances, if the rule base satisfies the constraints given in [Dri93]. These two adjusted rule bases will be employed in the simulation study later in this chapter.

6.3 Comparison between conventional- and fuzzy-aggregated rules

A series of simulation experiments have been performed with the model to investigate the scheduling performance. We assume that orders arrive continuously with inter-arrival times generated from a negative exponential distribution, which has a mean value chosen to create a certain expected shop utilization rate. The mean value is 5.427 hrs with a 80% utilization (refer to [Ber97] for detailed calculation). Each order follows a given process plan or a recipe that specifies the sequence of machines it must visit and the operations performed by these machines. Operation times are drawn independently from another negative exponential distribution with a mean of 5 hrs. Processing times of orders are known after their arrival at the job shop. The order due-date is decided according to the formula: $d_i = r_i + p_i + \beta$ when it arrives at the job shop (where d_i: due-date, r_i: release date or arrival time, p_i: total processing time of order i, β : due-date slack factor with its value chosen reflecting the tight or loose due-dates). Relative performance of dispatching rules can change with a change of the β factor [Bak81a].

The first series of simulation study is devoted to investigate whether the suggested fuzzy aggregated rule can provide good compromise between multi-objectives. The comparison results between the *FPFS* and the corresponding elementary dispatching rules, say the *SPT* and the *SLK/RO* rules, and between *FPFW* and the corresponding elementary dispatching rules, say the *SPT* and the *WINQ* rules are illustrated in Figure 6.2 and Figure 6.3. The abbreviations *mwlt*, *sdwlt*, *ml* and *mt* are used to represent the mean weighted lead time, standard deviation of weighted lead time, mean lateness and mean tardiness respectively. The units for *mwlt*, *sdwlt*, *ml* and *mt* are hrs. It can easily be observed that the *FPFS* and the *FPFW* provide intermediate performance compared to that of the elementary rules on which it composed. The results confirm that the fuzzy approach is indeed a good alternative for scheduling to achieve multi-objectives.

The second series of simulation study focuses on the comparison of *FPFS* and *FPFW* with their classical counterparts, *SPT&SLK/RO* and

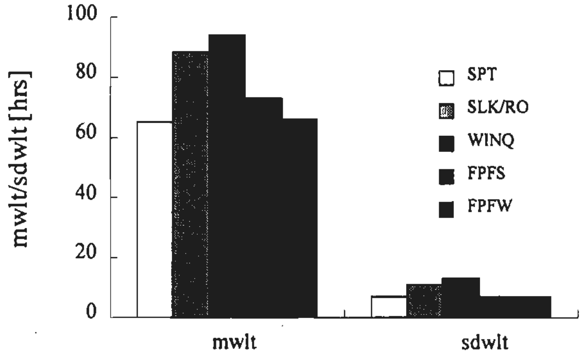

Figure 6.2: Compare the fuzzy aggregated rules versus elementary rules (lead time performance)

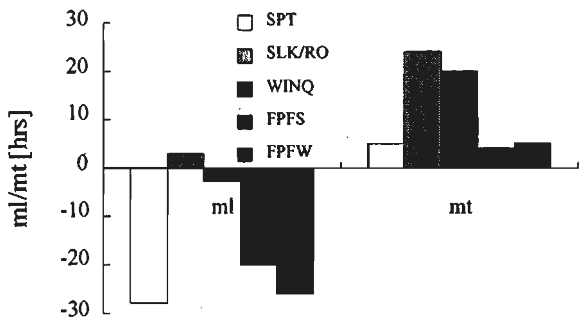

Figure 6.3: Compare the fuzzy aggregated rules versus elementary rules (due date performance)

SPT&WINQ respectively. There are different ways to form classical aggregated rules, for instance 'analytical' or 'logical' combinations [Gra94a]. We use 'analytical' combination by assigning the equal weighting factor, 0.5, for each dispatching rule in this study.

$$pr_{spt\&slk/ro} = 0.5pr_{spt} + 0.5pr_{slk/ro}$$

The performance by using each aggregated rule is evaluated through weighted lead time, lateness, tardiness and number of late orders under

	mwlt	sdwlt	ml	mt	nlo
spt&slk/ro	72	7	-18	10	1007
fpfs	73	7	-20	4	475
spt&winq	69	7	-24	6	529
fpfw	66	7	-26	5	499

Table 6.4: Simulation results

the same utilization. For *FPFS* and *FPFW* the standard symmetrical rule base which is presented in Table 6.1 is employed here. The simulation results are presented in Table 6.4, Figure 6.4 and Figure 6.5.

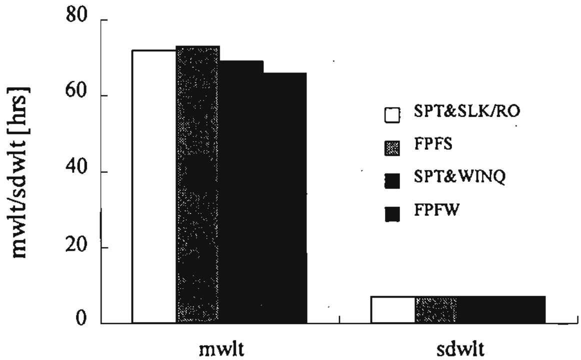

Figure 6.4: Compare the fuzzy aggregated rules with their classical counterparts (lead time performance)

The performance of *FPFS* is obvious better than the classical *SPT&SLK/RO*, refer to Table 6.4, *nlo* denotes number of the late orders. With a 1% longer mean weighted lead time by using *FPFS*, the due date performance is greatly improved. The number of late orders by using *FPFS* is much less than that by using *SPT&SLK/RO*, the difference is 36%. For aggregated rules it's important to look at the compromised achieved. The *FPFS* performs better in this sense. The performance of *FPFW* is even obvious better than the classical *SPT&WINQ*. With a 3% shorter mean weighted lead time, the number of late orders by using *FSFR* is also 2% less than that by using the *SPT&WINQ*.

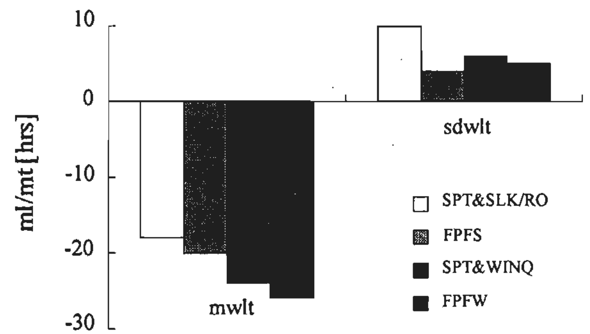

Figure 6.5: Compare the fuzzy aggregated rules with their classical counterparts (due date performance)

The last series of the simulation study deals with the adaptability of the fuzzy scheduler. To show the ability to adapt the scheduling compromise by means of adjusting the fuzzy decision rule base, simulation experiments have been run with the two different rule bases as aforementioned in Section 6.2, Table 6.2 and Table 6.3. From the simulation results, refer to Figure 6.6 and Figure 6.7, we can see that they confirm what we have expected (see Section 6.2). This kind of easy adaptable scheduler is a promising alternative for solving scheduling problems. The method doesn't depend on what elementary scheduling rules will be used. So any two elementary rules can be aggregated and adapted in a way as suggested in this chapter.

The suggested fuzzy scheduling approach presented in this chapter illustrates how fuzzy control concepts in a pragmatic and direct manner make the compromise between different dispatching rules possible. As the first step for the comparison study of fuzzy aggregated rules with their classical counterparts, the obtained results are satisfied. The results are expected better if the rule base can be extracted from experts' knowledge or operators' experience. Scheduling knowledge can then be accumulated and stored in such a rule base. This is also one of the advantages of using fuzzy scheduling approach. Another advantage of fuzzy scheduling is the flexibility. The balance of the elementary rules via the fuzzy decision rule base adjustment can be achieved intuitively when the systems' en-

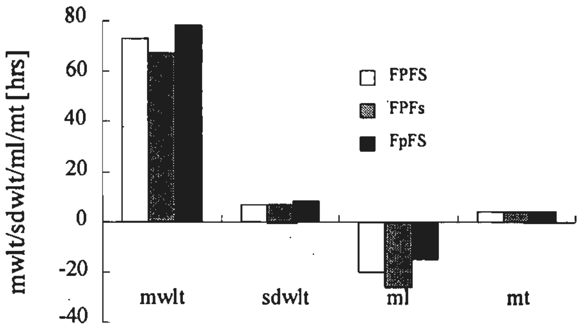

Figure 6.6: Compare the scheduling performance by using different rule bases (FPFS)

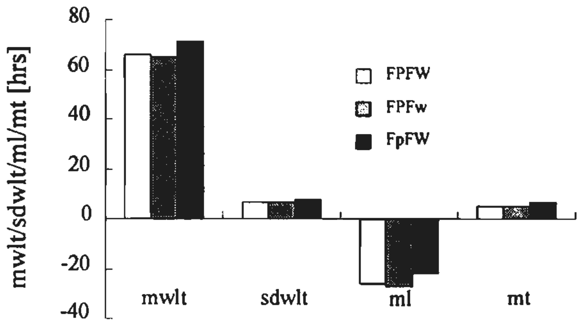

Figure 6.7: Compare the scheduling performance by using different rule bases (FPFW)

vironment changes. Any individual elementary dispatching rules can be combined by using this approach. Further study should be carried out on the further comparison of the classical and fuzzy aggregated rules, and on exploring a systematic procedure to design a fuzzy scheduler.

Chapter 7

Case Study: Fuzzy Control in an IC Wafer Factory

The previous chapters have been devoted to the development and the explanation of the fuzzy control concept and its application to various situations. Fuzzy control can be an appropriate alternative for controlling discrete event dynamic systems. Now is the time for us to illustrate the fuzzy control concept in practice by applying it in a real system. In this chapter the modelling and the implementation of a fuzzy control system in Philips' new wafer factory, MOS4YOU, will be presented. The control performance will be evaluated by means of a simulation study. After a brief introduction to MOS4YOU, the factory layout and the wafer processing will be illustrated in Section 7.2. Some assumptions are made for modelling and controlling. The factory with its control model is given out in Section 7.3. The simulational study on the fuzzy control performance of the MOS4YOU factory will be presented in Section 7.4.

7.1 The MOS4YOU wafer factory

The MOS4YOU wafer factory is a result of the semiconductor market booming. As stated in [Sin95]: the Integrated Circuit (*IC*) market has grown enormously over the last few years, and is expected to grow even more in the coming years, by about 15% a year. None of the *IC* manufacturers is able to meet this demand. This is why a lot of *IC* manufacturers are expanding their production capacity.

Philips Semiconductors, as a major *IC* manufacturer, is also expanding its production capacity. One of these expansions is the new wafer factory, MOS4YOU, built in Nijmegen. '*MOS*' stands for Metal Oxide Semiconductor, indicating the type of semiconductor which is produced. '*YOU*' stands for Yield, Output and Utilization, a philosophy by which the new factory is run. The Integrated Circuits (*ICs*) are produced according to the *CMOS* (Complementary Metal Oxide Semiconductor) technology. MOS4YOU produces 8-*inch* wafers using 0.35 micron technology.

Besides expanding the production capacity and increasing the scale of integration of *ICs* by means of developing new technologies and improving the manufacturing process, the *IC* manufacturers have started to realize that attention has also to be paid to the control of the manufacturing system in order to reduce the cost and ensure the quality. The most important criteria in concern are the lead time of the wafer lots and the throughput. One wafer lot contains 25 wafers. A good control needs to be realized to meet these criteria. In this study a fuzzy controller will be designed in order to control the MOS4YOU factory. Our attention is paid to planning and controlling the wafer-flow through the factory. Wafer lots releasing and scheduling processes, and their influence on the lead time and the throughput are investigated.

The MOS4YOU factory has a job shop layout. This means that all the machines are grouped functionally. The job shop character can also be seen from the often repeated process steps on one and the same type of machine, the various process steps and the varying operation times. The *IC* industry is capital-intensive. Therefore, a high utilization of machines or high throughput is desired. Because of the high targets for throughput of lots, the work-in-progress (*wip*) level in the factory will exceed the total number of lots that can be processed by all machines at one time. While in order to ensure a reasonable short lead time, the wip shouldn't be too high. A good compromise between the throughput and the lead time should be achieved by setting the appropriate *wip* level. MOS4YOU aims at a lead time/process time ratio of 3 or less.

7.2 The wafer manufacturing process

Manufacturing facilities are grouped functionally into 16 bays (workplaces) in MOS4YOU factory. The production level is expressed in waferstarts per week [Cam95]. The actual manufacturing facilities' capacity must be higher than the number of waferstarts per week. This is because test, monitor and engineering wafers also require capacity. Furthermore, rework might occur.

The input to the factory are wafers. These are *buy-in* products. The output from the factory are wafers with *ICs* built on. The manufacturing process is carried out in more than 200 different steps.

Manufacturing of *ICs* consists of the following production steps [Wol86, Smi92, Cam95]:

- manufacturing of raw silicon wafers
- manufacturing of *ICs* on wafers
- sawing and molding individual *ICs* (or a probe and dice operation)
- final testing of *ICs* and packaging

The first two steps are called the *front-end*, the last two the *back-end*. In this chapter only the manufacturing of *ICs* on wafers will be concerned. Six characteristic processes of manufacturing *ICs* on wafers can be distinguished [Wol86, Smi92, Cam95]:

- lithography
- etching and strip
- ion implantation
- thermal processing
- metallization
- dielectric film deposition

The lithographic machines put patterns on the wafer with the help of a *photolithographic* process. A wafer should first be coated with a light-sensitive photoresist to create a photo sensitive layer or region. The wafer is then developed after the selective exposition process in the stepper. A mask is used to obtain the desired selective exposure. Part of the layer is removed in the so-called dry and wet *etch* process. The developed photoresist in the litho process protects the relevant part of the wafer they cover, while the uncovered parts are removed. By repeating these steps several layers are grown on the wafer. The etch machines are also used to strip the photoresist from the wafer. Implantation machines use energy to *implant* charged ions (atoms or molecules) into wafers and introduce so-called dopants into the silicon. The dopants diffuse through the silicon by heating the wafer in the furnace. There are high energy, high current and medium current implanters. After the implantation the surface of the wafer may be damaged. The damage is healed by heating the wafer for a short while, so-called thermal annealing. The *thermal* treatment restores the damaged crystal lattice and builds the dopant ions into the monocrystal. Almost all thermal processes are preceded by a cleaning operation. The metallization machines deposit metal (mostly aluminium) on the wafer. The process *metallization* or sputtering is done to connect the components of the *IC* with each other and to provide bonding pads, where the *IC* is connected to the outside world (pins of the encapsulation). *Dielectric* films provide non-conducting regions within the *IC*, electrical insulation between metal-layers, and protection from the environment. The most common deposition methods are chemical vapor deposition at atmospheric-pressure, chemical vapor deposition at low-pressure, and plasma-assisted chemical vapor deposition. Beside these main processes, a wafer factory also contains cleaners, inspectors, transporters, and stockers. To successfully manufacture *ICs*, all process steps must be executed in an environment that is precisely controlled with respect to cleanliness, temperature, and humidity. Particulates must be avoided on wafers, hence all processes are carried out in a clean room. In a clean room the air is continuously filtered, re-circulated, and monitored with respect to particulates.

By definition, an *IC* integrates a large number of isolated tiny components into one chip, to be cut from one silicon wafer. Figure 7.1 shows a picture of a wafer. The basic building block of a CMOS *IC* is the MOS transistor. An *IC* contains up to millions of these transistors. With all these knowledge in mind we shall build a model of the MOS4YOU factory in the next section in order to conduct a simulation study of the system performance in Section 7.4.

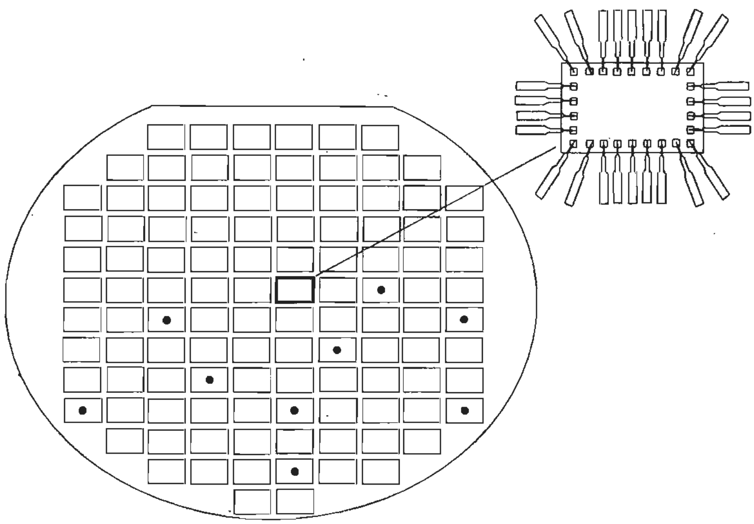

Figure 7.1: Wafer

7.3 Model of the IC wafer factory

The MOS4YOU factory consists of nine bayAreas, namely *AUX, DEL, RST, FUR, IMP, LIT, MET* and *PCM*.

The top layer of the model consists of a Customer (*Cu*), a Factory (*Fa*) and a Supplier (*Su*), refer to Figure 7.2. The Customer generates orders that are lots of wafers in this case. These lots are processed in the Factory. A lot is returned to the Customer after finishing processing. The Supplier is responsible for sending required material, raw wafers here, to the Factory. It is assumed that the Supplier is always capable to provide the required material in time.

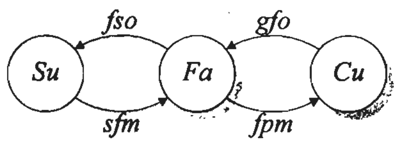

Figure 7.2: MOS4YOU system model

The Customer is composed of a Generator (G) and a Pile (P), see Figure 7.3. The Generator generates orders of lots and sends them to the Factory for processing. Each lot is one Customer order and contains 25 wafers. The *inter-arrival time* can be modelled either by a *constant* or by a *negative exponential* distribution which ensures the *Poisson* distributed arrival process of lots. Each order flows through the Factory following a certain recipe, with which the machines that the order should visit and the processing times of the order on the machines are specified. Each recipe is composed of *bayArea-oriented sub-recipes.* So each bayArea is responsible for a particular piece of the whole recipe each time. A sub-recipe consists of one or more process steps and ends with one or more inspection steps. It is assumed that a stable production situation exists and that there is a constant supply of work. The Pile receives the ready lots from the Factory.

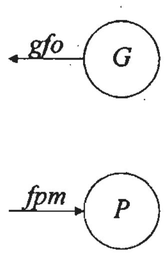

Figure 7.3: Customer model

The Factory consists of the Resources (R) and a FactoryController (FC). The FactoryController is responsible for accepting orders of lots from Customer and sending orders to Supplier for required material. It also takes care of releasing the orders of lots to the Resources. The actual manufacturing processes are taken place in the Resources. When all the manufacturing processes of an order are finished the order is returned to the FactoryController by the Resources. The product is delivered to the Customer. Figure 7.4 shows the Factory model.

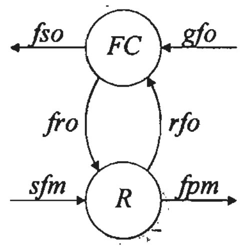

Figure 7.4: Factory model

The Resources are composed of a Store (Sr), a Transporter (Tr), nine bayAreas (BA) and a ResourcesController (RC), as illustrated in Figure 7.5. The ResourcesController receives orders of lots from the FactoryController. The orders will then be released to the bayAreas according to the work-in-process status. The ResourcesController will be implemented as a fuzzy controller to control the work-in-process. The input variables to the fuzzy controller are the real work-in-process ($rWip_{BA}$) and the potential work-in-process ($pWip_{BA}$) of the bayAreas. Since there are big number of processing steps in a recipe for each order, we should consider a reasonable and feasible way to calculate the potential work-in-process. At this moment we only update the potential work-in-process of those bayAreas that are invloved in one of the next 10 processing steps after the current processing step in the recipe. The influences of the potential work-in-process after the 10th step are trival to the control since they are normally less than 5% of the minimum processing times of the bayArea. The output variable is the acceptable work load (awl_{BA}) to the bayAreas. The controller is also responsible to assign the lot to an appropriate bayArea when the next operation on a lot can be performed in more than one bayArea. When an order is finished, ResourcesController returns the order to the FactoryController. The subscript i in Figure 7.5 takes values from 0 to 8, indicating the corresponding number of communication channels relevant to the nine bayAreas. The Store is for incoming and outgoing material. It receives raw material from the Supplier and informs the ResourcesController. It also receives the products from the Transporter and tries to send them back to the Customer. The Transporter is responsible to move material among the Store and the bayAreas. The transporting task is obtained from the ResourcesController.

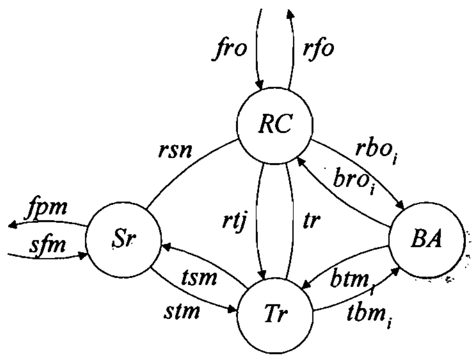

Figure 7.5: Resources model

Each bayArea consists of a Store (Sr), a Transporter (Tr), several ProductionUnits (PU) and a BayAreaController (BC). The BayAreaController only performs very simple control actions, like informing the ResourcesController when a lot has finished all the processing in the bayArea. Of course it also controls the local Transporter and the local Store. The BayAreaController receives the orders from the ResourcesController and sends them to the corresponding ProductionUnits according to the first next operation info of the order. Transporter is responsible to move material among the Store and the ProductionUnits. The Store is for incoming and outgoing lots of the Area. The Model of a bayArea is as shown in Figure 7.6.

Each ProductionUnit consists of several identical Machines (M), a Store (Sr), a Transporter (Tr) and a ProductionUnitController (PC), refer to Figure 7.7. The ProductionUnitController schedules the lots waiting in the Store for processing and assigns lots to the first machine becoming available. The heuristic dispatching rules are used here to solve the

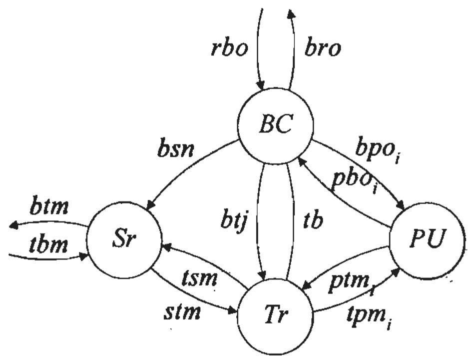

Figure 7.6: A bayArea model

scheduling problem. The fuzzy aggregated rule *FFFR (Fuzzy FIFO & shortest Remaining processing time)* is implemented here to schedule the lots. The Store here is necessary in order to prevent machines from being idle. Note that the assumption is made that all machines are always busy 24 hours a day and no maintenance takes place. There is also no scrap and no wafer rework that the specified number of products are manufactured. The machines have different batch sizes, some can only process one lot and others can process several lots at one time. The process times of the lots on the machines is supposed to be known and to be deterministic. Setup times are considered as part of the processing times. Machine starts at the moment the lots arrive at the idle machine.

In the next section simulation study of the system performance will be presented on the basis of the model described above.

7.4 Simulation study

Both the work-in-process (*wip*) control at the ResourcesController level and the scheduling at the ProductionUnitController level can have influences on the lead time and the throughput of lots. The system performance can be evaluated via the compromise between the lead time and

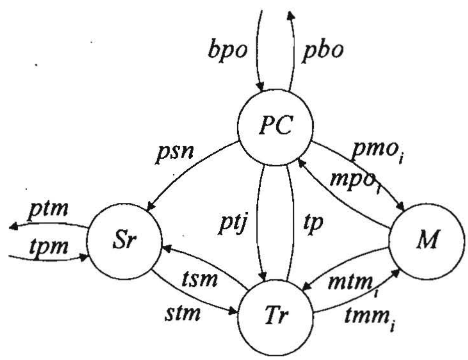

Figure 7.7: Production Unit

the throughput criteria. The maximum and the mean lateness, the maximum and mean tardiness and the number of late orders can be considered as criteria to evaluate the scheduling process.

A fuzzy order releasing controller (*FORC*) was implemented first to regulate the orders coming into the Resources. Each time an order is released the sum of the real work-in-process (*rWip*) and the potential work-in-process (*pWip*) of this order is added up to the load of the Resources. Here *rWip* and *pWip* are only counting for the first processing step. Since the load limit is chosen as twice of the total capacity of the Resources, the Resources is heavily overloaded. The simulation run with this controller takes very long time. There is no order comes out of the Resources after ten weeks time. Of course this situation happens when we don't let the fuzzy order dispatching controller (*FODC*) functioning.

The *FODC* is also at the ResourcesController level, where all the *rWip* and the *pWip* information of the nine bayAreas are collected. With the order releasing happens after each planning period, the order dispatching happens continuously during each planning period. The controller takes the *rWip* and the *pWip* information of each bayArea and returns the acceptable work (*awl*) of that bayArea.

The first study focus on the lead time performance of each bayArea. Since the wafer factory control is very complex, the study of the performance of each bayArea is a good start for further study of the whole Resources performance in order to achieve the compromise between lead time and throughput of lots. *FODC* ensures the constant lead times of the bayAreas. Figure 7.8 illustrates the lead time performance of one bayArea. This simulation is conducted with the First-In-First-Out (*FIFO*) scheduler at the ProductionUnit level. The number of processing steps of an order in each bayArea can be known from the order processing recipe. When the lead time of each bayArea can be controlled under the desired work-in-process. It can guarantee the order lead time and the throughput of the Resources. The lead time of an order can be estimated by add up the product of the number of processing steps in each bayArea and the mean lead time of the correspondent bayArea. We haven't done further simulation study due to the lack of time. The batch forming and transportation time have been taken into account. The transporter is able to transport more than one lot at a time.

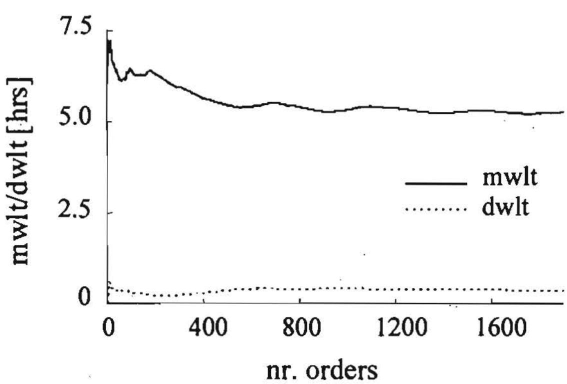

Figure 7.8: Lead time perfromance of a bayArea

To investigate the influences of the scheduling method on the control performances, a fuzzy scheduler at the ProductionUnitController level is implemented on the basis of the study in the previous chapter. The fuzzy *first-in-first-out* and *shortest remaining processing time* rule is being used here to sequence the lots, so we have the so-called *FFFR* scheduler.

FIFO is employed because it is the most common used method. Besides, it provided the best performance in the wafer factory control study as described in [Sim92]. The first series simulation study shows that there is no late order. But we should mention that the lateness and tardiness performance are related to the due date assignment in the first place. Second the number of finished orders collected from the simulation are not sufficient for us to draw conclusions at this moment.

A workable fuzzy work-in-process controller and a workable fuzzy scheduler are designed and implemented for the wafer factory control. We think it is feasible to apply the fuzzy control concepts in controlling such system. Further simulation studies should be carried out to investigate the factory performance under fuzzy control and fuzzy scheduling.

Chapter 8

Conclusions and Suggestions

Fuzzy control is supposed to be a good and attractive method in the sense that it can imitate human reasoning and thinking. The control process can automatically be done by a computer to replace human beings if such a fuzzy controller can be designed with good performance. Besides, control knowledge can be accumulated and improved in the course of time. These attractions were the drives for us to carry out the studies presented in this thesis.

The fuzzy control structure looks very general and simple, consisting of four units as illustrated in Chapter 2. However, very concrete decisions should be taken in each unit by choosing one alternative from numerous choices. It is extremely difficult, if not impossible, to say which choice in each unit is absolutely better than the others because all units of a fuzzy controller are in one way or another interrelated. The choice preferences mentioned in Chapter 3 are obtained by empirical studies and analysis, that are helpful for designing a reasonable or workable fuzzy controller. But it cannot be said that an optimal control solution can be found even given a very concrete case because of the lack of systematic design guidelines. One who is involved in the application of fuzzy control concepts often feels frustrated by the current status of fuzzy control theory. The conclusions related to the fuzzy controller design are:

- A feasible fuzzy controller can be obtained by the preferences that are established during the empirical study. But such a controller undergoes the *trial-and-error* process in order to get better control performance. It's not possible to guarantee an optimal control at this moment.

- It is important to find the correct physical domain for each of the variables involved in the control in the first place. One of the rational ways to decide such a domain is by recording the values of each variable and finding its 90% confidence interval.

- The control rule base derived from experts' knowledge and operators' experience should be possible to be adjusted in the course of time when systems and their environment change. A shifting and a rotating rule base adjustment method have been conceived from the studies in Chapter 5 and Chapter 6. Both rule base adjustment methods are easy and intuitive.

From the research described and the experience we have got from the study of fuzzy control application in manufacturing systems, a number of conclusions can be drawn:

- It is feasible to apply the fuzzy control concept in manufacturing systems' control. Reasonably good fuzzy controllers have been obtained for a single machine system and a simple job shop system. They work at least even good as the conventional method, like *load-oriented order release* control. But we should notice that the design and the adjustment process of such a fuzzy controller is really time consuming.

- Concerning manufacturing systems, especially job shop control, decomposing work-in-process (*wip*) into real work-in-process (*rWip*) and potential work-in-process (*pWip*) and by using both of them explicitly as control variables achieve more precise and good control.

- The application of the fuzzy control concept in scheduling is attractive in the sense that it can easily and intuitively make a good *compromise* between multi-criteria. The importance of each dispatching rule in the aggregated rule can be adjusted intuitively by adjusting the rule base. Fuzzy scheduling is better in this respect compared to its conventional counterpart.

- Wafer manufacturing is a very complex process involving hundreds of production steps. Its control is being considered to be very difficult. A workable fuzzy controller and scheduler have been designed for a such a system.

From the research described in this thesis, it is clear that the fuzzy control concept can be usefully employed in a manufacturing system control environment. Such a controller is flexible and can easily make a compromise between systems' multi-criteria. However, much research remains to be done before the methods described can be used in real industrial applications. A few suggestions for further study are:

- More detailed studies on the control related aspects, namely membership functions, inference process and defuzzification methods, should be carried out in order to conceive a guideline for systematic design of a fuzzy controller. Besides, methods resulting from this study for deciding the variable domain or range deserve a further study. Without proper data, the control results obtained are not reliable.

- The rule base shifting and rotating adjustment methods presented in this thesis deserve a further study. It is very useful to develop a systematic procedure for the rule base adjustment.

- The wafer factory control is rather complex. The control results obtained from this study are far from desired because of the lack of time of the researcher. Further studies can be carried out for investigating the appropriate structure of the control system, for instance, the right places for putting the fuzzy controller. Attention should also be paid to the variable domain chosen for $rWip$ and $pWip$.

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Curriculum Vitae

Hong Guang Wang was born in Taiyuan, China. From 1970 to 1981 she attended the Gong-yuan-lu primary school, the 29th secondary school and the 6th high school in the same city. In the fall of 1981 she started her study in electrical engineering at Xi'an Jiaotong University (XJTU). She graduated with the *B.Sc. degree* in electrical engineering in 1985. In 1988 she obtained the *M.Sc. degree* in electronic engineering at the same university, with the Master thesis "*Research on the Parameters of Mercury-Wetted Contact Relay in a Micro-Computer Controlled Data-Acquisition System*". Since then she has been an assistant lecturer at XJTU for two years. As the first time being abroad, she came to the Netherlands in May, 1990. She started the *Post-master* study and training on *CAD/CAM of discrete products*, at the Eindhoven University of Technology (TUE), The Netherlands. She finished her study in May of 1993 on the research project "*Object-oriented Design and Implementation of a Flexible Assembly Welding Cell (FALC) Transportation System Controller*". Her Ph.D. study started in May 1993 with the subject on the application of fuzzy control concept in manufacturing systems in the Section Systems Engineering of Dept. of Mechanical Engineering at TUE.

Stellingen

behorende bij het proefschrift

Fuzzy Control in Manufacturing Systems

Hong Guang Wang

1. Fuzzy theory, as a short name for fuzzy set and fuzzy logic theory, is well-defined and mathematically sound. It is crucial to realize that fuzzy theory is a theory of fuzziness, not a theory which is itself fuzzy. Just as the laws of probability are not random, so the laws of fuzziness are not vague.

This thesis

2. The lack of effective and systematic design techniques is a limiting factor for fuzzy control applications.

This thesis

3. The future of fuzzy control systems depends on their construction by men and their knowledge. It is not solely a technical or computer adventure but above all an adventure resulting from the application of human intelligence and team work. It can never be a good experience by struggling alone in such a field.

4. It is feasible to apply the fuzzy control concept in controlling the manufacturing systems, but what we should keep in mind is that the design and the adjustment process of such a fuzzy controller is very time consuming.

This thesis

5. Fuzzy control knowledge is derived from the load-oriented order release method. But by decomposing the work-in-process into real work-in-process and potential work-in-process and by using both of them as control variables achieve more precise and good control.

This thesis

6. Stressed or depressive becomes a modern term in this highly competitive society. Many people try very hard to search for a so-called permanent job for security. Does this permanent job make any sense if even one's life is temporal?

7. Artificial intelligence focuses only on study of human brain and its activities. From the oriental point of view. artificial intelligence also needs to study the human heart and its activities. In China, one can often encounter the expression: I think using my heart. Human beings make decisions by using both their brain and heart.

8. 中文无需动词变化及名词变格. 更无需冠词、动词语时态及名词数格从上下文即一目了然.中文之简洁常无意识的造成西文的不当使用.

   Translation:

   The Chinese language has virtually no conjugation for its verbs and no declension for its nouns. It of course doesn't need to bother the redundancy of articles. Most of the time it is quite clear from the context what tense or mood is intended for a verb, and what number or case is intended for a noun. But the unconsciousness influence from the simplicity of Chinese language often causes big trouble in using the Western language.

9. The human society is the most complex job-shop, where materials sometimes can also be resources. In such a job-shop the criteria are to lower the throughput and to maximize the lead time. This is contradicting with the usual job-shop criteria.

10. It is hard to become a mother of one twin. Finishing this statement means delivering of the first-born.