Decentralized Robust Capacity Control of Job Shop Systems with Reconfigurable Machine Tools

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M.Sc. Ping Liu

Gutachter: Prof. Dr. Jürgen Pannek
Gutachter: Prof. Dr.-Ing. Michael Freitag

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Abstract

Nowadays, manufacturing companies are confronted with various challenges from the perspective of customers individual requirements concerning variations of types of products, quantities and delivery dates. This renders the manufacturing process to be more dynamic and complex, which may result in bottlenecks and unbalanced capacity distributions. To cope with these problems, capacity adjustment is an effective approach to balance capacity and load for short or medium term fluctuations on the operational layer. Particularly, new technologies and algorithms need to be developed for the implementation of capacity adjustment. Reconfigurable machine tools (RMTs) and operator-based robust right coprime factorization (RRCF) provide an opportunity for a new capacity control strategy. Therefore, the main purpose of the dissertation is to develop a machinery-oriented capacity control strategy by incorporating RMTs and RRCF for a job shop system to deal with volatile customer demands effectively and efficiently.

In order to achieve quick responses to disturbances and less involvement with other workstations, a decentralized control structure is adopted in the capacity control system. Then the main research question is: How can a fast and robust state feedback be designed to facilitate disturbance rejection via decentralized RRCF capacity control for job shop systems using RMTs? As the work-in-process (WIP) level highly influences cost, throughput time and delivery reliability, the main control goal is to guarantee the WIP levels of all workstations on planned levels. As a high WIP level is one characteristic of job shop systems, so the system is assumed to be working at maximum capacity. Additionally, we assume that the demand fluctuations and transportation delays are Gaussian distributed, and that the sequencing policy of input orders is given in a first-in first-out (FIFO) manner.

Based on the question and assumptions, we first develop a mathematical model of a multi-workstation job shop system integrating the flexibility of RMTs. The reconfiguration delay, transportation delay and disturbances are incorporated in the model. Within the implementation of the RRCF control method, we start with a simple single-input single-output (SISO) system, and then increase the complexity to a multi-input multi-output (MIMO) system. In the control of the MIMO system, we design a decoupling controller to transfer the complex MIMO control to multiple simple SISO controls. In order to evaluate the effectiveness of the RRCF control algorithm, we additionally consider the classical proportional-integral-derivative (PID) control method as benchmark. The stability of both RRCF and PID control systems are analysed theoretically and a qualitative comparison is conducted. Then a quantitative analysis concerning PID and RRCF control algorithms is carried out by means of a numerical simulation of a four-workstation three-product job shop system. In the simulation part, we firstly analyse the dynamics and stability of these systems in three scenarios: (1) without delays and disturbances, (2) only with disturbances (i.e. rush orders) and (3) with delays and disturbances. Later, the uncertainties of the control systems, concerning the stochastic external customer demands and internal transportation delays, are analysed by using a Monte-Carlo simulation, respectively.

Thereafter, we conclude that both RRCF and PID control algorithms are applicable in the job shop capacity control system with reconfiguration delay, transportation delay and disturbances. In the PID control system, the computation of the control parameters and the evaluation of the feedback law are very simple. However, in this setting other workstations are considered to be disturbances, i.e. the orders input rate from other workstations are unknown to the controller and may lead to instability of the overall job shop system. Compared to the PID control algorithm, the computation of the RRCF control parameters is more involved, but is designed to balance these parameters automatically. Hence, instabilities from the interaction of workstations are avoided. Once computed, the evaluation of the feedback law is cheap. From the simulation results we show that the RRCF control method deals with the rush orders and delays within a shorter settling time and exhibits less overshoots than the PID control algorithm. The system uncertainties concerning the stochastic external customer demands and internal transportation delays are analysed, and results indicate that the RRCF shows an improved robustness property with lower variances of the errors between the planned and current WIP levels.

ZUSAMMENFASSUNG

Verarbeitende Betriebe stehen heute vor vielfältigen Herausforderungen durch die individuellen Anforderungen der Kunden an Variationen von Produkten, Mengen und Lieferterminen. Dadurch wird der Fertigungsprozess dynamischer und komplexer, was zu Engpässen und unausgewogenen Kapazitätsauslastungen führen kann. Um diese Probleme zu bewältigen, ist die Kapazitätsanpassung ein effektiver Ansatz, um Kapazität und Last bei kurz- oder mittelfristigen Schwankungen auf der operativen Ebene auszugleichen. Hierzu müssen neue Technologien und Algorithmen für die Umsetzung der Kapazitätsanpassung entwickelt werden. Rekonfigurierbare Werkzeugmaschinen (RMTs) und Operator-Based Robust Right Coprime Factorization (RRCF) bieten einen Ansatz für eine neue Kapazitätsregelung. Daher ist das Hauptziel der Dissertation die Entwicklung einer maschinenorientierten Kapazitätsregelung unter Einbeziehung von RMTs und RRCF in der Werkstattfertigung, um volatile Kundenanforderungen effektiv und effizient zu bewältigen.

Um eine schnelle Reaktion auf verschiedene Störungen und reduzierte Wechselwirkungen zwischen Werkstätten zu erreichen, wird eine dezentrale Regelungsstruktur verwendet. Dann ergibt sich die zentrale Forschungsfrage: Wie kann eine schnelle und robuste Ausgangsrückführung konzipiert werden, um die Reaktionsfähigkeit auf Störungen durch eine dezentrale RRCF-Kapazitätsregelung mit RMTs in der Werkstattfertigung zu gewährleisten? Da der Umlaufbestand (WIP) Kosten, Durchlaufzeiten und Liefertreue stark beeinflusst, ist das Hauptregelziel, den WIP aller Arbeitsplätze einem geplanten Niveau nachzuführen. Da in der Werkstattfertigung typischerweise ein hohes WIP-Niveau vorliegt, wird davon ausgegangen, dass das System mit der maximalen Kapazität arbeitet. Darüberhinaus wird davon ausgegangen, dass die Nachfrageschwankungen und Transportverzögerungen gaußförmig verteilt sind und die Sequenzierung der eingehenden Aufträgen dem FIFO-Prinzip (First in, first out) folgt.

Basierend auf den Fragen und Annahmen entwickeln wir zunächst ein mathematisches Modell eines Werkstattfertigungssystems, welches die Flexibilität von RMTs integriert. Die Rekonfigurationsverzögerung, Transportverzögerung und Störungen werden in das Modell integriert. Bei der Implementierung des RRCF-Regelungsalgorithmus beginnen wir mit einem einfachen Single-Input Single-Out-put (SISO)-System und erhöhen dann die Komplexität zu einem Multi-Input Multi-Output (MIMO)-System. Bei der Regelung des MIMO-Systems konzipieren wir eine Entkopplung, um die komplexe MIMO-Regelung auf mehrere einfache SISO-Regelungen zu übertragen. Um die Wirksamkeit des RRCF-Regelungsalgorithmus zu bewerten, betrachten wir zusätzlich den klassischen proportional-integral-derivativen (PID) Regler als Vergleichsmaß. Die Stabilität von RRCF- und PID-Regelsystemen wird theoretisch analysiert und ein qualitativer Vergleich durchgeführt. Anschließend wird eine quantitative Analyse der PID- und RRCF-Regelsysteme mittels einer numerischen Simulation eines Werkstattsystems mit vier Stationen und drei Produkten durchgeführt. Im Simulationsteil analysieren wir zunächst die Dynamik und Stabilität dieser Systeme in drei Szenarien: (1) ohne Verzögerung und Störung, (2) nur bei Störungen (d.h. Eilaufträge) und (3) bei Verzögerungen und Störungen. Später werden die Unsicherheiten der Steuerungssysteme hinsichtlich einer stochastischen externen Kundennachfrage und internen Transportverzögerungen mit Hilfe einer Monte-Carlo-Simulation an-lysiert.

Wir kommen zu dem Schluss, dass sowohl RRCF- als auch PID-Regelungsalgorithmen zur Kapazitätsregelung in der Werkstattfertigung mit Rekonfigurationsverzögerung, Transportverzögerung und Störungen anwendbar sind. Für den PID-Regler ist die Berechnung der Regelungsparameter und die Auswertung der Rückführung sehr einfach. In diesem Zusammenhang gelten jedoch andere Werkstätten als Störungen, d.h. die Auftragseingangsraten von anderen Werkstätten sind der Steuerung unbekannt, was zu Instabilität des gesamten Systems führen kann. Im Vergleich zu PID ist die Berechnung der RRCF-Regelungsparameter aufwändiger, gleicht diese aber zwischen Werkstätten automatisch ab. Dadurch werden Instabilitäten durch das Zusammenspiel von Werkstätten vermieden. Einmal berechnet ist die Auswertung des Feedback-Gesetzes einfach. Aus den Simulationsergebnissen schließen wir, dass die RRCF-Regelung Eilaufträge und Verzögerungen innerhalb einer kürzeren Einschwingzeit ausgleicht und weniger Überschreitungen aufweist als dies bei PID der Fall ist. Bezüglich der stochastischen externen Kundenanforderungen und internen Transportverzögerungen deuten die Ergebnisse darauf hin, dass RRCF verbesserte Robustheitseigenschaften mit geringeren Fehlerabweichungen zwischen dem geplanten und dem aktuellen WIP-Niveau aufweist.

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List of Abbreviations

The following abbreviations are used in this Dissertation:

RMT	Reconfigurable Machine Tools
DMT	Dedicated Machine Tools
FMT	Flexible Machine Tools
RMS	Reconfigurable Manufacturing System
DML	Dedicated Manufacturing Line
FMS	Flexible Manufacturing System
RFID	Radio-Frequency Identification
WIP	Work-In-Process
FIFO	First-In-First-Out
PID	Proportional Integral Derivative
LTI	Linear Time-Invariant
BIBO	Bounded Input Bounded Output
RCF	Right Coprime Factorization
RRCF	Robust Right Coprime Factorization
PSO	Particle Swarm Optimization
MIMO	Multi-Input Multi-Output
SISO	Single-Input Single-Output
MRMT	Mean of the number of Reconfigurable Machine Tools
SDRMT	Standard Deviation of the number of Reconfigurable Machine Tools
MAE	Mean Absolute Error
SDAE	Standard Deviation of Absolute Error
MIR	Mean Input Rate
MOR	Mean Output Rate
SDOR	Standard Deviation of Output Rate

1 Introduction

Manufacturing industries and logistics have a great contribution to global production and economy development. At the same time, they also face many challenges. As described in Figure 1.1, there are two flows between manufacturer and customer: information flow and product flow. In the first flow, the customer provides requirements about a product to the manufacturer, and then the latter produces the product according to these details. However, quickly changing demands of customers regarding types, quantities and delivery dates are a big challenge for manufacturers. In order to satisfy these volatile demands, manufacturers have to improve their flexibility and enhance their productivity. Moreover, the challenges not only come from customers, but also from complex manufacturing processes. Within the latter, shortages or unused capacity, bottlenecks and uncertainties (e.g., machine break down, transport congestions) may occur, which influence the productivity and increase the costs. Capacity adjustment is an effective approach to deal with these problems. This research focuses on the capacity control of manufacturing systems in short or medium term on the operational layer.

1.1. Research Motivation

Figure 1.2 shows the layers of production planning and control. In order to improve the competitiveness of manufacturers in today's markets, many of researchers worked on the production planning and scheduling layers from various perspectives, such as to minimize the makespan [8, 9, 10], improve the productivity [11, 12] and delivery reliability [13, 14]. These researches have made a great contribution on the development of manufacturing industries. However, customer demand fluctuations render the system to be increasingly dynamic, which has a major influence on the planning objectives. Capacity adjustment, on the lower process control layer, is one effective approach to handle dynamical systems in short or medium term.

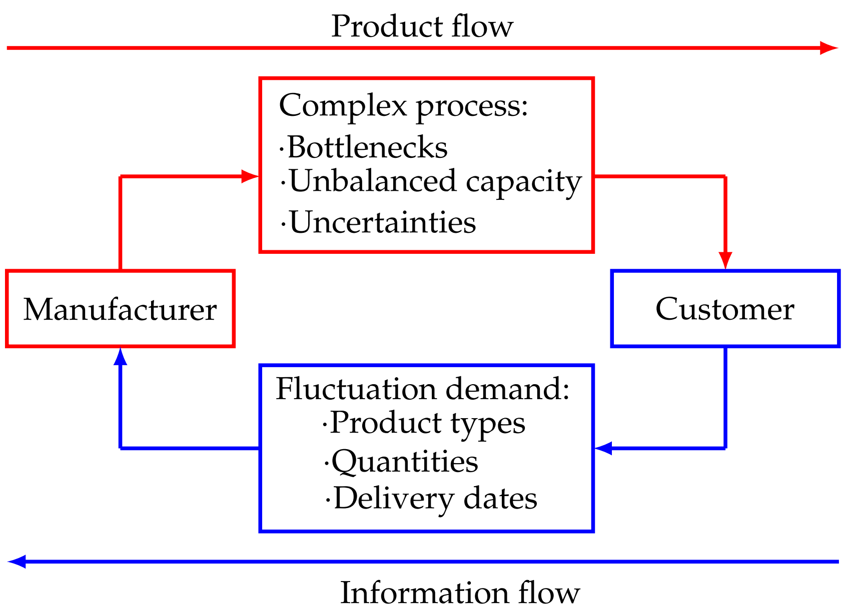

Figure 1.1.: Relationship between manufacturer and customer

Nonetheless, capacity control strategies are highly influenced by the field instruments layer. Nowadays, advanced technologies have been proposed, such as the Internet of Things (IoT) [15] and radio-frequency identification (RFID) [16], which provide more opportunities to control capacity adjustment process [17], whereas the respected control strategies still need to be developed.

There are a great number of approaches for the capacity adjustment, most of which are labour-oriented. As labour costs are increasing with the economic development, especially in the developed countries, machinery costs show a decreasing trend [16]. To solve this issue, machinery-oriented approaches were proposed based on the flexibility of machines [18, Chapter 26]. Compared to labour-oriented approaches, the latter still needs to be developed. Reconfigurable machine tool (RMT) [19] as one new technology of Industry 4.0, provides a new opportunity for machinery-oriented capacity control, but only few research studies exist on this topic. This motivates us to propose an effective machinery-oriented capacity control strategy for manufacturing systems in short or medium term.

1.2. RESEARCH CHALLENGE

For a manufacturing company, flexibility and productivity are two key enablers for competitiveness facing fast-changing market [20]. Capacity adjustment is of particular interest for the flexibility of manufacturing systems. Flow shop and job shop are two typical manufacturing systems [21]. In general, a flow shop system is designed to handle large volumes with high productivity at low cost, but with low

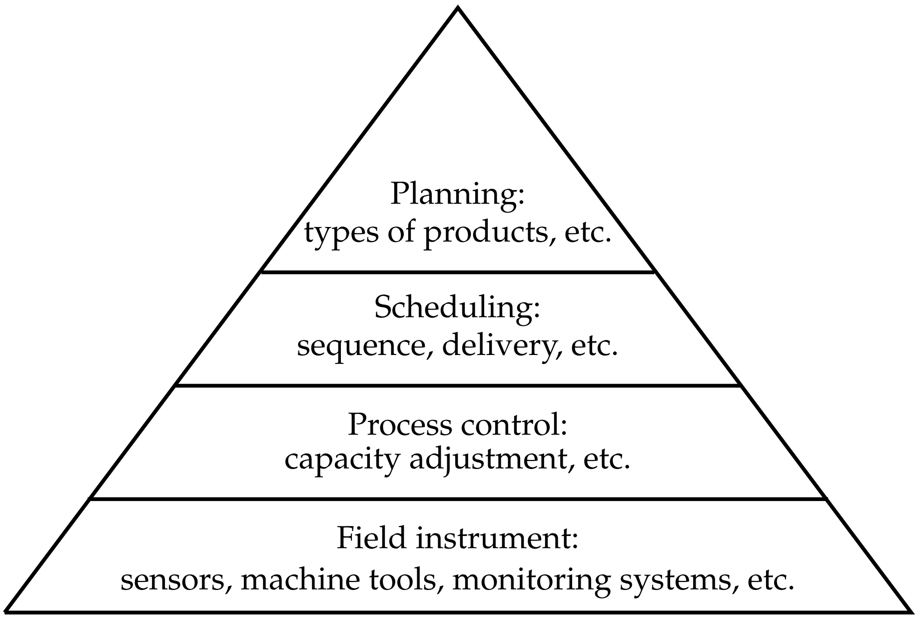

Figure 1.2.: The hierarchy of decision-making process (after [3])

flexibility [22, 23]. In contrast to that, job shop systems generally offer high flexibility for a variety of products in small or medium volumes but also exhibit high costs and low productivity [24]. Additionally, machinery-oriented capacity adjustment requires flexibility of machines, which also has great influence on the flexibility of the system. In [25], machine flexibility is defined as the ability to perform various operations without setup changes. In terms of the types of machine tools, dedicated machine tools (DMT) and flexible machine tools (FMT) are two traditional machine tools, which have been widely applied in practice [2]. The concept of RMT was proposed in the 1990s [26]. However, compared to labour-oriented approaches, the potential of these machine tools, especially RMTs, in the capacity adjustment still needs to be developed.

Machine tools are only an enabler for the capacity adjustment of manufacturing systems. To render the latter to be effective, we need to complement these tools with respective control strategies. Proportional integral derivative (PID) is a simple and easily applicable control method [27], which has been widely applied in practice, including the capacity control of manufacturing systems. However, it is difficult to achieve optimal performance via this method, especially for nonlinear problems. Manufacturing processes are typically complex nonlinear systems with delays, disturbances, constraints and couplings. These properties may decrease the performance of a PID control system. Therefore, a number of researchers investigated the potential of more advanced control techniques for manufacturing processes [28]. Operator-based robust right coprime factorization (RRCF) is one advanced control method [29]. This method has been developed for and applied to various difficult problems, which include nonlinearities, uncertainties and delays etc.. However, this method has not been taken into account for capacity control of manufacturing systems. Therefore, the implementation of this method is more challenging in the capacity control of manufacturing systems.

1.3. Problem Setting

From the above discussion, we see that capacity adjustment plays an important role in production planning and control. It is an effective approach for manufacturers to achieve planned objectives while responding quickly to volatile demands as well as maintaining or enlarging their market share. While various advanced technologies are available in the field by now, the respecting control strategies are not yet developed, especially machinery-oriented approaches to complement the increasing labour cost. This motivates to design an effective capacity control strategy for manufacturers. In order to achieve this objective, ensuring flexibility, improving productivity as well as stability and robustness of the capacity control system need to be considered.

In this dissertation, flow shop and job shop systems as two typical manufacturing cases are considered, resembling high productivity and high flexibility separately. Different from labour-oriented approaches, the machinery-oriented approach is relying on the flexibility of machine tools to perform various operations. For this reason, first, types of machine tools are analysed. Moreover, manufacturing processes are complex with various delays, uncertainties, ect., which additionally render it to be highly dynamic [30]. To cope with this aspect, the key requirement is the ability to provide or adjust the capacity efficiently within the manufacturing process [31]. To avoid shortages, the required capacity is typically overestimated during the strategic planning. Hence, if the capacity is static, i.e. the respective machine can be used for a single purpose only, the idle time of these machines will either be large, or if the required capacity is underestimated, functional shortages may occur. To circumvent these issues, capacity adjustment strategies can be used on the short or medium term level.

To avoid shortages and unused capacities of different workstations, the capacities of all workstations shall be considered simultaneously. While the controller should reflect the distributed physical nature of the system, the goal of the feedback is for one to dampen the negative effects of internal and external demand fluctuations, but secondly also to improve the reliability of the logistic efficiency of the manufacturing system, such as a stable work-in-process (WIP) level. To design such a feedback, the stability of the control system must be analysed. In this dissertation, the RRCF control method is considered. Additionally, to evaluate the effectiveness of this method, the classical PID control method is adopted as a benchmark for a quantitative and qualitative analysis.

1.4. Structure of Dissertation

In order to develop an effective machinery-oriented capacity control strategy, the main research structure of the dissertation is organized as shown in Figure 1.3. It mainly comprises four parts: background knowledge, mathematical model, implementations as well as conclusion and outlook.

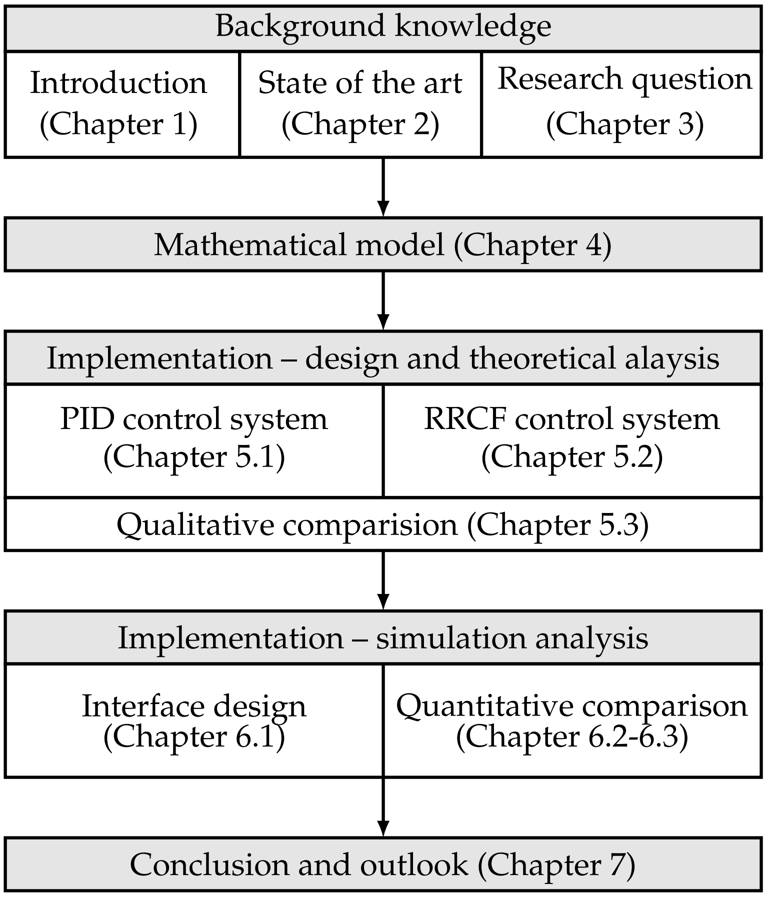

Figure 1.3.: Structure of dissertation

The background knowledge part contains three chapters. Chapter 2 surveys the state of the art on capacity adjustment for manufacturing systems to identify research gaps. Considering flexibility and productivity of manufacturing systems, the types of shop floor manufacturing systems and machine tools are reviewed. Flow shop and job shop systems are discussed in terms of the properties, challenges and respective research solutions. The types of machine tools including DMT, FMT and RMT, are discussed later. Then, the current research on labour-oriented and machinery-oriented capacity control approaches is reviewed. Last, PID and RRCF control methods are investigated from a development, application and design perspective. Based on the research gaps in Chapter 2, we propose the main research question and methodology for the capacity control of job shop manufacturing systems in Chapter 3.

The mathematical model part is contained in Chapter 4. Firstly, the related literature on modelling of manufacturing systems is discussed and then a basic model and assumptions are introduced. Thereafter, we integrate the flexibility of RMTs and productivity of DMTs in a combined model. The latter model is further extended considering disturbances as well as reconfiguration and transportation delays in the capacity adjustment process of manufacturing systems.

In the implementation part, PID and RRCF control methods are considered from a theoretical perspective (Chapter 5) and from a simulation perspective (Chapter 6), where PID serves as benchmark for the RRCF method. In Chapter 5, the design of PID and RRCF controllers is presented and the stability of these two control systems is analysed theoretically for three scenarios: (1) nominal case without delays and disturbances, (2) only with disturbances and (3) with delays and disturbances. For these cases, both control methods are qualitatively compared. Chapter 6 focuses on the simulation of PID and RRCF for a quantitative comparison in the same three scenarios. Here, a four-workstation three-product job shop manufacturing system is imposed and an abstract interface is proposed for the comparison. Later, the robustness of these two control systems regarding external and internal uncertainties, i.e. stochastic customer demands and stochastic transportation delays, is analysed and compared.

Chapter 7 concludes the dissertation on the robust decentralized capacity control of manufacturing systems with RMTs. The contribution and outlook of the research are also discussed.

1.5. SUMMARY

As the first chapter of the background knowledge part, we introduced the research motivation of the dissertation, which is to develop an effective machinery-oriented capacity control strategy on the operational layer to improve the competitiveness of manufacturers facing volatile customer demands and complex manufacturing processes. Then we discussed the research challenge on the capacity control of manufacturing systems considering productivity and flexibility before the main problem was set considering the research objectives. Last, we gave the main structure of the dissertation.

2 State of the Art

The above chapter illustrated the motivation, challenges, problems for the capacity control of manufacturing systems. For these problems, the related literature is reviewed in this chapter to introduce basic notations and denominations, and to identify the research gaps. Flow shop and job shop systems are two typical manufacturing systems with respectively high flexibility and high productivity. The properties, challenges and respective solutions of both systems are firstly reviewed. Then we investigate the literature of three types of machine tools, including dedicated machine tool (DMT), flexibility machine tool (FMT) and reconfigurable machine tool (RMT). Thereafter, current research on labour-oriented and machinery-oriented capacity control approaches is reviewed. Last, we review the related control techniques including proportional integral derivative (PID) and operator-based robust right coprime factorization (RRCF).

2.1. Manufacturing Systems

A manufacturing system can be an organization with various activities comprising machine tools in the technology operation [19, 32, 33] and behaviour division of labour [3, 34] and information flow [35, 36]. With these different technologies and organizational activities, a range of manufacturing systems were designed for various purposes. There are a variety of ways to classify the manufacturing systems, e.g., the complexity of material flow, types of produced products, facility layout and timing of production [37]. In [38], the authors concentrated on the ways of classification and pointed out flow shop and job shop were two typical manufacturing systems. In [1], the properties of these two types were discussed. The major properties of these two systems are illustrated in Table 2.1. A flow shop system typically exhibits dedicated routing of manufacturing processes, and machines and other types of equipment are ordered according to the process sequences of the products or parts of the products [22]. In general, this system is designed to handle large volumes with high productivity and low cost. Compared to the flow shop system, a job shop system consists of a set of versatile workstations with flexible producing paths, thereby providing high manufacturing flexibility for a variety of products [24]. Its structure allows for many different production paths for small or medium volumes. Due to the various properties, the challenges of these two types are also different. The associated research for them will be discussed in the following.

Name	Job shop systems	Flow shop systems
Varieties of products	High	Low
Flexibility	High	Low
Productivity	Medium	High
Cost	Medium	Low
Volume	Small or medium	Large

Table 2.1.: Properties of flow shop and job shop manufacturing systems [1]

2.1.1. Flow Shop Systems

Flow shop manufacturing systems are used for car assemblies, manufacturing of electronic circuits and so on [39]. As introduced in [40], based on the scheduling problem, flow shop system can be classified into classical flow shop systems and flexible or hybrid flow shop systems. In the first, there exists one path with multiple stages for different operations with only one machine at each stage. In flexible flow shop systems, there are multiple stages in series as well but with a group of identical machines in parallel. In order to satisfy customer demands and minimize the cost, flow shop scheduling and control are two vital research topics.

2.1.1.1. Flow Shop Scheduling

For classical flow shop scheduling, most researchers concentrated on the development of a sequence of jobs for various objectives. It is a problem of scheduling n jobs on m machines, where the machines are capable of processing at most one job at a time, and each job can be processed on at most one machine at any time [41]. It can be transformed into an optimization problem subject to different objectives. Taillard [8] proposed benchmarks for the basic scheduling problem with fixed processing times to find a permutation of the n jobs to minimize the makespan. With the development of optimization and artificial intelligence search techniques, many approaches were applied to solve this basic scheduling problem, such as genetic algorithms [10], tabu search algorithm [42], artificial immune system [41] and so on. Kouvelis et al. [43] increased the problem complexity to robust scheduling of a two-machine flow shop system with uncertain processing times by using exact and heuristic solution approaches. In this paper, the robustness of the schedule was defined as providing optimal hedges against the prevailing process time uncertainty while maintaining excellent expected makespan. Samarghandi [44] discussed the scheduling problem of a no-wait flow shop system with sequence-dependent setup time and server-side constraints via two genetic algorithms. Chen et al. [45] studied the complexity of late work minimization in the flow shop scheduling problem, and used particle swarm optimization to minimize the total size of late parts of all jobs.

The research on flexible flow shop scheduling problems is relatively more complex. Brah and Hunsucker [46] presented a branch and bound algorithm to optimize the maximum completion time of all jobs on the machines and minimize the mean flow time of the jobs. Hunsucker and Shah [47] compared and analysed the performance of the multiple processors flow shop system on the makespan, mean flow time and maximum flow time with various priority rules. In special, Gupta et al. [48] compared and analysed branch and bound and several heuristic methods on the scheduling of a two-stage hybrid flow shop system. Wang [40] collected and analysed the existing optimum, heuristics and artificial intelligence solutions for flexible flow shop scheduling. Considering the dynamic environment involved with re-entrant machines breakdowns and new incoming orders, Savino et al. [49] developed a flexible model for the flow shop system based on the concept of multi-agents. In order to satisfy the requirements of multiple decision makers in the flow shop scheduling process, Wong and Zhang [50] presented a model with the multiple objectives and constraints in the optimization problem. In the above research, the flow shop schedule was generally utilized to sequencing the jobs on the machines for various objectives. It is typically transformed into a static optimization problem. A great number of algorithms have been successfully applied in this problem, and evaluation of different heuristic algorithms in the scheduling also has been studied, such as a computer framework proposed in [51]. Moreover, considering uncertainties, disturbance, faults etc. in the system, robust schedule was proposed against poor performance or maintain the high performance [43], which was defined as the flexibility of the system in [49].

2.1.1.2. FLOW SHOP CONTROL

Next to the scheduling problem, flow shop control is another research branch on the flow shop systems. In [52], the authors developed an integrated intelligent scheduling and control system for an automated manufacturing flow shop system using a multilevel approach considering the uncertainties and perturbations in the control parameters and monitoring data. Li et al. [53] presented an average processing time and lever heuristic, integrated with a closed-loop feedback control scheme to obtain adaptive production scheduling and control to deal with disturbances. A trade-off between optimality and computation time of a heuristic was discussed considering dynamics in the scheduling. Aufenanger et al. [54] presented the dynamic production control for gaining flexibility and reducing cost by combining the simulation and knowledge-based dispatching rule selection. They also pointed out that flexibility and cost-efficiency are key factors for a successful company. In these articles, the control laws were used to deal with dynamics, disturbances or uncertainties in the system scheduling or rescheduling.

Nevertheless, flow shop control does not always involve scheduling. It was also used to control the production rates, capacity, work-in-process (WIP), job flow etc.. Plassart et al. [55] suggested a timed colored Petri net model to evaluate the performance of the flow shop system with a central controller on the production rates. Considering card setting problem in a flow shop system characterized by the presence of a batch processing machine, an efficient Constant Work in Process (CONWIP) control system was developed to balance the capacity, maximize the throughput and minimize the WIP level [32]. Silva et al. [56] compared and analysed three card-based production control systems on the job release and job flow in a flexible flow shop system for short delivery times and on-time deliveries. Additionally, in terms of various disturbances, uncertainties, etc., robustness and stability of the flow shop control system also attracted increasing attention. In [57], based on coordination mechanisms of insect colonies, a development approach for agent-based shop floor control systems was presented to deal with unanticipated disturbance situations in a distribution environment. Fuzzy max-plus algebra was used to control the flow shop systems with uncertain service times to deal on the quantitative aspects, and both stability and robustness of the system were analysed in [39]. In this control system, robust stability was defined as boundedness of job output delay despite uncertainties in service time and faults in the production system.

2.1.2. JOB SHOP SYSTEMS

Compared to flow shop systems with fixed producing paths, job shop systems offer the ability to satisfy changing demands regarding types of products due to its flexible producing paths. This system generally operates on the basis of make-to-order in small and medium-sized volumes [58]. The high flexibility and complexity of job shop systems has attracted the attention of a great number of researchers. Reiter [59] discussed a computerized management system for planning, scheduling and controlling of a job shop manufacturing system. Considering different layouts, designs and demand distributions, a simulation model was presented to assess the difference between traditional job shops and group technology shops in [60]. Pflughoeft and Hutchinson [61] provided several guidelines for process plan development and design and operation of flexible job shop systems. However, this type of system also has several drawbacks, such as high WIP levels, high cost and low productivity [58, 62, 63]. In this section, we will also review the literature on job shop scheduling and job shop control.

2.1.2.1. Job Shop Scheduling

Ryzin [64] defined the scheduling is the selection of times for future controllable events, such as the time to start an operation or move a part from a machine to a buffer, whose times may be selected by a manager or machine operator. Compared to flow shop systems, the scheduling of job shop systems is more complex due to highly flexible producing paths [65]. Some scholars tried transforming job shop systems into flow shop systems by purchasing additional machines [66]. However, this task is difficult to achieve due to the complexity. The literature on the job shop scheduling shows a variety of approaches. Dispatching rules for the scheduling in job shop systems have been discussed in [67, 68]. Some algorithms, which have been applied in the flow shop scheduling were also considered in job shop systems, such as tabu search metaheuristic [69], genetic algorithm [70], genetic programming based hyper-heuristic approach [71] and particle swarm optimization [72]. In [73], the authors explored the application of Lagrangian relaxation approach for the scheduling of job shop systems, and decomposed this problem into operation-level subproblems for the selection of start times and machine types, with given multipliers and penalty coefficients. Yin et al. [74] especially focused on scheduling numerical non-resumable and simultaneously available jobs on a single machine with several agents considering makespan, due date assignment cost, weighted number tardy jobs. An improved island model memetic algorithm with a new naturally inspired cooperation phase was proposed for the scheduling of multi-objective job shop systems in [75]. According to a real situation of a brewing company, Devassia et al. [76] developed a flexible job shop scheduling problem with resource recovery constraints, and adopted a metaheuristic based on a general variable neighbourhood search algorithm to optimize the makespan. Also, the robustness and stability of the scheduling were also discussed in [77, 78]. From the above literature, we obtain that although job shop scheduling problems are more complex than the flow shop scheduling ones, the approaches or methodologies may be re-used.

2.1.2.2. Job Shop Control

Job shop control has various definitions in the literature. Because production planning often determines the nature of the control and experiences influence future planning, the job shop control is linked with planning [58]. Therefore, some scholars adopted job shop control for scheduling, delivery and operation. Regarding the control in job shop scheduling, most approaches concentrated on the optimization of one or multiple objectives. In [79], job shop control was discussed using optimization in the scheduling with the influence of Chaos phenomena based on a Petri-net model. A Heuristic control policy for the scheduling of a job shop with delays was derived by using theoretical arguments and approximations in [64]. In order to deal with resource break-downs, a holonic control was proposed for fault-tolerant job shop assembly for automatic replanning in [80]. With the scheduling purpose to minimize the mean flow time and mean tardiness of orders, Hansmann and Hoeck [81] developed a neighbourhood search technique for performance measurements of production control. Regarding multi-criteria job shop scheduling problem, Ramkumar et al. [82] applied Fuzzy logic control to optimize machines' operation for profits and customer satisfaction considering processing uncertainty and constraints. Li and Cao [83] put forward an optimization model including selecting most suitable machines for the operation of a job and generating optimal operation sequences to reduce idle/unload emissions in a job shop manufacturing system.

Workload control is one topic in the job shop control. It generally focuses on the order release to balance the load. Onur and Fabrycky [84] presented a combined input/output control system to periodically determine the set of released jobs and the capacities of processing centers in a dynamic job shop systems. For a WIP control problem, adaptive input control for varying demands was discussed by using inverse queuing network analysis in [85]. Also, workload is one important variable in the job shop systems [86]. Land et al. focused on such concepts in [13, 87]. In their research, workload control concepts could buffer the shop floor against external dynamics by creating a pool of unreleased jobs. Then they studied the approach of order release in balanced and unbalanced job shop systems based on a queue model. Thürer et al. [88, 89, 90] not only studied the order release in the workload control, but also pointed out the importance of output control for job shop systems. In output control, capacity adjustment is an effective approach for dynamic systems and has a great influence on the performance, such as productivity, due date and WIP levels.

The above control system was mainly studied via quantitative indicators, such as due date, WIP and throughput. Another type indicator is a qualitative one, which can be used to reflect subjective views of expected behaviours, such as robustness and stability [91]. Robust control is an approach to cope with various internal or external disturbances and uncertainties. There are different concepts of the term robustness in the production system. In [92], the robustness of production systems was defined as the capability to maintain short-term service, which was the probability of the short-term fill-rate remaining in a pre-specified range. It was analysed through uncertainty analysis by using the Monte-Carlo method. In [63, 93], a manufacturing system was called robust if the performance did not significantly deteriorate in the face of fluctuations and disturbances. An overview on robustness measures and the trade-off between robustness of operation performance and cost-efficiency on the capacity adjustment of job shop systems was discussed in [63]. Stricker and Lanza [94, 95] reviewed and discussed the classification of robustness and the correlations to flexibility, changeability, resilience and risk. They defined the robustness of a production system as its ability to remain working on a stable and high performance level despite varying conditions or risks. Also, they put forward that robustness could be measured by the absolute value and deviation of the performance indicator on a tactical and operational level. Luft and Besenfelder [96] specially focused on the assessment of flexibility and robustness of manufacturing systems in a volatile and unpredictable environment. They defined robustness as one kind of flexibility, which enables the system to withstand a certain amount of change. Different from optimization-based control, robust control systems are generally designed in a decentralized architecture to reduce the complexity and obtain a fast response [80, 97, 98]. Currently, the development of technologies, such as electric sensors, bar-code, radio-frequency identification (RFID) and wireless networks, allows to advance monitoring systems of the manufacturing process to be more accurate and reliable [16, 99]. Additionally, they also allow the collection and synchronization of the real-time field data from manufacturing workstations (or workshops). These technologies on the one hand contribute on the development of manufacturing control, but also increase the numbers of control criteria, which leads to an increasing attention on developing more advanced control theories for manufacturing systems [100].

To wrap up, considering the challenges of flexibility and productivity in manufacturing systems, the properties of flow shop and job shop systems were analysed. Flow shop systems are typically designed for high productivity but low flexibility. In order to improve the latter, the concept of flexible flow shop system was proposed, while influences the productivity. For job shop systems on the other hand, high flexibility renders this type of system to be more competitive than flow shop systems facing demand changes, but also influences the productivity. Scheduling and control are two issues for competitiveness improvement of these two systems. From the above review, we obtain that a flow shop system could be a special type of job shop systems with fixed producing routes. Especially, facing various internal and external disturbances and uncertainties, robust control of job shop systems is an effective opportunity, which may highly improve manufacturers' competitiveness. The development of various advanced technologies, such as RFID, allows to apply advanced control techniques in manufacturing systems, which still need to be investigated. Therefore, our research will focus on the gap to develop an effective robust control strategy for manufacturing systems, especially for job shop systems.

2.2. MACHINE TOOLS

Machine tools are another decisive factor for productivity and flexibility of manufacturing systems. In [101], a machine tool was defined as a machine for shaping or machining metal or other rigid materials, usually by cutting, boring, grinding, shearing or other forms of deformations. There are various ways to classify the types of machine tools. According to the operation flexibility, machine tools are classified into dedicated machine tools (DMTs), flexible machine tools (FMTs) and reconfigurable machine tools (RMTs) [2]. They are proposed sequentially to satisfy the varying production requirement [102]. So far, DMTs and FMTs have been successfully applied in production systems, and have a large impact on industry development. The concept of RMTs was proposed with the requirement of manufacturers in the middle of 1990s [2]. The main properties of these machine tools are summarized in Table 2.2. It illustrates that DMTs typically offer high productivity and low cost but low flexibility. In contrast to DMTs, FMTs have high flexibility but low productivity and high cost. The concept of RMTs could combine the advantage of DMTs and RMTs for cost-effectively customized flexibility. The related literature is discussed in this section.

Name	DMTs	RMTs	FMTs
Machine structure	Fixed	Adjustable	Fixed
Scalability	No	Yes	Yes
Flexibility	low	Customized	High(General)
Productivity	Very High	High	Low
Cost	Low	Medium	High
Simultaneously operating tools	Yes	Yes	No

Table 2.2.: Properties of three types of machine tools [2]

2.2.1. DEDICATED MACHINE TOOLS

A DMT is a common type of machine tool in large manufacturing companies. This type of machine tool is custom-designed with a fixed structure, for specific operation requirements and, therefore, its resources are minimized, the machine cost is low and its performance is robust [19]. There is numerical research on the design, model and evaluation of DMTs [103, 104]. Various DMTs, such as drilling [105], cutting [106], milling [107], have been designed to satisfy various manufacturing requirements with high accuracy, high productivity and automation [108]. This machine has many tools to work on a single part and are generally adopted in the companies with low number of variants of products. Dedicated Manufacturing Lines (DMLs) or transfer lines are used by this kind of companies, which are based on inexpensively fixed automation and produce the company's core products or parts over a long period at high volume [2]. Each dedicated line is designed to manufacture a single type of product at high production rate by using all tools simultaneously [109]. A DML is based on a collection of simple machines, such as various types of DMTs for cutting, drilling and grinding operations. Due to the high production volume, DMLs are mostly adapted to mass production with relatively low cost. Additionally, this system is economically profitable when large quantities of identical products are needed [110]. However, with the development of industry and economy, customer demands are also quickly changing in the types of products and quantities. Thus, product life cycles have become shorter and new products are introduced more quickly. Consequently, when the demand decreases, the ability of DML is underutilized, so the cost per unit becomes higher. As the production lines are limited in terms of reactivity and are not designed for future changes, these conditions render them unprofitable [109, 110]. In summary, as listed in Table 2.2, DMTs have fixed structure, high productivity and low cost, but no scalability and low flexibility. However, they still play an important role in today's manufacturing, and can be used in flow shop systems and job shop systems [111]. However, these machines cannot be cost-effectively converted when the demand changes.

2.2.2. FLEXIBLE MACHINE TOOLS

In order to compensate the drawback of DMTs, the concept of FMT was proposed [112]. The introduction of numerically controlled (NC) machine tools made it possible to perform highly flexible on a single machine, and the following proposed computer numerically controlled (CNC) machine tools improved the accuracy for more rigid construction and precision mechanical components [113]. Various scholars have studied the design, control and analysis of these machine tools. In [114], Pritschow et al. discussed the contribution of open controller architecture in the

CNC products on the world-wide research activities. Altintas et al. [115] reviewed the design and control of feed drive systems used in machine tools (CNCs), and presented the engineering principles and challenges in the design, analysis and control of feed drive on the influence of the quality and productivity of machine tools. Moreover, Wang et al. [116] introduced the modular design of the CNC machine tool products for remanufacturing considering product life cycle and disassembly criteria. Excepting the research of the machines, the tool's performance also has been studied to improve the accuracy and shorten the process time [117, 118, 119, 120]. These general-purpose CNC machine tools and other programmable automata comprise a flexible manufacturing system (FMS) [2, 121]. Due to the flexibility of machine tools, this system also shows high flexibility to produce a variety of products, which also makes the system more complex. Maccarthy and Liu [121] summarized the definitions and classification of FMS, and discussed the characteristics and the configuration of the processing elements in the systems. Plenty of research has contributed on the modelling, control, design and performance analysis of this system and solved various complex problems [122, 123, 124, 125]. However, for a single-tool operation of FMTs, the throughput is relatively low compared to DML [2]. Additionally, Shin [113] pointed out that the payment of FMTs took about more than 75% of the money spent on machine tools. It implies that the high cost of the machine tools increases the cost of product. In all, we obtain that FMTs offer higher flexibility, but also higher cost and lower productivity than DMTs'. Moreover, as it is designed before knowing the operation requirements, so there may exit wasted resources and customer pay for these unnecessary features [19]. Furthermore, as more new operation required, these machines may not be able to satisfy manufacturing requirements [2].

2.2.3. RECONFIGURABLE MACHINE TOOLS

The concept of RMT was proposed to fill the gap between DMTs and FMTs. In Koren and Kota's patent, a concept of RMTs was introduced and has been widely accepted. They defined that an RMT should have multiple units to support the desired tools, each of which is easily reconfigurable to perform a variety of processes on a family of parts [26]. Therefore, RMT is designed with customized-flexibility to be cost-effectively converted as manufacturing requirements are changed. Most research of RMTs focuses on the design [126, 127]. Landers, Min and Koren [19] discussed the systematic design tools in the manufacturing requirements, control requirements and mechanical requirements for RMTs to distinguish the difference between RMTs to other traditional machine tools. The design methodologies and principles are discussed in [128, 129]. The software design in the programming language and computation of supervisors for RMTs were introduced in [130]. Gadalla and Xue [131] reviewed recent research and challenges of RMTs in the architecture design, configuration design, and controller design. Special RMTs, such as modular RMTs [132, 133], reconfigurable micro-machine tools [134, 135] were also designed to satisfy different requirements. Within this research, many prototypes of RMTs have been developed for the design of manufacturing processes [126, 132, 134, 136, 137, 138], which allow the implementation of multiple operations. One of the prototypes is based on multi-technology, which integrates different technologies in one machine workspace [25]. The modules of these RMTs can be configured by means of a construction kit, and the submodules are also reconfigurable. This kind of RMTs can deal, e.g., with tasks of turning, milling, chamfering, and drilling by means of reconfiguration. The NSF Engineering Research Center for Reconfigurable Manufacturing Systems in the University of Michigan has designed and built several RMTs, such as arch-type RMT [136]. In the coming future, more new RMTs are expected to be designed and applied in real companies.

Regarding the application of RMTs, most researchers focus on the reconfigurable manufacturing system (RMS), the main components of which are RMTs and CNC machines [2, 109]. Koren et al. defined that an RMS is designed at the outset for rapid change in structure, as well as in hardware and software components, in order to quickly adjust production capacity and functionality within a part family in response to sudden changes in the market or in regulatory requirements [2]. They also put forward the design methodologies, characteristics and principles. In the literature, there are numerous papers on the design, modeling and evaluation of RMS [109, 139, 140, 141]. Especially, many scholars reviewed the literature of RMS. Mehrabi, Ulsoy and Koren [142] focused on the development of manufacturing techniques and sciences issues related to RMS. The strategies for the design requirements of RMS were discussed in [143]. The components, capabilities, challenges of RMS and comparisons of RMS to FMS and DML were introduced in [144, 145]. They also discussed the research on the cost of reconfigurability and variable selection in RMS. Existing solutions in software, hardware and mixed requirements in the design of RMS were summarized in [110], and the authors introduced an open direction about predictive monitoring approaches for RMSs. Different from the previous review, Bortolini, Galizia and Mora [146] identified five research streams in the field of RMS (e.g., reconfigurability level assessment, analysis of RMS features, analysis of RMS performances, applied research and field applications, and reconfigurability toward Industry 4.0 goals). From this literature, we can get that RMS has great potential in manufacturing development, but it is still in the prototyping stage. As some real RMTs have been produced, the application of these machines should not be limited to RMS. Scholz-Reiter et al. [31] showed the effectiveness of

RMTs in the capacity adjustment of job shop systems, in which all machines were reconfigurable. However, the potential of RMTs in current production settings needs to be analysed more rigorously.

From the literature of machine tools in the manufacturing system, we obtain that DMTs and FMTs play important roles in today's manufacturing factories. The potential of RMTs as a novel tool still needs to be developed. Considering that machinery-oriented capacity control relies on flexibility of machine tool, FMTs and RMTs are two available choices, but RMTs are more competitive due to cost-effectively customized flexibility. Nevertheless, few researchers contributed on using RMTs in capacity control of manufacturing systems. Hence, it is urgent to develop the potential of RMTs in the machinery-oriented capacity control of manufacturing systems. Concerning this gap, the current capacity control approaches are reviewed in the following section.

2.3. CAPACITY CONTROL

Capacity control is an effective approach to deal with customer demand fluctuations, bottlenecks etc. in short or medium terms for special logistic objectives considering low work in process inventories, short lead times, high machine utilizations and high adherence to delivery dates [11]. In [18, Chapter 26], the fundamental principles of capacity control were introduced. The first is to orient the system on the planned output (or the customer demands), which supports the reliability of delivery time and the compliance with planned stock levels. Another one is the bottleneck principle, which determines the yield and WIP inventory level of the system. From Section 2.1, we know that manufacturing processes are complex, dynamic and nonlinear systems with various external and internal disturbances, delays, uncertainties, etc., which render the process control to be difficult. To analyse and control the system's behaviour, the crucial task is to match the time-phased capacity requirements with the available capacities, which relies on the capacity flexibility. Considering workforce and machines flexibility, labour-oriented and machinery-oriented capacity control approaches are reviewed in this section.

2.3.1. LABOUR-ORIENTED CONTROL

The labour-oriented approaches mostly control the capacity based on the flexibility of workforce, which mainly comprises of flexibility of work hours, flexibility of working speed as well as flexibility in engaging or dismissing the workforce and their cross-training [18, Chapter 26]. Considering these, Lödding classified, introduced and compared the labour-oriented approaches including the backlog control, plan-oriented control, due date-oriented control, output rate maximizing control and inventory-based control [18]. He classified backlog control and due date oriented control to be on high degree of details as the control is applied to the entire system, the others including backlog control to be on low degree of details as the control is applied to the individual workstations. The purpose of backlog control is to ensure the actual output attains the planned output despite disruption of a workstation or system, so that to improve the schedule reliability [11]. Plan-oriented capacity control is designed to guarantee the capacity on the planned level [18]. Different from backlog control, the aim of due date oriented control is to satisfy customer demands even if the capacity exceeds the planned level. The output rate maximizing capacity control is to maximize the output rate (e.g., in bottleneck situations), at the same time preventing waste of excessive WIP or unused capacity [18]. Inventory based capacity control is designed to regulate the inventory in defined limits, and generally combined with other methods, such as Kanban control [147]. In these methods, the capacity control ascertains the workers' hours and operator works on relative machine hours [18].

Also, there are other methods based on the labour-oriented control. In [12], the number of employees was considered as the capacity flexibility to evaluate the throughput by using the workload-dependent capacity control in production-to-order systems. Nyhuis and Filho [4] discussed the dynamic capacity planning and control for the reduction or elimination of static and dynamic bottlenecks. With the development of automatic control, the capacity of machines and workers were considered in the logistic performance analysis about the WIP levels, throughput times, delivery reliability and capacities utilization in [148]. In [149], a Basestoch Kanban CONWIP control policy was proposed to minimize the inventory and backlog of a multi-production system. Wiendahl and Breithaupt [11, 17] introduced backlog control and central WIP control in the automatic production control to eliminate the backlog and set WIP on a defined level by controlling the flexibility of work time based on a discrete funnel model. Duffie et al. adopted control theoretical methods to design the WIP, inventory, backlog, lead time and output control in the production planning and control systems [150, 151, 152, 153]. Specially, to maintain the desired fundamental dynamic behaviour and regulate the WIP levels of work systems, Duffie et al. [154] considered coordination of multiple capacity adjustment modes (including floaters, temporary workers, overtime) with constant delay. Moreover, Chehade and Duffie continuously optimized dynamic behaviour of the multiple modes capacity control system for delays and disturbances in [155]. The capacity adjustment cost of different production capacity levels (e.g., overtime, employee shift, subcontracting or equipment replacement) in a single-item lot-size system was discussed in [156].

As another vital part in the competitive performance, long-term capacity control was proposed in terms of cost, delivery speed, dependability and flexibility [157]. Regarding the cost of the capacity flexibility in workers and working time of flow shop production lines, Sillekens et al. [158] proposed a mixed integer linear programming approach considering change cost and buffers in the mid-term planning horizon. Pac et al. analysed the workforce capacity in the inventory management of a manufacturing firm under temporary labour supply uncertainty [159]. They also pointed out that contingent workers as one part of capacity flexibility have higher cost because of the varying productivity. Neubert et al. [160] specially discussed the influence of contingent workforce in the capacity adjustment of supply chain management. In [161], the authors also predicted that the workforce cost would increase in the coming future, and automatic technologies would decrease the production cost. Therefore, the machinery-oriented approach was proposed to complement labour-oriented approach.

2.3.2. Machinery-oriented Control

In contrast to the labour-oriented approaches, machinery-oriented approaches adjust capacity based on the flexibility of machinery capacity. Lödding introduced some available choices, such as changing the amount or intensity of machinery, subcontracting orders or operations, shifting maintenance measures or shifting to alternative machinery [18, Chapter 26]. In the literature, these opportunities have been considered. The capacity of machines was adjusted by controlling the production rate of machines to control the WIP or inventory levels [24, 162, 163]. In [164], the capacity of machines for multiple-part-type systems with disturbances was considered to fulfil customer demands and to reduce the WIP inventory and cycle time. In order to control the WIP level and maximize the throughput, the capacity was defined as the production rate of machines and was controlled in the face of rush orders, delays, etc. [165]. Deif and ElMaraghy [166] studied a WIP-based control multi-stage production system, which was controlled via the production rate in the dynamic capacity of these systems. They also analysed the operational complexity of the dynamic capacity associated with stochastic demands, internal stage delay and capacity scaling delay time. Considering the average backlogged orders, WIP inventories and tardy jobs, Geogiadis and Michaloudis [62] analysed the dynamic performance of a stochastic capacities arbitrary job shop system, in which machine capacity was controlled by the setup frequency. In [63], the machine capacities as the internal fluctuations were investigated in the robustness performance analysis of dynamic job shop systems. Sagawa et al. [167, 168, 169] adopted bond graphs in the modelling of dynamic manufacturing systems, and included the processing frequency of machines as the variable in the capacity control of production systems.

With the development of automation and intelligence technology, machinery-oriented methods reveal new flexibility regarding machines to compensate for this issue. As we introduced in Section 2.2, machine tools are generally divided into three types: DMTs, FMTs and RMTs. DMTs are custom-designed for specific operation requirements with high productivity and low cost [109]. However, these machines are not cost-effectively converted to adjust manufacturing capacity. FMTs exhibit flexible functionality for producing a high number of variants with low volume and high cost [2]. RMTs are permanently, quickly adaptable to new manufacturing processes, and designed for a specific, customized range of operation requirements and may be cost-effectively converted when the demands change [19]. Therefore, FMTs and RMTs have the ability to adjust the capacity because of high or customized flexibility. In capacity control based on FMTs, most research focused on the FMSs, where the capacity was controlled by changing the processing time of operations [81, 170, 171, 172]. Also, the production rate of operations in FMTs was controlled to deal with dynamic problems [173, 174, 175]. Regarding capacity control based on RMTs, the approaches focused on RMSs [139, 176, 177], which are still on the prototyping stage. The potential of such applications was developed for the capacity control of job shop systems based on harmonization of throughput-time to plan the delivery dates and analyse the inventory range of each workstation considering reconfiguration delay in [31]. At present, the capacity control by using RMTs still need to be developed. There are other approaches based on the control theoretical algorithms, which are not only applicable for labour-oriented approaches, but also for machinery-oriented approaches [98, 152, 153, 154, 155, 6, 178, 179]. These papers indicated the importance of control theory on the capacity control of manufacturing systems.

In summary, we obtained that both labour-oriented and machinery-oriented approaches were effectively applied to deal with difficult problems, such as volatile customer demands and bottlenecks. From Industry 4.0, Smart Manufacturing or Internet of Things, we obtain that advanced technologies (e.g., machine tools) tend to play more important roles in the coming manufacturing industry. However, there are still limitations on the application of machine tools, especially RMTs, to incorporate them in control algorithms in the capacity control of manufacturing systems.

2.4. CONTROL STRATEGIES

From the above introduction, we obtain that control theory plays an important role in the capacity control of manufacturing systems, which are dynamical nonlinear systems with various delays, disturbances, couplings or constraints. The overview of earlier research concerning control theory concepts in production control was discussed in [28], where most approaches were classical PID which still plays an important role in today's manufacturing systems. The scholar also pointed out the potential of other control approaches. For instance, Karimi et al. [179] applied the H_∞ control method to maintain WIP level of job shop systems. Shabaka and ElMaraghy [140] optimized the process plan of RMS by using Genetic Algorithm. Mehrabi and Kannatey-Asibu [180] designed a multi-sensor monitoring of RMS in mapping theory. In this section, as the classical PID control method has been applied in the production process control, especially capacity control, the related literature will be reviewed. Another control method is RRCF. It is an advanced control method and has been used to deal with delays, disturbances, coupling and constraints on various complex problems. Therefore, the related research of this method is also discussed in this section.

2.4.1. PID

The PID control is a simple and easily applicable method, and takes an important place in practical applications and academic research. Since the concept was proposed, this method has been widely used in various areas, especially production industry. A PID controller comprises three control terms: proportional, integral and derivative for the present, past and future of the process variables, respectively. In general control systems, there are feedback, feedforward or both control structure [84]. In the PID control system, most cases are feedback control, and the controller is able to calculate and minimize the error between the desired set point and the measured process variable over time. As the problems differ, the design of control systems also differ. For instance, in recent research, the design of PID controller was studied to consider different disturbances, delays or constraints [181, 182, 183, 184, 185]. The performances of the control systems including the dynamic, stability and robustness were analysed in [186, 187, 188, 189]. In [187], the authors discussed the dynamic model of a Quadrotor in PID control and analysed the dynamic and robust response of the system. To assess the tracking performance of PID control systems, Yu et al. [188] studied the closed-loop response and established the lower bounds of integrated absolute errors under changing setpoints in step, ramp and other general types. Taking into account the delays, load disturbances, setpoint response, model uncertainty and measurement noise, Garpinger et al. proposed the criterion, trade-off and a software tool for the PID design, and analysed the robust and tracking performance of the control system in [189]. The setting of the PID controller parameters has great influence on the performance of the control systems. Therefore, research on tuning of the PID controller has attracted much attention. He et al. [190] present a fuzzy self-tuning method by using classical and refined Ziegler-Nichols formula. To meet user-specified gain margin and phase margin, Ho et al. [27] introduced a simple formula to tune the PI and PID controllers. For unstable first-order time-delayed systems, Park et al. [191] proposed an enhanced PID auto-tuning method. Self-Tuning PID controllers design by using genetic algorithms were proposed to deal with unknown or time-varying parameters in [192]. Considering robustness, Tan, Ferdous and Huang [193] put forward a closed-loop automatic tuning of PID control systems with a high feedback gain, which induced a control chattering phenomenon. In order to damp power system oscillations, Tavakoli and Seifi proposed an adaptive self-tuning PID fuzzy sliding mode controller with a PID switching surface in [194]. These methods could work well for simple linear systems. More tuning methods were summarized in [195, 196].

Though the PID control method is simple and widely applicable, it is difficult to guarantee a good performance. Therefore, some improved PID control methods have been proposed for special purposes. For a flexible-joint robot arm with uncertainties driven by a dc motor, Malki et al. [197] introduced a fuzzy PID controller with self-tuning capabilities. A variable structure PID control method was presented prevention of windup in the continuous and discrete-time implementations in [198]. With the purpose to improve the robustness of PID control, Skoczowski et al. [199] proposed a two-loop model following control system comprising a nominal model of the controlled plant and two PID controllers. To stabilize a fractional-order system with time delay, Hamamci put forward a fractional order PID controller [183], which has received increasing interest in recent years, more results were summarized in [200]. In a boiler drum level system, Surendran and Kumar [201] considered a neural network to estimate the ultimate gain and optimum proportional and integral value of PI controller within affordable time limits and safe input range. An improved particle swarm optimization was discussed for the gains of a PID control process of bar rolling in [202]. In [203], Li and Xu incorporated an improved sliding model control and a PID control in the motion tracking control of a micromanipulator system with piezoelectric actuation. In conclusion, we obtained that incorporating optimization algorithms, such as fuzzy algorithm [204], neural network [184, 205], particle swarm optimization [206, 207] and sliding mode approach [203, 208], into the PID controller design could improve the performance of the relative control systems, but also increase the complexity of the controllers. With more software tools developed, such as Matlab toolbox [209, 210], it provides an opportunity to simplify these approaches.

As to the control of production systems, the PID control method still plays a vital role. From the previous sections, we see that this method has made a big contribution on the production planning and control. Ortega and Lin summarized the research of control theory, especially the PID control method, in the applications of production systems to reduce inventory variation and demand amplification, as well as optimize ordering rules [211]. They also discussed the control theory tools, such as block diagram algebra, Mason's gain formula, Bode plots, Laplace transform, Z-transform and optimal control, for the design and analysis of control systems. Pritschow and Wiendahl [5] discussed the dynamic behaviour of a WIP control system, where the capacity is the controller output by using a P controller for a closed-loop production logistics system with fixed delay and disturbances. Then Wiendahl et al. [11, 17, 30] continued the research and adapted the control theory in the automatic production control concept, where the backlog and WIP were controlled through capacity adjustment. Duffie et al. extended the research and more specifically analysed the setting of the PID (PI, P, PD) control parameters on the performance influence on the capacity control of single workstation systems and coupled multi-workstation systems with delays and disturbances [98, 100, 150, 151, 152, 153, 154, 6, 178, 212]. Duffie et al. [100] also reviewed the recent research on the classical control theoretical modelling of the transient behaviour and fundamental dynamics of production planning and control systems. They also proved the potential applications of control theory in analysing many aspects of production systems, and confirmed the significant contributions of control theory to understand the dynamics of these systems [100]. These reviews illustrated the applicability of PID (including PI, P, I, PD etc.) in the capacity control of production systems.

2.4.2. RRCF

Different from the PID control method, operator-based robust right coprime factorization (RRCF) is a relatively novel control method, which is developed from a mathematical theory [29]. One advantage of the theory is that it doesn't depend on the precise model and it is accessible to ensure the stability of the nonlinear systems by using the Bezout identity. Especially, robust stability against perturbations can be guaranteed under an inequality condition [213]. In this method, the plant is factorized into two operators, and then the compensation operators are designed based on respective lemmas, such as Bezout identity [214]. As to the factorization of plants, there are various approaches. In the earlier research, most scholars focused on the theoretical analysis and the investigation of the existence of the factorization. For example, based on five assumptions, Desoer and Kabuli [215] discussed the right factorization and right coprime factorization of a class of nonlinear continuous time-varying plants with a uniformly completely controllable linear part in state space description. Sontag showed that the right coprime factorization exists for the input-to-state mapping of a continuous-time nonlinear system, and proved the smooth feedback stabilization problem of this system was solvable in [216]. Glover and McFarlane [217] and Walker [218] studied the perturbed linear systems' normalized coprime factorization and analysed the robust stabilization of the control systems. Banos [219, 220] studied the right coprime factorization of a class linearisable systems and analysed the stability based on a generalized Bezout identity. Verma and Hunt [221] proved that the existence of a stabilizing state feedback implied the existence of a right coprime factorization for the input-output map for affine linear systems and feedback linearizable nonlinear systems. Han and Rao [222] presented sufficient and necessary conditions for the existence of right coprime factorization, and they discussed controller design for finite-gain stabilization of nonlinear systems. Deng et al. [223] discussed the tracking condition for a class of perturbed nonlinear systems by using RRCF approach.

With the theoretical analysis, the design of the right coprime factorization also attracted increasing attention. Miyamoto and Vinnicombe [224] proposed a synthesis method to exploit the freedom to choose a coprime factorization of controllers for saturation nonlinear plants. For open-loop unstable systems, Loh and Chiu [225] proposed some formulations and criteria on the stable factorization approach for the design of robust decentralized controller. Chen and Han [226] introduced the concept of robust right coprime factorization of nonlinear feedback control systems and derived some general conditions for the robustness of the system for unknown bounded perturbations. They also present a new framework for the robust stabilization design of general linear and nonlinear systems. Deng et al. [227] discussed a design problem of a model output following control system based on almost strictly positive real characteristics and the command generator tracker theorem for linear plants with time delays. In [228], Zhou and Ren proposed a feedback controller architecture including a performance analysis without uncertainties and a robustness analysis for uncertainties or external disturbances. Deng et al. [213, 229] proposed an inequality condition for the RRCF design of a class of nonlinear plants with unknown bounded perturbations, and analysed robust stabilization and tracking performance of the control systems. Bu et al. [230] adapted the isomorphism approach and passivity property into the RRCF design of nonlinear systems. The robust control design, robust stability and tracking performance of nonlinear plants with perturbation was studied in [231, 232]. Bi et al. [233] extended the research to the operator based robust nonlinear control system design and tracking design for a class of multi-input multi-output (MIMO) systems, and proposed a sufficient condition for the robust stabilization of the MIMO systems. They also studied the robust decoupling control design of MIMO systems by using the definition of a Lipschitz operator and the contraction mapping theorem [234, 235]. Robust stabilization and output tracking control of nonlinear uncertain systems with unknown time-varying delays were considered by using the RRCF approach and delay compensating operator [236, 237]. Wang et al. [238] concentrated on robust nonlinear multi-variable tracking control and perfect tracking control design of disturbed MIMO systems with uncertainties to improve the trajectory of the systems. Wen et al. [239] adopted the particle swarm optimization algorithm in the optimal tracking control design for nonlinear affine systems with unknown bounded disturbances based on the particle swarm optimization algorithm. Tao et al. [240] developed a different unimodular operator to establish a sufficient condition for stability of disturbed nonlinear feedback systems without calculating the inverse of the operator, which extends the applicability of the RRCF approaches.

With the development of the RRCF design approaches, this method also has been utilized to deal with various complex problems. Coprime factorization of an unknown plant was adapted in a frequency-response identification technique to setup an iterative scheme to achieve a high-performance control in [241]. Franco et al. [242] introduced normalized right coprime factorization for the design of a robust linear H_∞ controller for a nonlinear system with model uncertainties by transforming the nonlinear system to a linear system. A fault detection design technique based on the RRCF approach was investigated in [213, 228, 243]. Deng et al. considered the input constraints in the stable robust feedback control system design and the fault detection in the nonlinear systems in [244]. Han et al. [245] deeply discussed the input constraints in the robust control system design of a direct current governor system by using RRCF approach. Wen et al. applied the RRCF approach in the distributed control system of a multi-tank process in [246, 247]. At the same time, they also extended the applicability of the approach to complex practical planar gantry crane system control [248, 249] and thermal control with peltier devices [250, 251]. Moreover, this approach has been utilized in the networked nonlinear controller design of a water level process with time-varying delays and input disturbance in [252]. In [253], the authors combined the passivity and RRCF approach in an adaptive nonlinear sensorless control of an uncertain miniature pneumatic curling rubber actuator. Gao et al. [254] indicated the ability of RRCF approach in robust control of the wireless power transfer system. The sensitivity analysis of the operator-based nonlinear control system with disturbances was studied in [255]. They also proposed the insensitivity conditions of the design RRCF control systems.

From this overview, we obtain that RRCF is an effective approach to control and analyse the dynamic and stability performances of a class of nonlinear systems with delays, disturbances, constraints and couplings. Especially the realization of the multi-tank process control including the water-level process control and water-flow process control [247] is of interest as it corresponds to the WIP level control and capacity control of production systems with a funnel model [11, 17]. Though the model and theory differ, the ideas are similar. This implies the possibility of the method to be applied in production control, including capacity control of complex job shop systems. In this dissertation, we will utilize this approach to design controllers for the capacity adjustment of job shop systems with RMTs, and analyse the dynamic and stability performance of the system with delays, disturbances, couplings and constraints.

2.5. SUMMARY

In this chapter, we surveyed the current research related to the capacity control of manufacturing systems. Considering the research challenges on flexibility and productivity of manufacturing systems, we analysed the properties of two typical manufacturing systems — flow shop and job shop, and three types of machine tools including DMT, RMT and FMT. Then we defined the research gap on the capacity control of job shop systems with DMTs for productivity and RMTs for flexibility. Later on, the capacity control approaches including labour-oriented and machinery-oriented ones, were reviewed for the possibilities of developing a new application degree of RMTs. To this end, the control methods comprising the classical PID and novel RRCF were surveyed considering designing and analysis tools. As PID has been widely applied in the capacity control, this method will be considered as a benchmark for the RRCF method in the machinery-oriented capacity control approach.

3 Research Question and Methodology

In order to propose an effective capacity control method for the manufacturers to deal with the internal and external challenges, we reviewed the related literature in Chapter 2 considering the flexibility and productivity in types of manufacturing systems and machine tools. Additionally, current research on the capacity control approaches and related control strategies were also reviewed, and several research gaps were proposed on the capacity control of manufacturing systems. Based on the gaps, the main research question and methodology are proposed in this chapter.

3.1. Research Question

From the above discussion, we obtained that capacity control is an effective approach to deal with volatile customer demands and bottlenecks in the manufacturing process in short or medium terms [11]. As illustrated in Section 2.1, job shop manufacturing systems are designed with flexible producing paths for a variety of products, which makes this type of system more popular than the flow shop systems. Because of fixed routing and shared scheduling and control approaches, a flow shop system could be seen as a special simple job shop system. Thus we concentrate the research on job shop systems. Furthermore, job shop control is one importation issue on the operational layer to support upper layers on scheduling and planning. Here, the complex producing paths and high flexibility also induce high work-in-process (WIP) levels, high cost and low productivity in the job shop system [58, 62, 63]. With regards to these problems, numerous approaches were proposed for various quantitative performance indicators, such as minimizing cost or makespan [54, 83]. Especially, various internal and external disturbances increase the importance of several qualitative performance indicators, such as robustness and stability [91]. With the development of various advanced technologies on the field instrument layer, such as radio-frequency identification (RFID) and wireless network, monitoring system of manufacturing process are now more advanced, accurate and reliable [99]. This also brought up a challenge in the process control on the operational layer to develop more advanced control strategies, especially capacity control strategies, for crucial performance indicators.

In order to detect the possibility of machine tools in the machinery-oriented capacity control approach, properties of three types of machine tools, including dedicated machine tool (DMT), flexible machine tool (FMT) and reconfigurable machine tool (RMT), were discussed in Section 2.2. Considering the cost-effectively customized flexibility of RMT, the gap on developing the potential of RMTs in the capacity adjustment was discussed. Due to a high percentage of parallel machines, job shop manufacturing is of particular interest for the use of RMTs in the capacity adjustment. Because of the high productivity, DMTs are also considered to improve the productivity of job shop systems. The review of capacity control approaches illustrated the importance of control theory in the manufacturing process control. The classical proportional-integral-derivative (PID) control method, due to its simplicity and easy applicability, plays an important role in manufacturing control [6, 178]. However, this approach may perform poorly in some applications, such as nonlinearities. Therefore, some control approaches have been investigated in the literature, but more advanced control approaches are still required to be developed for various complex manufacturing problems. From Section 2.4.2, we obtained that operator-based robust right coprime factorization (RRCF) [29] is one opportunity, which has been developed and successfully adopted to cope with, e.g., nonlinearities, disturbances, delays and couplings of complex problems, which are also embodied in the manufacturing system. This outlines the potential of this method in the capacity control of job shop systems.

As to the qualitative performance indicator, stability and robustness are two key criteria for control systems [78]. Especially, a stable job shop system can decrease overload or shortage risks and ensure service reliability. However, various external and internal disturbances, e.g., rush order, volatile customer demand and machine breakdown, may destroy stability. This requires robustness to reject these disturbances and ensure stability. Here, robustness and stability are defined following [63], which states that for a stable system the actual performance does not deviate significantly from the planned performance, and for a robust system, the performance does not significantly deteriorate in face of disruptions and fluctuations. The robustness can be measured by the mean absolute value and standard deviation of the performance indicator on a tactical and operational level [63, 94, 95]. In the design of robust control, a decentralized architecture has an advantage of responding quickly for the feedback state [80, 97, 98]. In order to improve the competitiveness of job shop manufactures facing fast-changing customer demands, we especially focus on the design of a fast and robust capacity control system for the disturbance rejection in a decentralized form. Based on the latter, we develop the main research question as:

How can a fast and robust state feedback be designed for disturbance rejection in decentralized RRCF capacity control of job shop systems using RMTs?

To answer this question, three specific questions shall be solved, which are given as follows:

- **RQ1:** How can RMTs be integrated in the modelling of a job shop system?
- **RQ2:** How may a job shop system be decoupled to allow for an integrated design of a decentralized controller?
- **RQ3:** How should a decoupled system be controlled to ensure robust stability of the overall system?

The framework including these questions is described in Figure 3.1, which also displays the work package of the RRCF control system design. **RQ1** is the basis for the design of a capacity controller. **RQ2** and **RQ3** are questions for the RRCF controller design.

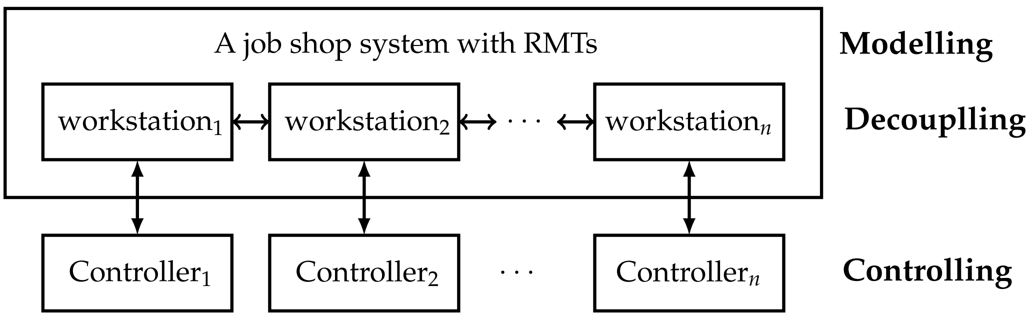

Figure 3.1.: RRCF control system framework

In terms of quantitative performance indicators, the work-in-process (WIP) level of job shop systems is the one key performance indicator, which highly influences cost, throughput and delivery reliability [98, 256]. Due to the complex material flow, WIP levels in job shop systems are typically high from an operational perspective. From an economic perspective, WIP should be low. Considering this conflict, WIP in this system is expected to be on a planned level, which is the main purpose of the control system. Additionally, a stable WIP level also can display the orders output rate satisfying the input rate, which represents customer demand. In all, for a make-to-order job shop manufacturing system, the capacity control system shall be designed to ensure the WIP levels to be robustly stabilized on predefined levels. Additionally, to verify the effectiveness of the RRCF control system, PID will be considered as the benchmark.

3.2. Research Methodology

To answer the research questions proposed in the above section, the following work packages are considered:

- Modelling and analysis of properties of RMTs as well as job shop manufacturing systems
- Applying PID method on the model, analysing the performance and simulating the results
- Implementing RRCF method to compute a controller for a basic single-input single-output (SISO) subsystem and analysing its performance
- Increasing the complexity from SISO to a multi-input multi-output (MIMO) system in RRCF method, analysing the performance and simulating the results
- Incorporating disturbances or uncertainties into the MIMO system and assessing the properties of both PID and RRCF.

Based on these work packages, we propose the respective research methodology in this section.

3.2.1. Modelling of Manufacturing Systems

In order to properly design a controller for a manufacturing system with the new component of RMTs, we first need to design a proper model resembling the properties of this system. To obtain such a model, we parametrize both input and output of the system as well as the percentage of RMTs. Additionally, we predefine the number of the reconfigurable operations as well as the required time for a reconfiguration. We specifically consider an academic basic scenario allowing for all possible dynamical changes, which is illustrated in Figure 3.2.

The model will be constructed in time-domain and consists of n workstations (e.g., 4 in Figure 3.2) with respective operations. Each workstation j will be composed of n_j^{DMT} DMTS and n_j^{RMT} RMTS. The DMTs will perform only one operation, but the RMT may be used to execute any of the n operations. The manufacturing system can produce m different products (e.g., 3 in Figure 3.2). Given the configuration status of the n^{RMT} RMTs, the dynamics of the job shop model changes can be considered as a switched or hybrid system.

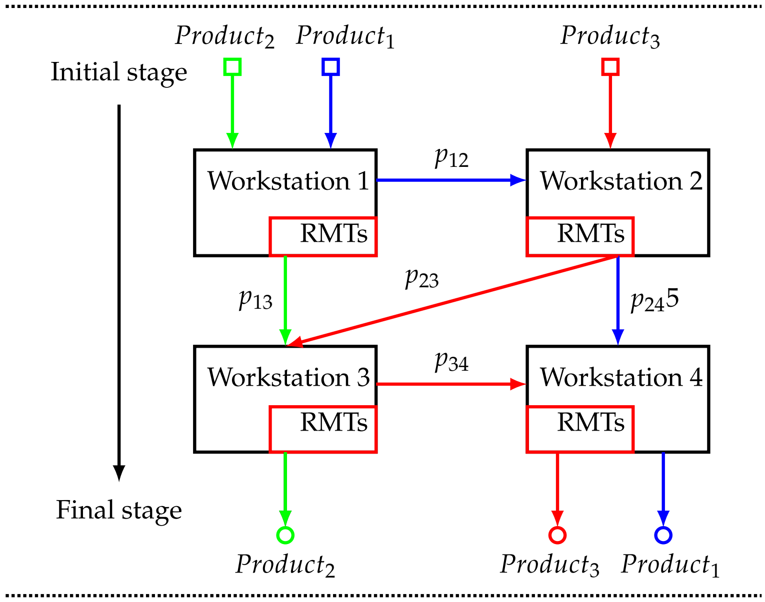

Figure 3.2.: A job shop manufacturing system with RMTs

3.2.2. PID CAPACITY CONTROL

Based on the model, we firstly implement the classical PID control approach [186] in the capacity adjustment. Each workstation j has its local PID controller j, cf. Figure 3.3. In each local control system, we first need to define the purpose of the control system and set the reference input signal r, and output signal y of the control system. Here, the planned WIP can be the reference input signal and the current WIP level is the output signal of the control system. The control purpose is to minimize the error e_j between the planned and current WIP level of each workstation. Then we can analyse the stability theoretically and compute the stable area of the control parameters. In order to guarantee the stability of the control system, the parameters of the controllers should be set by choosing a tuning method, such as the Ziegler-Nichols method [257]. Moreover, we analyse the stability of the control system in three different scenarios: (1) nominal case without delays and disturbances, (2) with disturbances and (3) with delays and disturbances. Here, we note that the disturbances, in the above cases, are presented by rush orders. Then a numerical simulation results are given to analyse the dynamic and stability of the control system in these three scenarios using Matlab.

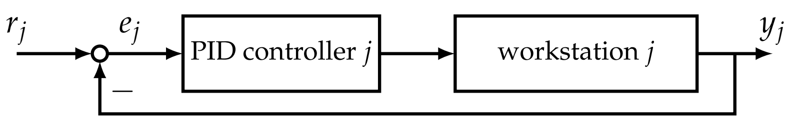

Figure 3.3.: PID control of the job shop system

3.2.3. RRCF CONTROL OF SISO SYSTEMS

In the RRCF control of the job shop systems, we will first implement this method for a simple SISO system, such as one workstation, and then increase the complexity to a MIMO system. For a SISO system, we can derive a concept for the RRCF control on a general level based on the analysis from the modelling of job shop systems with RMTs, cf. Figure 3.4. Here, we first need to ensure finite-gain input-output stability of each workstation, i.e. each workstation combined with a respective local controller shall be finite-gain input-output stable. Thereafter, we can develop a tracking controller to configure the operation of the RMTs to the capacity adjustment of the system depending on its current status. For simplicity, we focus on a simple SISO subsystem only. In particular, we apply RRCF to ensure finite-gain input-output stability of the system and the tracking controller to steer the output to the required set point. The values of the tracking controller parameters are identified by means of an optimization method. With regards to the latter, particle swarm optimization (PSO) is one possibility [239]. Last, stability of the control system will be analysed theoretically using the three different scenarios from Section 3.2.2.

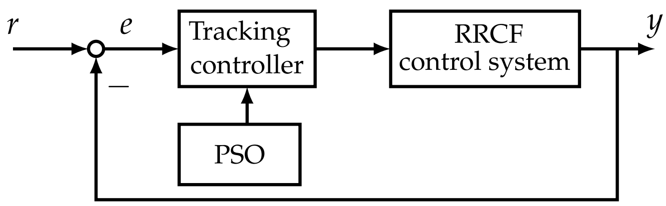

Figure 3.4.: RRCF feedback control system

3.2.4. RRCF CONTROL OF MIMO SYSTEMS

After the implementation of a simple SISO subsystem, we increase the complexity of the basic SISO system to a MIMO system. Here, we re-introduce the coupling given by the production network illustrated in Figure 3.2. While necessary to reflect reality, coupling the subsystems drastically increases the complexity of the combined system. Here, we will utilize decoupling methods to divide the complexity of MIMO system into multiple SISO systems while maintaining overall properties like stability. By these means, we obtain problems which are similar to those from Section 3.2.3, yet different to mimic the coupled behaviour. Consequently, we will analyse stability theoretically and compare the performance of the controller with PID qualitatively for the three scenarios from Section 3.2.2. Then, we will analyse the simulation results with regards to the effects of the decoupling technique, and compare with the PID control system quantitatively for these scenarios.

3.2.5. ROBUST CONTROL

PID and RRCF control of MIMO systems allow us to characterize the behaviour of the job shop model in the case without stochastic disturbances. However, disturbances from customer demands and transportation delays are natural occurring parts of manufacturing systems. Therefore, we will extend our feedback design to cope with both internal and external disturbances. The particular difficulty in this case is the switched or hybrid nature of the system dynamics, as described in Section 3.2.1. Hence, our goal is not necessarily to drive the system in the optimal state at all times. Here, we will analyse the ability of PID and RRCF to robustly stabilize the system by using a Monte-Carlo simulation. Then we derive suitable robust key performance indexes and estimates for the robustness trade-off, i.e. the additional costs raised by incorporating the robustness property into these two control strategies. Moreover, we will discuss the quantitative comparison of PID and RRCF for robust control.

3.3. SUMMARY

In this chapter, based on the research gaps through literature review in Chapter 2, we proposed the main research question as: How can a fast and robust state feedback be designed for disturbance rejection in decentralized RRCF capacity control of job shop systems using RMTs? For this question we proposed the research methodology. Firstly, we need to model the job shop system integrating RMTs, which is introduced in Chapter 4. Then we focus on the implementation of RRCF algorithm in the capacity control, theoretically stability analysis and qualitative comparison with PID control method in Chapter 5. Later on, the quantitative comparison of these two control systems on the dynamic, stability and robustness performance is discussed through numerical simulation in Chapter 6.

4 Mathematical Model

According to the proposed work packages in Chapter 3, the first work is to propose a suitable mathematical model integrating reconfigurable machine tools (RMTs), which will be concentrated on in this chapter.

4.1. Related Research Work

From Chapter 2, we obtained that there are plenty of approaches in the modelling of the manufacturing systems for various objectives, for instances, a discrete-event model for assignment of delivery date [171] and a model based on colored timed object-oriented Petri nets for the reconfiguring process [141]. These models are discrete for single events. On the other hand, a continuous model plays a vital role in the production planning control, which allows attaining the special planned objectives on the operational layer [258]. In the literature, Deif and EIMaraghy introduced a dynamic continuous time domain model for a reconfiguration manufacturing system (RMS) to improve capacity scalability in response to sudden demand changes [139]. In [30], a continuous model of a single production system was proposed based on the funnel model, which was used to control the work-in-process (WIP) and backlog through controlling the capacity and input rate. In this model, the units of the capacity and order input rate were hours per shop calendar day. For the decentralized planning and control of large production networks, Duffie and Shi [98] developed a linear discrete-time model displaying the dynamic flow of orders into, out of and between work systems based on the funnel model, in which units of production rate and order input rate were orders per shop calendar day. Nevertheless, few of them considered the machinery capacity in the model.

As discussed in Chapter 3, RMTs and dedicated machine tools (DMTs) shall be integrated into the model for the capacity adjustment, and also WIP for a planned perspective should be displayed in the dynamic capacity adjustment process, which was not considered in the literature. With control theory applied in the production planning and control, a continuous funnel model was adopted to display the dynamic behaviours of system integrating delays, disturbances for the various objectives, such as planned WIP level. The effectiveness and efficiency of the model for the control theory based capacity control were proved in the literature, see e.g., [5, 6, 11, 17, 30, 98, 100, 150, 152, 153, 154, 178]. Describing the dynamic system in a continuous time model increases the possibility for applying more advanced control algorithms [179]. Therefore, this model is considered as the basis for developing a mathematical model of a job shop manufacturing system integrating machines' capacity and dynamic process with delays and disturbances.

In the funnel model, orders input rate, output rate and WIP level can be described in Figure 4.1 [4, 5]. It shows the production process of orders at the workstations or work centers. The filling of the funnel represents the WIP level of the workstation including the orders waiting in the buffer and processing in the machines. The red line represents the planned WIP level of the workstation. Here, the input and output orders can be calculated in shop calendar days or hours, which also can be presented as the orders input or output rate. On the operational layer, in order to decrease the WIP level, we can increase the capacity or the output orders. The process can be described in a continuous time mathematical model [6], in which not the individual events are of interest, but the variables like orders input rate, output rate and WIP level. In this model, we focus on the operational layer, where the orders directly flow from an initial stage into the system, and flow out to a final stage (or customer). Here, we impose the following assumptions:

- the sequence of input orders is known, e.g., first-in first-out (FIFO),
- the finished orders are dispatched to the customers directly,
- the demand fluctuations are bounded and Gaussian distributed,
- the planned WIPs are given with high level,
- the production rates of all products are identical at same workstation,
- the percentage of RMTs in the manufacturing system is fixed,
- the reconfiguration of RMTs between each operation is less than two hours.

In the following sections, we firstly will introduce the basic funnel model. Then we will extend the model by integrating the capacity of RMTs and DMTs. To this end, the model will be further developed by including various delays and disturbances. The related variables in the model are defined in Table 4.1.

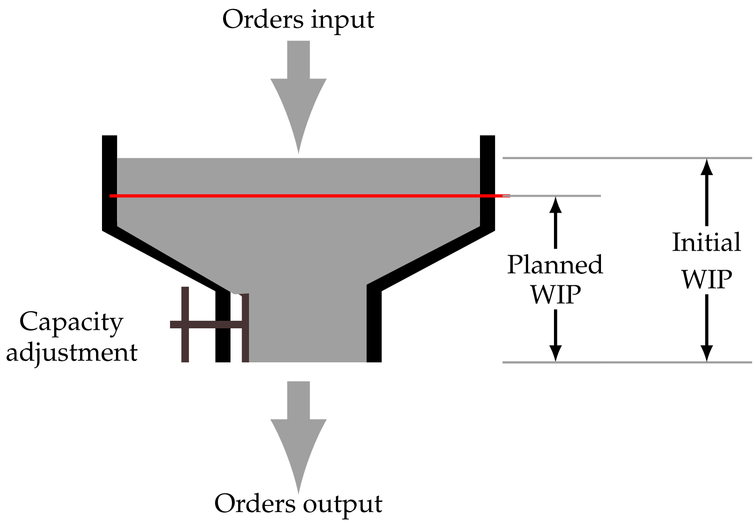

Figure 4.1.: Description process of workstation, after [4, 5]

Table 4.1.: Variables within a job shop system with RMTs

Variable	Description
$x_{kj}(t)$	Orders input rate from workstation k to j for $k, j \in \{1, \ldots, n\}$
$x_j(t)$	Orders input rate of workstation $j \in \{1, \ldots, n\}$
$x^l(t)$	Orders input rate of product $l \in \{1, \ldots, m\}$
$x(t)$	Orders input rate of the system
$w_{jk}(t)$	Orders output rate of workstation j to k for $j, k \in \{1, \ldots, n\}$
$w_j(t)$	Orders output rate of workstation $j \in \{1, \ldots, n\}$
$w^l(t)$	Orders output rate of product $l \in \{1, \ldots, m\}$
$w(t)$	Orders output rate of the system
$u_j(t)$	Number of RMTs in workstation $j \in \{1, \ldots, n\}$
$y_j(t)$	WIP level of workstation $j \in \{1, \ldots, n\}$
$c_j(t)$	Current capacity of workstation $j \in \{1, \ldots, n\}$
$\bar{c}_j(t)$	Maximum capacity of workstation $j \in \{1, \ldots, n\}$
p_{jk}	Flow probability from workstation j to k for $j, k \in \{0, \ldots, n\}$
p^l_{jk}	Flow probability of product l from workstation j to k for $j, k \in \{0, \ldots, n\}$
p_{j0}	Flow probability from workstation $j \in \{1, \ldots, n\}$ to final stage
p_{0j}	Flow probability from intial stage to workstation $j \in \{1, \ldots, n\}$
n^{RMT}	Number of RMTs in the system
n^{DMT}_j	Number of DMTs in workstation $j \in \{1, \ldots, n\}$
n^{DMT}	Number of DMTs in the system, which is equal to $\sum_{j=1}^{n} n^{DMT}_j$
v^{DMT}_j	Production rate of DMTs in workstation $j \in \{1, \ldots, n\}$
v^{RMT}_j	Production rate of RMTs in workstation $j \in \{1, \ldots, n\}$
$d_j(t)$	Disturbances in workstation $j \in \{1, \ldots, n\}$
τ_1	Reconfiguration delay
τ_2	Transportation delay

4.2. BASIC MATHEMATICAL MODEL

For the purpose of gaining insight into the fundamental dynamics of the system and the effects of various choices of controllers, the following basic funnel model can be used [6, 152]. For a job shop system with n workstations and m types of products, the simplified model of the jth ($j = 1, 2, \ldots, n$) workstation is illustrated in Figure 4.2, cf. [6]. The input rate of the workstation is the sum of output rates from all workstations, including the workstation itself and a possible initial stage, to workstation j. The output rate of the workstation is given by the current capacity.

Figure 4.2.: Simplified model of workstation without RMTs [6]

The workstation receives orders from an initial stage ($k = 0$) and workstations $k \in \{1, 2 \ldots, n\}$, and delivers its products (or parts of product) to a final stage ($i = 0$) and workstations $i \in \{1, 2, \ldots, n\}$. Thus, for the jth workstation, the output is the current capacity, which is also the orders output rate

$$w_j(t) = \sum_{i=0}^{n} w_{ji}(t) = \sum_{i=0}^{n} p_{ji} \cdot w_j(t),$$

where $\sum_{i=0}^{n} p_{ji} = 1$ for all $j \in \{1, \ldots, n\}$, and $p_{ji} = \sum_{l=1}^{m} p_{ji}^{l}$ for all $l \in \{1, \ldots, m\}$. The orders input rate of the jth workstation is

$$x_j(t) = \sum_{k=0}^{n} x_{kj}(t) = x_{0j}(t) + \sum_{k=1}^{n} w_{kj}(t),$$

where x_{0j} is the orders input rate from the initial stage to workstation j. The current WIP of jth workstation is the integral difference between the orders input and output rate plus disturbances (such as rush order) over time

$$y_j(t) = y_j(0) + \int_0^t (x_j(\tau) - w_j(\tau))d\tau. \tag{4.1}$$

The latter variable is of particular importance as for a high level of WIP (4.1), we have that the orders output rate is equal to the capacity of the workstation, that is

$$w_j(t) = c_j(t) = \sum_{i=0}^{n} p_{ji} c_j(t).$$

The orders input and output rate of the system are the sums of all workstations input rate received from initial stage and of the output rate delivered to the final stage, respectively, i.e.

$$x(t) = \sum_{j=1}^{n} x_{0j}(t) \qquad \text{and} \qquad w(t) = \sum_{j=1}^{n} w_{j0}(t).$$

On the other hand, they also can be the sums of all products input rate from initial stage and of the output rate delivered to the final stage, respectively, i.e.

$$x(t) = \sum_{l=1}^{m} x^l(t) = \sum_{l=1}^{m} \sum_{j=1}^{n} x_{0j} p_{0j}^l(t) \qquad \text{and} \qquad w(t) = \sum_{l=1}^{m} w^l(t) = \sum_{l=1}^{m} \sum_{j=1}^{n} w_{j0} p_{j0}^l(t).$$

4.3. MATHEMATICAL MODEL INTEGRATING RMTS

The presented basic model clearly describes a job shop system with n workstation and m products, but does not reflect the functionality of RMTs for capacity adjustment. Thus, as illustrated in Figure 4.3, we propose an extended model of a job shop system with DMTs and RMTs, cf. Figure 4.4 for a sketch of workstation j with an assigned number of RMTs. Due to the high productivity of DMTs, this kind of machines will also be adopted in the system. The overall system includes n^{RMT} RMTs and n^{DMT} DMTs. We suppose that all RMTs can be used within all workstations, but only perform one operation at a specific period. Moreover, each DMT can only process one operation and is assigned to a specific workstation. Hence, each workstation consists of a fixed number of DMTs and a variable number of RMTs.

As we assumed that the production rates of all products are identical at the same workstation, then the maximal capacity of a workstation is given by

$$\bar{c}_j(t) = n_j^{DMT} \cdot v_j^{DMT} + n_j^{RMT} \cdot v_j^{RMT}.$$

Now, we consider the number of RMTs in each workstation to be our new degree of freedom. If we change the association of an RMT to a workstation over time via $u_j(t)$, this renders the maximal capacity to be time variant. Assuming a high WIP level (4.1), each workstation is operating at its maximal capacity and its output rate

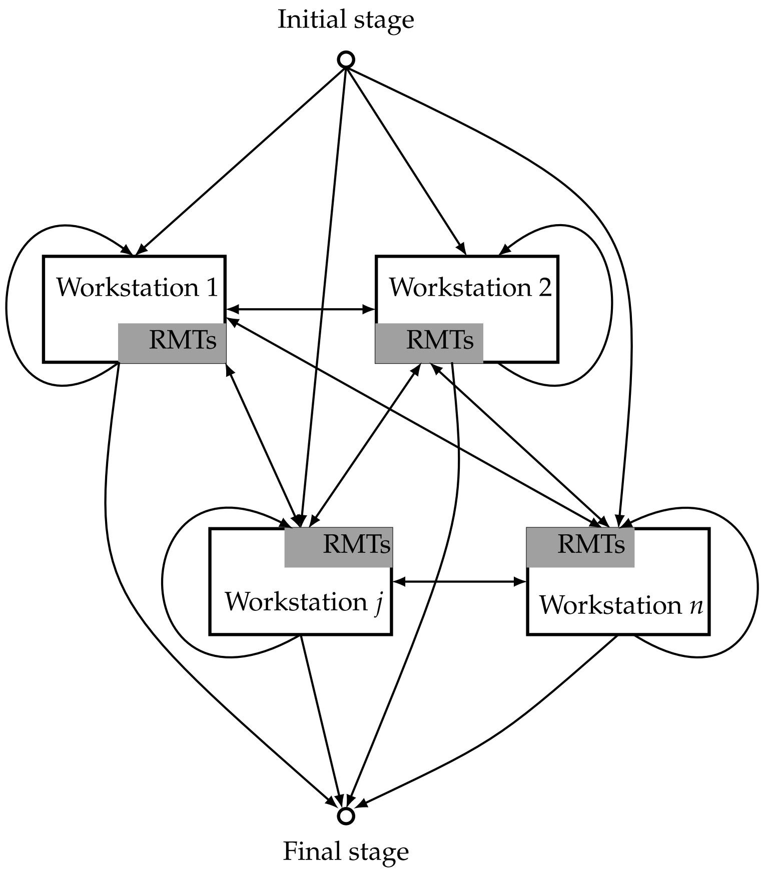

Figure 4.3.: Job shop manufacturing systems with RMTs

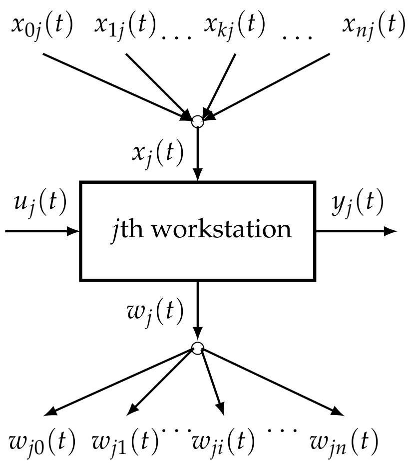

Figure 4.4.: Model of *j*th workstation with RMTs

is given by

$$w_j(t) = n_j^{DMT} \cdot v_j^{DMT} + u_j(t) \cdot v_j^{RMT}. \tag{4.2}$$

Then the WIP of the each workstation is described as

$$\begin{aligned} y_j(t) =& y_j(0) + \int x_{0j}(t) + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(t) \cdot v_k^{RMT}) \\ &- (n_j^{DMT} \cdot v_j^{DMT} + u_j(t) \cdot v_j^{RMT}) dt. \end{aligned} \tag{4.3}$$

This allows us to control the WIP level and the orders output rate via the function $u_j(\cdot)$ for all workstations. Additionally, we assume the number of RMTs in the system to be limited by n^{RMT}, and each workstation contains at least 0 RMTs. This reveals the control constraints

$$u_j(t) \in \mathbb{N}_0 \qquad \text{and} \qquad \sum_{j=1}^{n} u_j(t) \leqslant n^{RMT}. \tag{4.4}$$

Note that similar to n_j^{DMT} but in contrast to the input and output values $x_j(\cdot)$ and $w_j(\cdot)$, our control $u_j(\cdot)$ is integer instead of continuous. Although it is not the primary concern in this model, we include the case of WIP being lower than the full capacity of a workstation by including a logistic operating function similar to [152, 6]. In this case, the WIP level of the workstation is proportional to the output rate, and the arriving orders are processed directly after input [18, Chapter 3].

4.4. Mathematical Model with Delays and Disturbances

In a practical job shop system, delays and disturbances always exist and have a great influence on the dynamic performance. As shown in Figure 4.5, there are delays (τ_1 and τ_2) and disturbances (d_j). τ_1 is the reconfiguration delay, which exits when RMTs change the operation from one to another. We assume the reconfiguration time among all operations is less than two hours and dedicated to δ. τ_2 is the transportation delay, which exits when the products are transferred between workstations. According to the layout, the transportation time between workstations maybe varying, so we assume it is around 1 hour, which can be the internal uncertainty of the system. d_j is the disturbance of the jth workstation, such as rush order. Additionally, as customer demand is volatile, then we assume the orders input rate of each product from the initial stage $x_0^l(t)$ is bounded and follows a Gaussian distribution. When the orders flow from the initial stage to other workstations, there also exists a transportation delay. The volatile input rate of each product is considered as external uncertainty of the system.

Thereafter, we obtain the extended mathematical model including delays and dis-

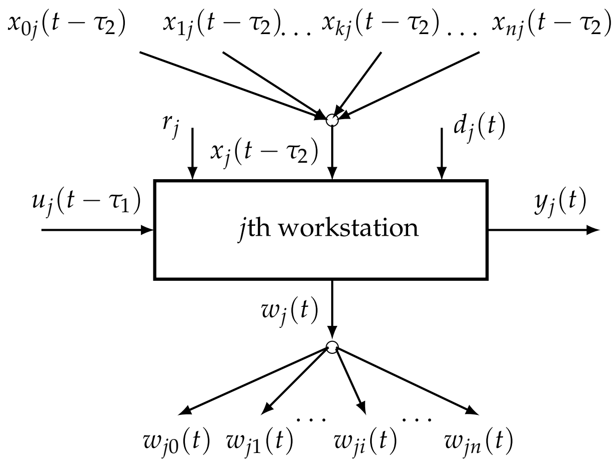

Figure 4.5.: Model of jth workstation with delays and disturbances

turbances for job shop systems with RMTs via

$$\dot{y}_j(t) = x_{0j}(t-\tau_2) + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(t-\tau_2-\tau_1) \cdot v_k^{RMT}) \\ + d_j(t) - (n_j^{DMT} \cdot v_j^{DMT} + u_j(t-\tau_1) \cdot v_j^{RMT}). \tag{4.5}$$

In particular, we note that if an RMT is reconfigured from workstation j to workstation k, the capacity of workstation k increases only after a lag δ (e.g., 2 hours) while the capacity of workstation j decreases immediately. This reveals the description

$$\tau_1 = \begin{cases} \delta & u_j(t^+) \geq u_j(t^-), \\ 0 & \text{else}, \end{cases} \tag{4.6}$$

where δ is a constant. Here, we give an example of one workstation system in four cases to explain the reconfiguration delay in the discrete input signal u_j, cf. Figure 4.6. In the example, the sample time dt is 1 hour and the reconfiguration delay δ is 2 hours. The blue and red lines present the given number of RMTs from the controller and the real number of RMTs at the workstation, respectively. The initial value of RMTs of the workstation is assumed to be same to the given value of the controller. According to the current state of the workstation, the controller calculates the number of RMTs to be assigned to the workstation. Then the workstation may show various reactions according to the input signal, which can comprise four cases: (1) repeated assigning, (2) repeated de-assigning, (3) firstly de-assigning and assigning and (4) firstly assigning and then de-assigning:

- **Case (1):** In this case, one RMT was initially working at the workstation. Then,

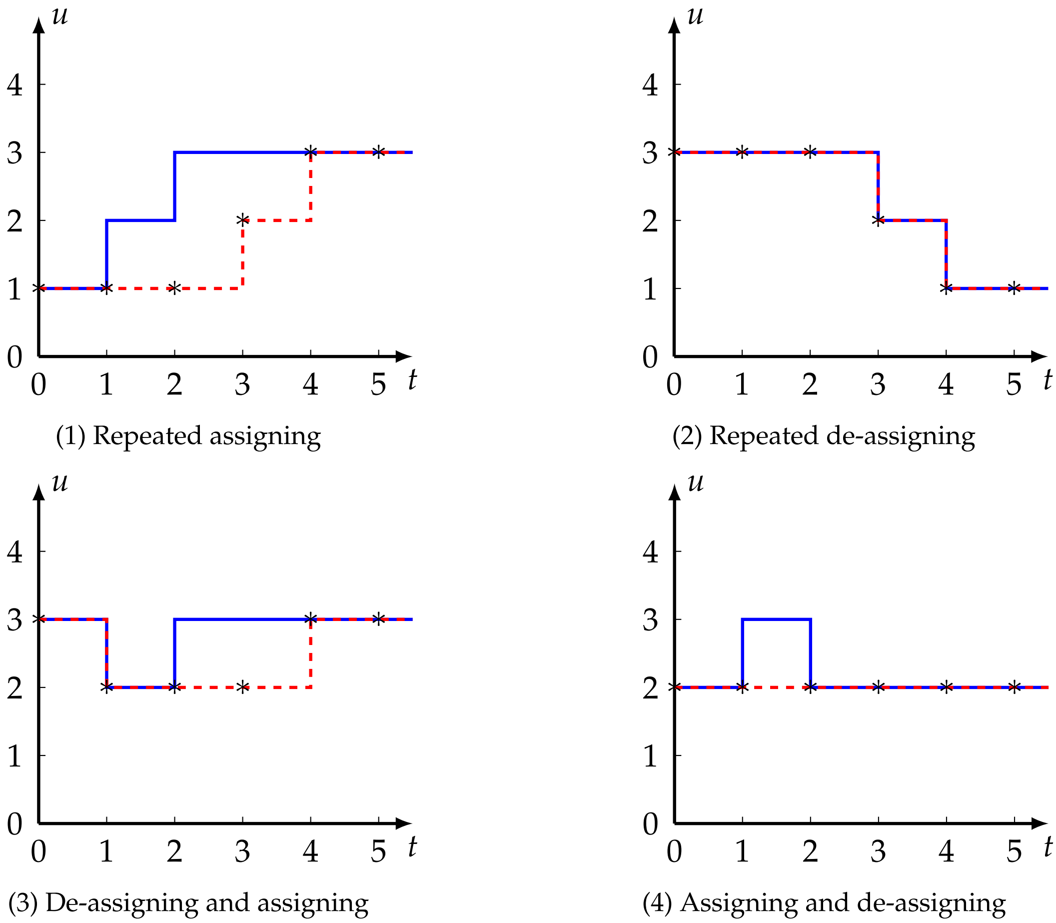

Figure 4.6.: Examples of reconfigurable delay

the controller repeatedly assigned RMT to the workstation one by one at the 1st and 2nd hour, and also additional one RMT was triggered to configure its function to this workstation at these two moments. The triggered RMT finished the reconfiguration after 2 hours. In this case, only the first situation, cf. $u_j(t^+) \geq u_j(t^-)$ in (4.6), exists.

- **Case (2):** In this case, three RMTs were initially working at the workstation. At the 3rd and 4th hour, the given number of RMTs from the controller was decreased from 3 to 2 and then to 1. The real number of RMTs at the workstation was also decreased immediately in correspondence with the controller. In this case, there is no delay, which is the second situation in (4.6).

- **Case (3):** Different from the previous two cases, this case includes two situations in (4.6) starting with the second situation. With the initial setting of 3 RMTs, the given value of RMTs from the controller was decreased to 2 at the 1st hour and then was increased to 3 again at the 2nd hour. While the number of RMTs at the workstation was also decreased to 2 at the 1st hour, and additional RMT was triggered to start the reconfiguration at the 2nd hour. It took 2 hours for the reconfiguration.

- **Case (4):** This case also includes two situations in (4.6) but starting with the first situation. In this case, the initial setting of RMTs was 2. At the 1st hour, the given value of RMTs from the controller was increased to 3, and additional RMT was triggered starting the reconfiguration. Whereas, in the next hour, the given value was decreased to 2 again. At this moment, the reconfiguring RMT, which was triggered at the 1st hour, was stopped the reconfiguration. Therefore, there were 2 not 3 RMTs at the 3rd hour.

The above is the developed mathematical model for the capacity control of job shop systems integrating the machine tools, disturbances and delays. In the control of the system, we note that similar to n_j^{DMT} but in contrast to the input and output rate values, the control $u_j(\cdot)$ needs to be chosen from the integer set $\mathbb{N}_0$. In proportional integral derivative (PID) and operator-based robust right coprime factorization (RRCF) control methods, the truncation $\lfloor \cdot \rfloor$ is utilized to deal with this restriction. Moreover, only a predefined number of RMTs is available to be assigned to workstations, which reveals the constraint $\sum_{j=1}^{n} u_j(\cdot) \leq n^{RMT}$. To deal with this constraint, we can apply the fractional approach from [259] given by

$$\hat{u}_j(\cdot) = \begin{cases} \lfloor u_j(\cdot) \rfloor, & \text{if } \sum\limits_{j=1}^{n} u_j(\cdot) \leq n^{RMT} \\ \left\lfloor \dfrac{n^{RMT}}{\sum\limits_{k=1}^{n} u_k(\cdot)} u_j(\cdot) \right\rfloor, & \text{else.} \end{cases} \tag{4.7}$$

4.5. SUMMARY

In this chapter, we mainly developed a mathematical model for the capacity control of a job shop system by integrating RMTs, delays and disturbances. Firstly, we reviewed the related literature on the modelling of manufacturing systems and specially pointed out a funnel model from the literature as the basic model of the job shop system. Then we discussed the basic continuous time domain funnel model of a n-workstation m-product job shop system. Considering job shop systems with high WIP levels, we then extended the model by integrating RMTs and DMTs, where the capacity of each workstation can be adjusted through the number of RMTs. Also, the WIP level of each workstation can be controlled by adjusting the number of RMTs for a planned level. Later on, the model was further extended by including various disturbances and delays. We considered rush orders and stochastic input orders from customer as the disturbances. Two typical delays, including reconfiguration delays of RMTs and transportation delays between each workstation, were integrated into the model. In terms of the reconfiguration delay, we discussed an example in 4 cases. Based on this model, the capacity can be controlled by the number of RMTs (input signal) to ensure the WIP of each workstation (output signal) on a planned level (reference signal). In the following chapter, the design of the controllers as well as their theoretical analysis and qualitative comparison will be introduced.

5 Capacity Control Systems

Based on the developed mathematical model in Chapter 4, the implementation of the operator-based robust right coprime factorization (RRCF) control method in the capacity adjustment of job shop systems is conducted. According to the proposed research methodology in Section 3.2, the classical proportional-integral-derivative (PID) control method is considered as benchmark, so the implementation of this method is also considered. In the control system, the number of reconfigurable machine tools (RMTs) is controlled to adjust the capacity and further to control the work-in-process (WIP) of each workstation on a planned level. A decentralized control architecture is used, where each workstation has its own local controller. In this chapter, the stability of the PID control system is theoretically analysed in Section 5.1. Then the RRCF controller is designed and stability of the control system is also theoretically analysed in Section 5.2. A qualitative comparison of these two control methods is provided considering the structure and parametrization of controllers in Section 5.3.

5.1. Capacity Control by Using PID

PID is a simple and easily applicable method and has been adopted in the manufacturing process control [6, 178]. As a benchmark for the RRCF control method, the stability of the control system is theoretically analysed in the frequency-domain because of various useful techniques and tools being available for this formulation. The Routh-Hurwitz and Nyquist criterion are two useful tools for the controller design and for assessing stability of the system. Here, the preliminaries are introduced and then the stability is analysed regarding the following three scenarios:

Scenario 1: without delays and disturbances

$$\begin{aligned} y_j(t) =& y_j(0) + \int x_{0j} + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(t) \cdot v_k^{RMT}) \\ &- (n_j^{DMT} \cdot v_j^{DMT} + u_j(t) \cdot v_j^{RMT}) dt, \end{aligned} \tag{5.1}$$

Scenario 2: only with disturbances

$$\begin{aligned} y_j(t) =& y_j(0) + \int x_{0j}(t) + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(t) \cdot v_k^{RMT}) + d_j(t) \\ &- (n_j^{DMT} \cdot v_j^{DMT} + u_j(t) \cdot v_j^{RMT}) dt, \end{aligned} \tag{5.2}$$

Scenario 3: with delays and disturbances

$$\begin{aligned} y_j(t) =& y_j(0) + \int x_{0j}(t-\tau_2) + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(t-\tau_2-\tau_1) \cdot v_k^{RMT}) \\ &+ d_j(t) - (n_j^{DMT} \cdot v_j^{DMT} + u_j(t-\tau_1) \cdot v_j^{RMT}) dt. \end{aligned} \tag{5.3}$$

The definition of the variables was given in Table 4.1. In the first two scenarios, the Routh-Hurwitz criterion is used to analyse the stability. The Nyquist criterion is applied for the time-delayed and disturbed system in Scenario 3.

5.1.1. PRELIMINARIES

In this section, we consider a general linear time-invariant (LTI) scalar system in time-domain form

$$\dot{x}(t) = Ax(t) + B^T u(t), \qquad y(t) = C^T x(t) + Du(t), \tag{5.4}$$

where $u(t)$ is the input vector, $x(t)$ is the state vector and $y(t)$ is the output vector. $u(t), x(t)$ and $y(t) \in \mathbb{R}$. A, B^T, C^T and D are the matrix of the system. To show the stability of such a system, the definition of it is given as follows:

Definition 5.1 (BIBO stability)
Consider an LTI scalar system in (5.4). Then the system is called bounded input bounded output (BIBO) stable, if $\forall\ 0 < a < \infty$ with $\|u(t)\| \leq a$, $\exists\ 0 < b < \infty$ such that $\|y(t)\| \leq b$.

In order to analyse the stability of the system by using the Routh-Hurwitz and Nyquist criterion, we can transform it into frequency-domain by using Laplace transform, defined as follow.

Definition 5.2 (Laplace transform)
For a time-domain function $x(t)$ with $t \geq 0$, the Laplace transformed function is given by

$$X(s) = \mathscr{L}(x(t)) = \int_0^\infty e^{-st} x(t) dt, s \in \mathbb{C}$$

and the map $\mathscr{L}$ is called the Laplace transform.

Considering the properties of a job shop system (cf. (5.3)) and PID controller (cf. (5.8)), the related properties for the Laplace transform is summarized in Table 5.1. Here, a time-domain variable presented by a lowercase letter (e.g., x) is represented by the respective uppercase letter (e.g., X) in the frequency-domain.

Property	Time domain	Frequency domain
Linearity	$a_1 x_1(t) + a_2 x_2(t)$	$a_1 X_1(s) + a_2 X_2(s)$
Differentiation	$\frac{d^n x(t)}{dt^n}$	$s^n X(s) - s^{n-1} x(0) \cdots - x^{(n-1)(0)}$
Integration	$\int_0^t x(\tau) d\tau$	$\frac{X(s)}{s} + \frac{x'(0)}{s}$
Delay	$x(t - \tau_0)$	$e^{-\tau_0 s} X(s)$

Table 5.1.: Properties of the Laplace transform

By using the Laplace transform, the time-domain system in (5.4) can be transformed into frequency-domain. The relationship between variables can be represented by a transfer function. The definition is given as follow.

Definition 5.3 (Transfer function)
For an LTI scalar system, the relationship between the input and output can be described via the block diagram shown in Figure 5.1. $G(s) = \frac{Y(s)}{U(s)}$ is called the transfer function of the system, where $U(s)$ is the input and $Y(s)$ is the output.

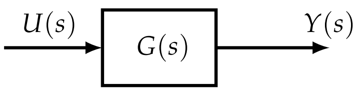

Figure 5.1.: Block diagram of a linear system

For this LTI scalar system in (5.4), the transfer function $G(s)$ is given as a factorized polynomial. The roots of the denominator polynomial are called the poles, and the roots of the numerator polynomial are called the zeros. In frequency-domain, the BIBO stability of the system is given by the following theorem.

Theorem 5.4 (BIBO stability [260, 261])
Consider an LTI scalar system in (5.4). *If all poles of the transfer function $G(s)$ are contained in the open left complex plain, then the system is BIBO stable.*

For the closed-loop feedback control of the LTI system in (5.4), the block diagram is shown in Figure 5.2, and the transfer function is given by

$$T_{rf}(s) = \frac{Y(s)}{R(s)} = \frac{G^c(s)G(s)}{1 + G^c(s)G(s)H(s)} = \frac{p(s)}{q(s)} \tag{5.5}$$

where $G^c(s)$ is the forward controller, $H(s)$ is the feedback controller, and $G^c(\cdot)$, $H(\cdot)$, $G(\cdot)$, $p(\cdot)$ and $q(\cdot)$ are polynomials. $q(s) = 0$ is called the characteristic equation of the system. To analyse the BIBO stability of the closed-loop feedback control system, the Routh-Hurwitz and Nyquist criterion are given as follows.

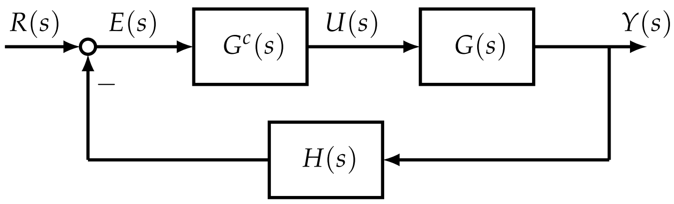

Figure 5.2.: Block diagram of a closed-loop feedback control system

Theorem 5.5 (Routh-Hurwitz criterion [260, 261])
A closed-loop control system with transfer function $T_{rf}(s) = \frac{p(s)}{q(s)}$ with polynomials $p(\cdot)$ and $q(\cdot)$, is BIBO stable, if and only if the number of roots of the characteristic equation $q(s) = \sum_{j=0}^{n} a_j s^j$ with positive real parts is equal to the number of changes of sign of the coefficients in the first column of the Routh-scheme

$$\begin{array}{c|cccc}
s^n & a_{01} = a_n & a_{02} = a_{n-2} & a_{03} = a_{n-4} & \cdots \\
s^{n-1} & a_{11} = a_{n-1} & a_{12} = a_{n-3} & a_{13} = a_{n-5} & \cdots \\
\vdots & \vdots & \vdots & \ddots & \\
s^1 & a_{n-1,1} & a_{n-1,2} & a_{n-1,3} & \cdots \\
s^0 & a_{n,1} & & &
\end{array}$$

where $a_{ij} = \dfrac{a_{i-1,j}a_{i-2,j+1} - a_{i-2,j}a_{i-1,j+1}}{a_{i-1,j}}$, for $i = 2, \cdots, n$ and $j = 1, 2, \cdots$.

Theorem 5.6 (Nyquist stability criterion [260, 261])
Consider a closed-loop feedback control system $T_{rf}(s) = \frac{G^c(s)G(s)}{1+G^c(s)G(s)H(s)}$, the characteristic equation is given by

$$F(s) = 1 + L(s), \tag{5.6}$$

where $L(s) = G^c(s)G(s)H(s)$. Then the system is BIBO stable if and only if the contour Γ_L in the $L(s)$-plane, the number of counterclockwise encirclements of the $(-1, 0)$ point, is *equal to the number of the poles of $L(s)$ with positive real parts. If the contour Γ_L does not encircle the $(-1, 0)$ point, the system is BIBO stable if the number of poles of $L(s)$ in the right-hand s-plane is zero.*

The above definitions and theorems are fundamentals in classical control theory, which has been widely used. In this dissertation, the proofs of the above theorems were omitted, for the details in [260, 261]. In the following section, these definitions and theorems are used for the design and stability analysis of the job shop system using PID.

5.1.2. THE PID CONTROL SYSTEM

With the continuous time-domain model proposed in Chapter 4, the PID capacity control system is given in Figure 5.3. In a decentralized control architecture, each workstation j has its own PID controller to adjust the capacity. The PID controller is comprised of three actions including proportional, integral and derivative.

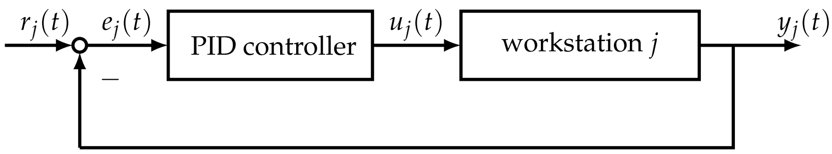

Figure 5.3.: PID control of jth workstation in a job shop system with RMTs

The controller is designed to minimize the error between planned WIP and current WIP level and ensure the orders output rate to equal the input rate of each workstation, where the number of RMTs used in workstation j is the control variable. The respective error $e_j(t)$ is given by

$$e_j(t) = y_j(t) - r_j(t). \tag{5.7}$$

According to the standard design of a PID controller, the control signal $u_j(t)$ takes the form

$$u_j(t) = K_j^p \cdot e_j(t) + K_j^i \cdot \int e_j(t)dt + K_j^d \cdot \frac{de_j(t)}{dt} \tag{5.8}$$

where K_j^p, K_j^i and K_j^d are non-negative real numbers, and are the design parameters of the different PID controllers for each workstation $j \in \{1, \ldots, n\}$.

Using the preliminaries from Section 5.1.1, stability of the PID capacity control system is theoretically analysed in this section. From the Laplace transform in Definition 5.2, the transfer function $G^c(s)$ of the PID controller is given as

$$G_c(s) = \frac{U_j(s)}{E_j(s)} = K_j^p + \frac{K_j^i}{s} + K_j^d s. \tag{5.9}$$

In the following three Sections 5.1.2.1, Section 5.1.2.2 and Section 5.1.2.3, stability of the scenarios listed at the end of Section 5.1 will be discussed.

5.1.2.1. Capacity Control without Delays and Disturbances

Without considering delays and disturbances, the Laplace transform of the mathematical model in (5.1) is given as

$$Y_j(s) = \frac{\hat{X}_j(s)}{s} - \frac{U_j(s) \cdot v_j^{RMT}}{s}, \tag{5.10}$$

where $\hat{X}(s) = X_{0j} + \sum_{k=1}^{n} X_{kj}(s) - n_j^{DMT} \cdot v_j^{DMT}$. The closed-loop control block diagram of the system is depicted in Figure 5.4. Here, the variables in frequency-domain presented by uppercase letter are corresponding to their time-domain representation by respective lowercase letters, cf. Figure 5.3 and Figure 5.4.

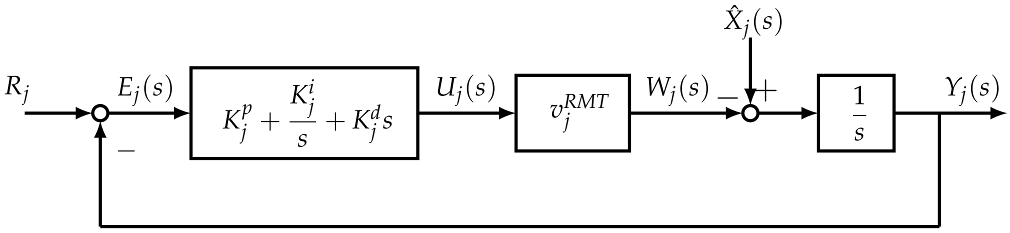

Figure 5.4.: Capacity control of the jth workstation in the job shop system with RMTs

Then we utilize the Routh-Hurwitz criterion from Theorem 5.5 to analyse the stability of the system.

Theorem 5.7. *Consider the closed-loop shown in Figure 5.4. If K_j^p, K_j^i and K_j^d are positive real numbers, then the system is BIBO stable.*

Proof. From Figure 5.4, we obtain that the output $Y_j(s)$ is given by

$$\begin{aligned} Y_j(s) = & \frac{s}{(1 + v_j^{RMT} K_j^d)s^2 + v_j^{RMT} K_j^p s + v_j^{RMT} K_j^i} \hat{X}_j(s) \\ & - \frac{v_j^{RMT}(K_j^d s^2 + K_j^p s + K_j^i)}{(1 + v_j^{RMT} K_j^d)s^2 + v_j^{RMT} K_j^p s + v_j^{RMT} K_j^i} R_j. \end{aligned}$$

Therefore, the characteristic equation of the closed-loop control system is

$$q_j(s) = (1 + v_j^{RMT} K_j^d)s^2 + v_j^{RMT} K_j^p s + v_j^{RMT} K_j^i.$$

As v_j^{RMT}, K_j^p, K_j^i and K_j^d are positive, thus the roots of $q_j(s)$ are negative real. The Routh array of q_j now reveals

$$\begin{array}{c|cc} s^2 & 1 + v_j^{RMT} K_j^d & v_j^{RMT} K_j^i \\ s^1 & v_j^{RMT} K_j^p & \\ s^0 & v_j^{RMT} K_j^i & \end{array}$$

Since v_j^{RMT}, K_j^p, K_j^i and K_j^d are positive, then the numbers in the first column of the Routh array, $1 + v_j^{RMT} K_j^d$, $v_j^{RMT} K_j^p$ and $v_j^{RMT} K_j^i$ are also positive. According to the Routh-Hurwitz criterion from Theorem 5.5, the number of roots of $q_j(s)$ with positive real parts is 0, which is equal to the number of changes in sign of the first column of the Routh array. Therefore, the above control system is stable if K_j^p, K_j^i and K_j^d are positive. □

5.1.2.2. Capacity Control with Disturbances

Including disturbances such as customer demand fluctuations and rush orders, the control system is more complex. The respective model in (5.2) is then given by

$$Y_j(s) = \frac{\hat{X}_j(s) + D_j(s)}{s} - \frac{U_j(s) \cdot v_j^{RMT}}{s}, \tag{5.11}$$

where $\hat{X}(s) = X_{0j}(s) + \sum_{k=1}^{n} X_{kj}(s) - n_j^{DMT} \cdot v_j^{DMT}$. The input rate from the initial stage $X_{0j}(s)$ is the bounded representing the demand, and $D_j(s)$ is an occasional disturbance such as a rush order. The block diagram of this disturbed system is shown in Figure 5.5. For this setting, the following holds:

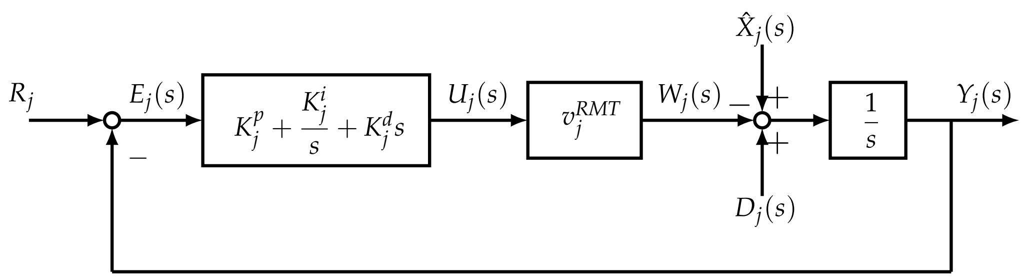

Figure 5.5.: Capacity control of the jth workstation in the job shop system with disturbances

Theorem 5.8. *Consider the disturbed control system shown in Figure 5.4 with bounded disturbances. If K_j^p, K_j^i and K_j^d are positive real, then the system is BIBO stable.*

Proof. Similar to Theorem 5.7, we obtain the output $Y_j(s)$ via

$$Y_j(s) = \frac{s}{(1+v_j^{RMT}K_j^d)s^2 + v_j^{RMT}K_j^p s + v_j^{RMT}K_j^i}(\hat{X}_j(s) + D_j(s)) - \frac{v_j^{RMT}(K_j^d s^2 + K_j^p s + K_j^i)}{(1+v_j^{RMT}K_j^d)s^2 + v_j^{RMT}K_j^p s + v_j^{RMT}K_j^i} R_j.$$

From Theorem 5.7, it follows that $\hat{X}_j(s)$ is bounded if $D_j(s) \equiv 0$. Since $D_j(s)$ is bounded, then also $\bar{D}_j(s) = \hat{X}_j(s) + D_j(s)$ is bounded. Hence, the characteristic equation of the closed-loop system is still given by

$$q_j(s) = (1 + v_j^{RMT}K_j^d)s^2 + v_j^{RMT}K_j^p s + v_j^{RMT}K_j^i.$$

Utilising identical arguments as in the proof of Theorem 5.7, we obtain that the disturbed control system is BIBO stable if K_j^p, K_j^i and K_j^d are positive. □

5.1.2.3. CAPACITY CONTROL WITH DELAYS AND DISTURBANCES

After the stability analysis of the disturbed job shop system, we increase the complexity by including delays, which comprise reconfiguration and transportation delays. Introducing these elements, the model in (5.3) is given by

$$Y_j(s) = \frac{\hat{X}_j(s)e^{-\tau_2 s} + D_j(s)}{s} - \frac{U_j(s)\cdot v_j^{RMT}e^{-\tau_1 s}}{s}. \tag{5.12}$$

The capacity control of the time-delayed and disturbed job shop system is shown in Figure 5.6. As to the time-delayed system, the characteristic equation is not polynomial. For this system, the Nyquist stability criterion, cf. Theorem 5.6, can be utilized to analyse the stability of the closed-loop.

Theorem 5.9. *Consider the disturbed and time-delayed control system shown in Figure 5.6 with $2 > \tau_1 > 0$ and suppose that the disturbance is bounded. If the parameters K_j^p, K_j^i and K_j^d are positive and satisfy $K_j^d = K_j^p = 2K_j^i = K \in (0, 0.9/v_j^{RMT}]$, then the system is BIBO stable.*

Proof. Since coupling can be interpreted as disturbance of a system [229], the control system in Figure 5.6 is equivalent to Figure 5.7, where

$$\bar{D}_j(s) = \hat{X}_j(s)\cdot e^{-\tau_2 s} + D_j(s).$$

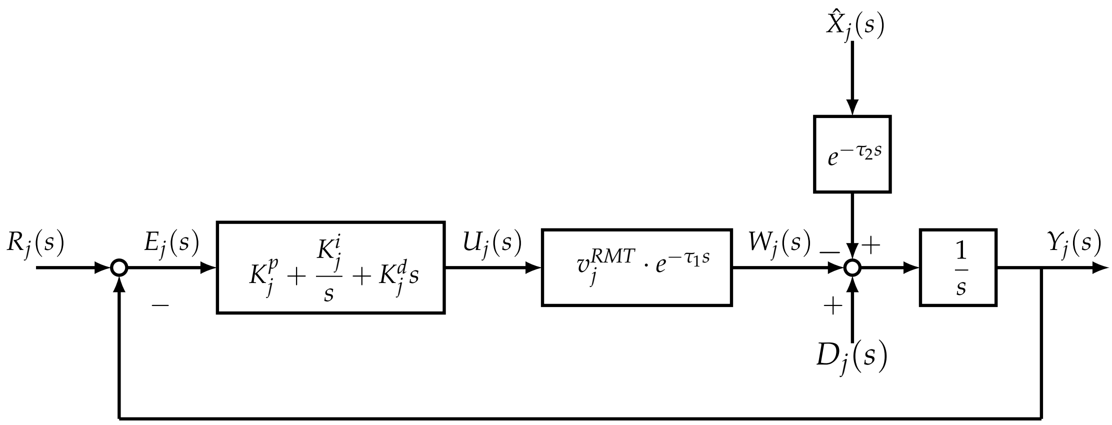

Figure 5.6.: Capacity control of the jth workstation in the job shop system with delays and disturbances

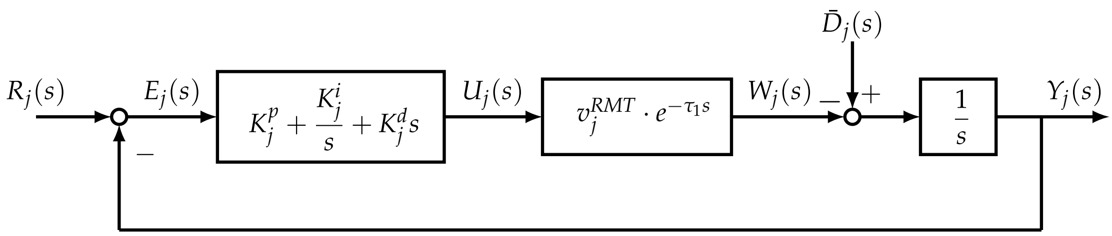

Figure 5.7.: Equivalent of Figure 5.6

Owing to $u_j(t) \in \mathbb{N}_0$, $\sum_{j=1}^{n} u_j(t) \leq n^{RMT}$ and $0 \leq p_{kj} \leq 1$, so $x_j(t-\tau_2) < x_{0j}(t) + \sum_{k=1}^{n}(n_k^{DMT} \cdot v_k^{DMT} + n \cdot v_j^{RMT})$ is therefore bounded. Consequently, the new disturbance $\bar{d}_j(t)$ is bounded. We obtain the characteristic function of the closed-loop system via

$$1 + L_j(s) = 1 + \frac{v_j^{RMT}(K_j^d s^2 + K_j^p s + K_j^i)e^{-\tau_1 s}}{s^2} = 0$$

with

$$L_j(s) = \frac{v_j^{RMT}(K_j^d s^2 + K_j^p s + K_j^i)e^{-\tau_1 s}}{s^2}. \tag{5.13}$$

Now the number of poles of (5.13) in the positive s-plane is also 0. According to the Nyquist stability criterion in Theorem 5.6, for the contour Γ_{L_j} in the $L(s)$-plane, the number of counterclockwise encirclements of the $(-1, 0)$ point should be zero. When $s = j\omega$,

$$L_j(j\omega) = |L_j(j\omega)|e^{j\Phi(\omega)} = |L_j(j\omega)|\angle\Phi(\omega). \tag{5.14}$$

Let $K_j^d = K_j^p = 2K_j^i = K/v_j^{RMT}$, then the magnitude and phase are

$$|L_j(j\omega)| = K\sqrt{1 + \frac{0.25}{\omega^4}}, \tag{5.15}$$

$$\Phi(\omega) = \arctan\frac{\omega}{0.5 - \omega^2} - \tau_1\omega - \pi. \tag{5.16}$$

For $\omega \to +\infty$, we obtain that $|L_j(j\omega)|$ decreases to K. The approximate contour of L_j is given in Figure 5.8. In order to ensure stability, the point of the contour first crossing the real negative axis should be on the right of the $(-1, 0)$ point, therefore, the first cross frequency ω_x should satisfy the following conditions:

$$\begin{cases} |L_j(j\omega_x)| = K\sqrt{1 + \frac{0.25}{\omega_x^4}} < 1, \\ \Phi(\omega_x) = \arctan\frac{\omega_x}{0.5 - \omega_x^2} - \tau_1\omega_x - \pi = -\pi, \end{cases}$$

where $0 < \omega < \sqrt{0.5}$. When τ_1 is increased from 0 to 2, ω_x decreases. When $K = 0.9$, the Nyquist and Bode diagrams for $\tau_1 = 1$ and $\tau_1 = 2$ are given in Figure 5.9 and Figure 5.10.

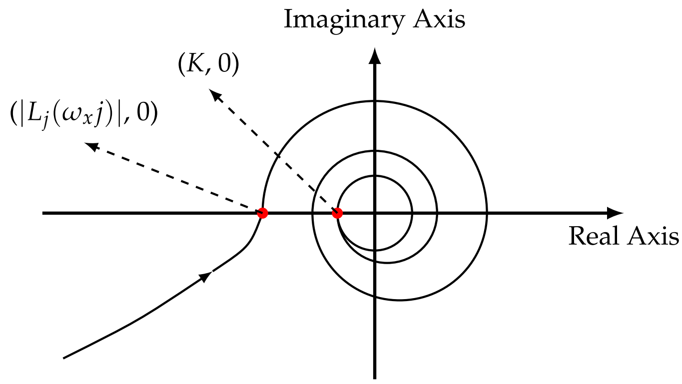

Figure 5.8.: Approximate Nyquist diagram of (5.13)

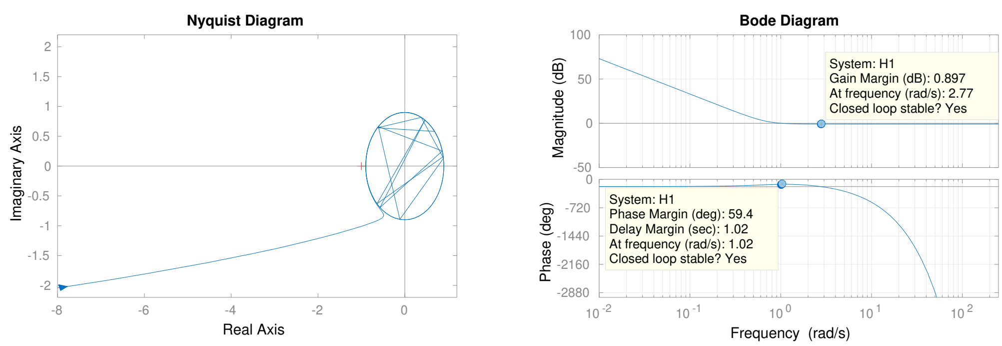

Figure 5.9.: Diagrams of (5.13) with $\tau_1 = 1$

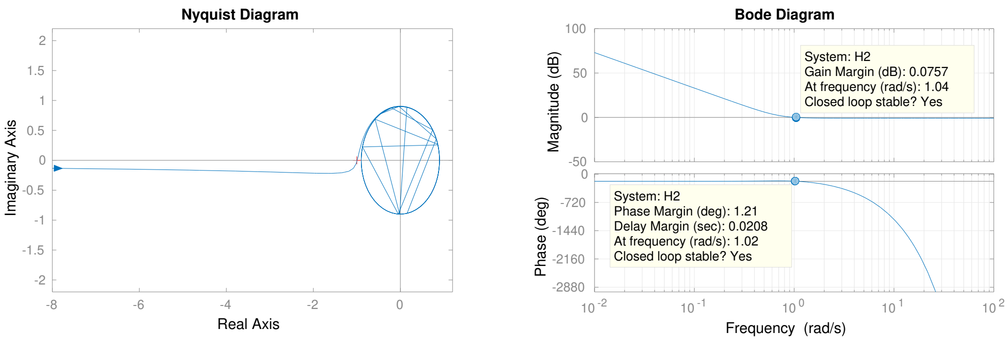

Figure 5.10.: Diagrams of (5.13) with $\tau_1 = 2$

In Figure 5.10, when $K = 0.9$ and $\tau_1 = 2$, the contour Γ_L in the Nyquist diagram crossed closely on the right of the $(-1, 0)$ point, and the number of counterclockwise encirclements of the $(-1, 0)$ point is 0. This is equal to the number of poles of $L_j(s)$ with positive real parts, so the system is stable. From (5.15), with K decreasing, the magnitude $L_j(j\omega_x)$ also decreases, while the stability increases. Then, we obtain that the closed-loop system with $\tau_1 = 2$ is stable when $K \in (0, 0.9]$, which can also be seen from the Bode diagram.

From the Nyquist diagram of $K = 0.9$ and $\tau_1 = 1$ in Figure 5.9, we obtain same result as $\tau_1 = 2$ in Figure 5.10. However, when τ_1 is decreased from 2 to 1, the gain margin and phase margin in the bode diagram increase. This illustrates that when τ_1 is decreased, the stability is increased.

In all, for $\tau_1 \in [0, 2]$, positive parameters K_j^p, K_j^i and K_j^d satisfying $K_j^p = K_j^i = 2K_j^d = K \in (0, 0.9/v_j^{RMT}]$ render the closed-loop to be BIBO stable. □

From the above analysis, we conclude that the PID control method is applicable for the capacity control of job shop systems considering delays and disturbances. In the PID control system, each workstation has its own local controller to ensure the stability for the WIP on a planned level. The couplings between each workstation are considered to be disturbances, which may highly influence the performance.

5.2. CAPACITY CONTROL BY USING RRCF

Compared to the PID control method, RRCF is a relatively novel method and the potential of it in the manufacturing domain needs to be developed. This section focuses on the implementation of RRCF in the capacity control of a general job shop manufacturing system with RMTs. The preliminaries of the RRCF method for a general class of nonlinear systems are introduced at the beginning of this section. In the implementation of the method, we first consider capacity control of a single-input single-output (SISO) system, and then increase the complexity to a multi-input multi-output(MIMO) system, which is solved by using a decoupling method to transform the capacity control of the MIMO system to multiple SISO systems.

5.2.1. MATHEMATICAL PRELIMINARIES

In this section, we consider general nonlinear input–output systems of the form

$$P : U \to Y \tag{5.17}$$

where the input and output spaces U and Y are two normed linear spaces over the field of complex numbers, endowed, respectively with norms $\|\cdot\|_U$ and $\|\cdot\|_Y$. We denote the set of all (non-linear) operators by $\mathcal{N}(U, Y)$ and call $\mathcal{D}(P)$ and $\mathcal{R}(P)$ the domain and range of P. A (semi)-norm on (a subset of) $\mathcal{N}(D_s, Y)$ is defined via

$$\|P\| := \sup_{x,\tilde{x} \in D_s \& x \neq \tilde{x}} \frac{\|P(x) - P(\tilde{x})\|_Y}{\|x - \tilde{x}\|_U}.$$

Given such a system, our aim is to show stability of the system, which is formally defined as follows:

Definition 5.10 (Finite-Gain Input-Output Stability)
An operator $P \in \mathcal{N}(U_s, Y_s)$ with $U_s \subseteq U$ and $Y_s \subseteq Y$ is called finite–gain input–output stable if

1. it is input–output stable, i.e. $P(U_s) \subseteq Y_s$, and if
2. the norm $\|P\|$ is well defined and finite, i.e. $\|P\| < \infty$.

Here, we call U_s the stable input subspace and Y_s the stable output subspace of the operator P. Moreover, an operator P is called causal, stabilizable or unimodular if

1. for the projection (causal)

$$Q_T(x(t)) = \begin{cases} x(t), & 0 \leq t \leq T \\ 0, & T \leq t \leq \infty \end{cases}$$

   we have $Q_T \circ P \circ Q_T = Q_T \circ P$ for all $x(t) \in U$ and all $T \in [0, \infty)$,

2. there exists an operator $Q : \mathcal{D}(Q) \to \mathcal{D}(Q)$ such that $P \circ Q$ is input-output stable, (stabilizable)
3. P is stabilizable and $P^{-1} \in \mathcal{N}(Y_s, U_s)$. (unimodular)

This definition can describe the finite-gain of the BIBO stability in Definition 5.1, if the stable input space U_s and output space Y_s of P are bounded [213]. Also, the above three properties allow us to introduce our main tool to show finite–gain input–output stability:

Definition 5.11 (Right Coprime Factorization (RCF))
Let $P : \mathcal{D}(P) \to \mathcal{R}(P)$ be a causal and stabilizable operator. We say that P has a right coprime factorization illustrated in Figure 5.11, if there exist finite–gain input–output stable and causal operators $D : \mathcal{D}(P) \to \mathcal{D}(P)$, $N : \mathcal{D}(P) \to \mathcal{R}(P)$ as well as $A : \mathcal{R}(N) \to \mathcal{D}(P)$ and $B : \mathcal{R}(D) \to \mathcal{D}(P)$ such that

1. D is causal, invertible and $P = N \circ D^{-1}$ holds on $\mathcal{D}(P)$, and

2. for the unimodular operator $M : \mathcal{D}(P) \to \mathcal{D}(P)$, we have the Bezout identity

$$A \circ N + B \circ D = M. \tag{5.18}$$

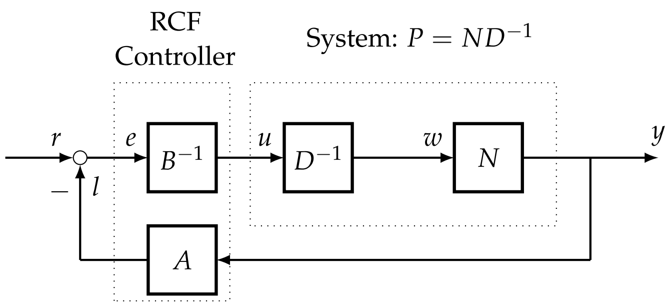

Figure 5.11.: RCF feedback control system

Here, y, w and u represent the output, quasi-state and input signal respectively, cf. [226] for details. r is the reference input, l is the feedback state and e is the error between r and l. Then, the latter definition allows us to convert the control system (5.17) to a dynamical system.

Theorem 5.12. *Consider the closed-loop control system shown in Figure 5.11. If a causal and stabilizable operator $P : \mathcal{D}(P) \to \mathcal{R}(P)$ has right coprime factorization, then the respective closed-loop is finite–gain input–output stable. Moreover, for any reference r, the closed-loop simplifies to $y = N \circ M^{-1}(r)$.*

Proof. As P has a right coprime factorization, we can utilize Figure 5.11 to obtain $l = A \circ N(w)$ and $e = B \circ D(w)$. Therefore, we have $r = l + e = (A \circ N + B \circ D)(w)$. Again by the right coprime factorization property, we can apply the Bezout identity (5.18) to obtain $r = M(w)$ and $w = M^{-1}(r)$. Hence, by $y = N(w) = N \circ M^{-1}(r)$, cf. Figure 5.12, the second assertion follows.
Regarding finite–gain input–output stability, we first utilize unimodularity of M

and finite–gain input–output stability of N to obtain

$$P(U_s) = N \circ M^{-1}(U_s) \subseteq N(U_s) \subseteq Y_s,$$

which shows input–output stability. Similarly, we obtain by unimodularity of M

$$\begin{aligned} \|P\| = \|N \circ M^{-1}\| :&= \sup_{x,\tilde{x} \in U_s \& x \neq \tilde{x}} \frac{\|N \circ M^{-1}(x) - N \circ M^{-1}(\tilde{x})\|_Y}{\|x - \tilde{x}\|_U} \\ &= \sup_{x,\tilde{x} \in U_s \& x \neq \tilde{x}} \frac{\|N(x) - N(\tilde{x})\|_Y}{\|M(x) - M(\tilde{x})\|_U}. \end{aligned}$$

Now, we utilize finite–gain input–output stability of N to conclude $\|P\| < \infty$, which completes the proof.

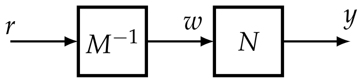

Figure 5.12.: Equivalent of Figure 5.11

□

In order to include model uncertainties, we modify the mapping P respectively, i.e., we integrate an unknown but bounded operator ΔN in parallel to N.

Definition 5.13 (Robust Right Coprime Factorization (RRCF))
Consider $P : \mathcal{D}(P) \rightarrow \mathcal{R}(P)$ to be a causal and stabilizable operator with right coprime factorization and suppose a bounded model disturbance to act as shown in Figure 5.11. Then P has robust right coprime factorization if the two operators A and B satisfy the Bezout identity $A \circ (N + \Delta N) + B \circ D = \tilde{M}$, where $\tilde{M}$ is a unimodular operator.

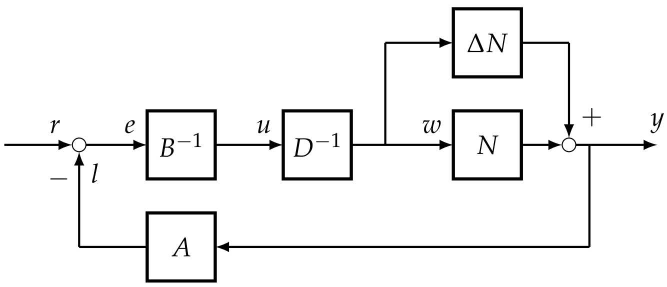

Figure 5.13.: RRCF feedback control system with disturbances

Similar to Theorem 5.12, the closed-loop in Figure 5.13 can be simplified to a dynamical system, cf. Figure 5.14.

Corollary 5.14

Consider the closed-loop shown in Figure 5.13. If a causal and stabilizable operator $P : \mathcal{D}(P) \to \mathcal{R}(P)$ has robust right coprime factorization, then the respective closed-loop is finite–gain input–output stable. Moreover, for any reference v, the closed-loop simplifies to $y = (N + \Delta N) \circ \tilde{M}^{-1}(v)$, with $\tilde{M}$ from Definition 5.13.

Proof. Completely analog to the proof of Theorem 5.12 where N is replaced by $(N + \Delta N)$. □

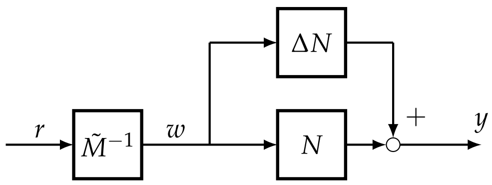

Figure 5.14.: Equivalent of Figure 5.13

Using these definitions and theorems reveals an effective approach to control and analyse stability and performance of a class of nonlinear control systems, which includes job shop systems.

5.2.2. CAPACITY CONTROL OF SISO SYSTEMS

A single-workstation job shop manufacturing system is a typical single-input single-output (SISO) system, and the input-output model is described as

$$P : y(t) = y(0) + \int_0^t X_0 + d(\tau) - (v^{DMT} n^{DMT} + v^{RMT} u(\tau - \tau_1)) d\tau, \tag{5.19}$$

where $u \in U$ is the number of RMTs, $y \in Y$ is the WIP level, and $0 \leqslant u(t) \leqslant n^{RMT}$. $X_0 + d(t)$ is the orders from the initial stage to the workstation, which comprises decisive X_0 and uncertain $d(t)$. Here, $d(t)$ is bounded and includes the stochastic uncertainty and occasional disturbance (e.g., rush order). The stability of the SISO system is analysed for the same three scenarios as the PID control system.

5.2.2.1. CAPACITY CONTROL WITHOUT DELAYS AND DISTURBANCES

Firstly, without delays and disturbances, the above SISO system can be re-expressed as

$$P : y(t) = y(0) + \int_0^t X_0 - (v^{DMT} n^{DMT} + v^{RMT} u(\tau)) d\tau. \tag{5.20}$$

Considering RCF control of the above system, cf. Figure 5.11, we have following result:

Theorem 5.15
Consider a SISO system (5.20). *Then the controllers*

$$A(s(\cdot)) = (1-K)\cdot(s(\cdot))' \tag{5.21}$$

$$B^{-1}(s(\cdot)) = \frac{X_0 - v^{DMT}n^{DMT}}{v^{RMT}} - \frac{(s(\cdot))}{Kv^{RMT}} \tag{5.22}$$

with constant parameter $K \in (0,1)$ *render the closed-loop system shown in Figure 5.11 to be finite-gain input-output stable.*

Proof. Choosing

$$D^{-1}(s(\cdot)) = X_0 - (v^{DMT}n^{DMT} + v^{RMT}\cdot s(\cdot)) \tag{5.23}$$

$$N(s(\cdot)) = y(0) + \int s(\cdot)dt \tag{5.24}$$

a right factorization according to Definition 5.11 is obtained. N and D are stable operators and D is invertible. Combining (5.21) and (5.22) with (5.23) and (5.24), we get

$$l(t) = A(y(t)) = (1-K)\cdot y'(t) \tag{5.25}$$

$$u(t) = B^{-1}(e(t)) = \frac{X_0 - v^{DMT}n^{DMT}}{v^{RMT}} - \frac{e(t)}{Kv^{RMT}} \tag{5.26}$$

where A and B are stable operators and B is invertible. Moreover, $A \circ N(w) + B \circ D(w) = I(w)$ satisfies the Bezout identity. Therefore, from Theorem 5.12, we obtain $N(s(\cdot)) = y(0) + \int s(\cdot)dt$, and the Lipschitz semi-norm of it is

$$\|N\| := \sup_{s,\bar{s}\in D_s \& s\neq\bar{s}} \frac{\|N(s) - N(\bar{s})\|_{Y_s}}{\|s-\bar{s}\|_{U_s}} < 1 < \infty, \tag{5.27}$$

Which completes the proof.

□

Based on the stability of the RCF control system, we continue to analyse the stability of the feedback tracking control system as shown in Figure 5.15. Here, the controller C is designed via

$$C(s(\cdot)) = C_0 s(\cdot) + C_1 e^{-ht} s(\cdot) \tag{5.28}$$

where C_0, C_1 and h are tracking control parameters. The equivalent form of Figure 5.15 with regards to Theorem 5.12 with $M = I$ is given in Figure 5.16. Then, we can show the following:

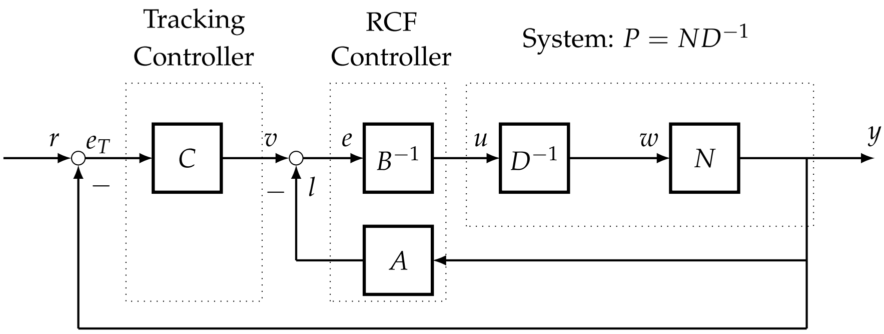

Figure 5.15.: Feedback tracking control system

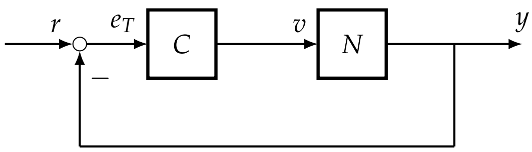

Figure 5.16.: Equivalent of Figure 5.15

Theorem 5.16
Consider a SISO system (5.20). *Then the feedback tracking control system shown in Figure 5.15 with the tracking operator C from* (5.28) *is finite-gain input-output stable.*

Proof. From Figure 5.16, we obtain for $y = NC(e_T)$ that

$$\begin{aligned} y(t) &= y(0) + \int C_0(e_T)(t) + C_1 \cdot e^{-ht}(e_T)(t)dt \\ &= y(0) + \int C_0(r-y)(t) + C_1 \cdot e^{-ht}(r-y)(t)dt. \end{aligned} \tag{5.29}$$

Calculating the derivative of (5.29), we get

$$y'(t) + (C_0 + C_1 e^{-ht})y(t) = (C_0 + C_1 e^{-ht})r.$$

Then, the solution reads

$$\begin{aligned} y(t) &= \hat{P}(r)(t) \\ &= y(0) \cdot e^{-\int (C_0 + C_1 e^{-ht})dt} + e^{-\int (C_0 + C_1 e^{-ht})dt} \cdot \int (C_0 + C_1 e^{-ht}) r \cdot e^{\int (C_0 + C_1 e^{-ht})dt} dt. \end{aligned} \tag{5.30}$$

Moreover, we have the Lipschitz semi-norm

$$\begin{aligned}\|\hat{P}\| := & \sup_{T\in[0,\infty)} \sup_{r\neq\hat{r}} \frac{\|[\hat{P}(r)]_T - [\hat{P}(\hat{r})]_T\|}{\|[r]_T - [\hat{r}]_T\|} \\ = & \sup_{T\in[0,\infty)} \left| e^{-C_0 t + \frac{C_1}{h} e^{-ht}} \cdot \int (C_0 + C_1 e^{-ht}) e^{C_0 t - \frac{C_1}{h} e^{-ht}} dt \right| \leq 1.\end{aligned} \tag{5.31}$$

Hence, the criteria from Definition 5.10 are satisfied, which shows the assertion. □

In order to improve the tracking performance and minimize the error between the planned and current WIP level, the setting of the tracking controller parameters can be obtained by using, e.g., particle swarm optimization (PSO) to minimize $\|(I + NC)^{-1}\|$, cf. [239] for details.

5.2.2.2. Capacity Control with Disturbances

When a bounded disturbance $d(t)$ — modelling, e.g., the stochastic uncertainty and occasional disturbance (e.g., rush order) — is integrated in the SISO system, the model is re-expressed as

$$P : y(t) = y(0) + \int_0^t X_0 + d(t) - (v^{DMT} n^{DMT} + v^{RMT} u(\tau)) d\tau. \tag{5.32}$$

For this disturbed system $P + \Delta P = (N + \Delta N)D^{-1}$, the RRCF control is shown in Figure 5.13. For the RRCF control of the job shop system, we have following theorem.

Theorem 5.17
Consider a SISO system with bounded disturbance (5.32)*. Then the controllers A and B in* (5.21) *and* (5.22) *render the closed-loop system shown in Figure 5.13 to be finite-gain input-output stable.*

Proof. Completely analog to the proof of Theorem 5.15, where N is replaced by $(N + \Delta N)$. The Lipschitz semi-norm of $N + \Delta N$ is

$$\|N + \Delta N\| := \sup_{s,\bar{s}\in D_s \& s\neq\bar{s}} \frac{\|(N+\Delta N)(s) - (N+\Delta N)(\bar{s})\|_{Y_s}}{\|s - \bar{s}\|_{U_s}} < 1 + |d(t)|. \tag{5.33}$$

As the disturbance $d(t)$ is bounded, so $\|N + \Delta N\|$ is also bounded. Therefore, according to the Definition 5.10, the above feedback control system with bounded disturbances is also finite-gain input-output stable. □

Based on the RRCF control, the tracking control of the disturbed system is given in Figure 5.17, which can be re-expressed in Figure 5.18 based on the Corollary 5.14. For this system, the following theorem holds:

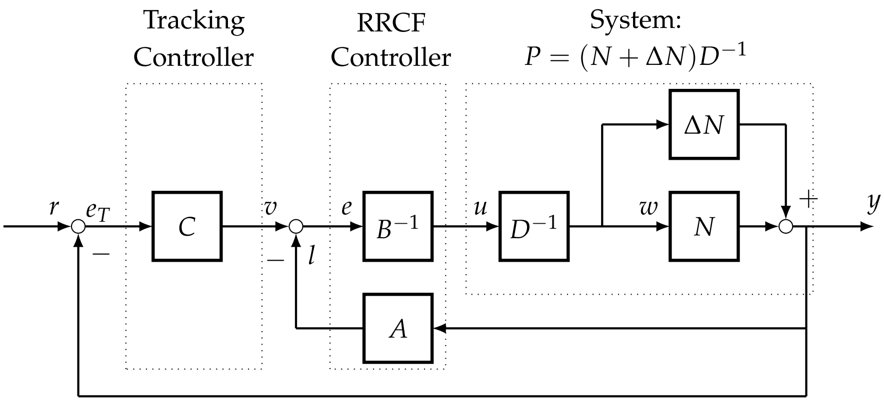

Figure 5.17.: Feedback tracking control system with disturbance

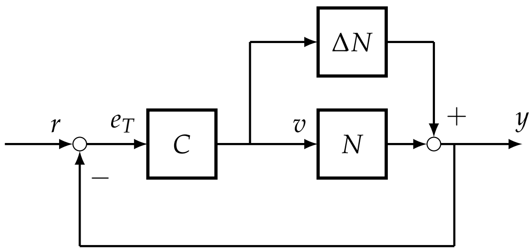

Figure 5.18.: Equivalent of Figure 5.17

Theorem 5.18
Consider a SISO system with bounded disturbance (5.32). *Then the feedback tracking control system shown in Figure 5.17 with the tracking operator C from* (5.28) *is finite-gain input-output stable.*

Proof. Completely analog to the proof of Theorem 5.16, where N is replaced by $(N + \Delta N)$. □

5.2.2.3. CAPACITY CONTROL WITH DELAYS AND DISTURBANCES

Considering the disturbed and time-delayed SISO system (5.19), the RRCF control and tracking control of the system are illustrated in Figure 5.19 and 5.20, respectively. In [236], the delay was considered to be a bounded disturbance in ΔD. Then, the disturbed and time-delayed system is given as $P + \Delta P = (N + \Delta N)(D + \Delta D)^{-1}$.

Let $\tilde{u}(t) = u(t - \tau_1)$, then the system is $P + \Delta P = (N + \Delta N)D^{-1}(\tilde{u}(t))$. Then the following related results hold true:

Theorem 5.19
Consider a SISO system with delay and bounded disturbance (5.19). *If τ_1 is fixed, then the RRCF controllers A and B from* (5.21) *and* (5.22) *render the closed-loop system shown in Figure 5.19 to be finite-gain input-output stable.*

Proof. Completely analog to the proof of Theorem 5.17.

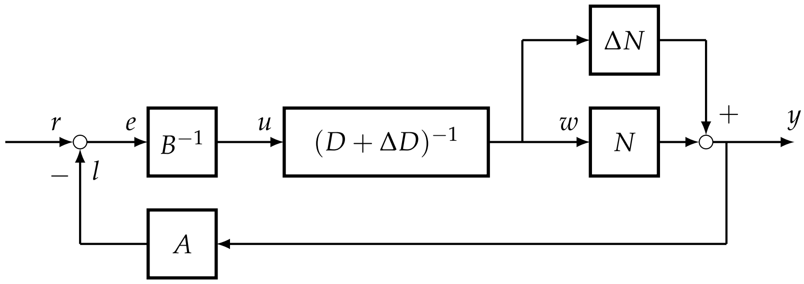

Figure 5.19.: RRCF control system with delay and disturbance

□

The tracking control of the system in Figure 5.20 is equivalent to the Figure 5.18 from Theorem 5.12. Therefore, we have same result as in Theorem 5.18.

Theorem 5.20
Consider a SISO system with delay and bounded disturbance (5.19). *Then the feedback tracking control system shown in Figure 5.20 with the tracking operator C from* (5.28) *is finite-gain input-output stable.*

Proof. Completely analog to the proof of Theorem 5.18.

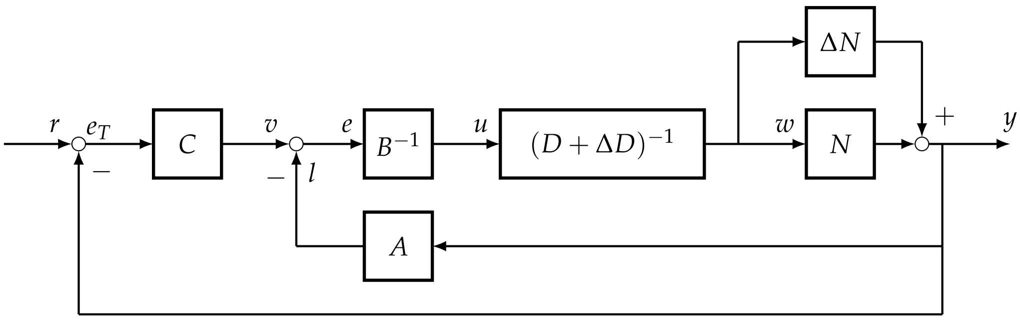

Figure 5.20.: Feedback tracking control system with delay and disturbance

□

To summarize, the capacity control of a single-workstation job shop system comprises of two stages. First, the RRCF controller A and B considering the orders input and output rate of the workstation are derived. Based on the RRCF control, the tracking controller C is designed to ensure that the WIP level is steered to a planned level. Considering bounded disturbance and delay, if the number of RMTs is sufficiently large, then the control system is finite-gain input-output stable.

5.2.3. CAPACITY CONTROL OF MIMO SYSTEMS

After the theoretical analysis of a single-workstation system, we increase the complexity to a multi-workstation job shop system. A decoupling controller is designed to transform the complexity of the MIMO system to multiple SISO systems. The input-output model of the MIMO system with n workstations reads

$$\begin{aligned} P_j : y_j(t) =& y_j(0) + \int_0^t x_{0j} + d_j(t) + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(\tau - \tau_2 - \tau_1) \cdot v_k^{RMT}) \\ & - (n_j^{DMT} \cdot v_j^{DMT} + u_j(\tau - \tau_1) \cdot v_j^{RMT}) d\tau. \end{aligned} \tag{5.34}$$

For this system, we perform a similar stability analysis as for the SISO system.

5.2.3.1. DECOUPLING CONTROL

From (5.34), we obtain the right factorization of the system via

$$\begin{aligned} w_j(\cdot) &= (D_j + \Delta D_j)^{-1}(u_k)(u_j)(\cdot) \\ &= x_{0j}(\cdot) + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(\cdot) \cdot v_k^{RMT}) \\ &\quad - (n_j^{DMT} \cdot v_j^{DMT} + u_j(\cdot) \cdot v_j^{RMT}) \\ y_j(\cdot) &= N_j(w_j(\cdot)) + \Delta N_j(d_j(\cdot)) = y_j(0) + \int_0^{(\cdot)} w_j(\tau) + d_j(\tau) d\tau. \end{aligned}$$

Within the latter equation, there exists a coupling between the workstations, which is a $n \times n$ system of linear equations. By solving the above equations, we can get the input signal

$$u_j(\cdot) = \sum_{k=1}^{n} (D_{jk} + \Delta D_{jk})(w_k)(\cdot), \quad j = 1, 2, \ldots, n.$$

To avoid the difficult computation of an RRCF control for the MIMO system, we utilize decoupling as proposed in [235] to transform it into multiple SISO systems.

To obtain n independent SISO systems, the decoupling operators H and G as shown in Figure 5.21 need to satisfy the following theorem, cf. Theorem 1 in [235].

Theorem 5.21 (Decoupled RRCF Control)
If G_j is linear and

$$\sum_{k=1,k\neq j}^{n} [H_{jk}(w_j)](w_k) + G_j \circ D_{jk}(w_k) = 0 \tag{5.35}$$

$$H_{jj}(w_j) + G_j \circ D_{jj}(w_j) = F_j(w_j) \tag{5.36}$$

hold, then the MIMO system is decoupled and F_j is stable and invertible. Here, $\mathbf{F} = (F_1, \ldots, F_n)$ represents the decoupling operator with $v_j = F_j(w_j)$.

Applying the latter to our case, we can conclude the following proposition.

Proposition 5.22 (Decoupled RRCF Control for Job Shop System)
Consider a plant (5.34) as well as decoupling parameters h_j with $\frac{1}{v_j^{RMT}} \neq |h_j| < \infty$ for $j = 1, \ldots, n$ and let $\mathbf{G} = (G_1, \ldots, G_n)$ be the identity operator, H_{jj} unimodular for $j = 1, \ldots, n$, such that

$$\sum_{k=1,k\neq j}^{n} [H_{jk}(w_j)](w_k) = - \sum_{k=1,k\neq j}^{n} G_j \circ D_{jk}(w_k),$$

holds. Then

$$F_j(w_j) = (h_j - \frac{1}{v_j^{RMT}}) \cdot w_j - \frac{v_j^{DMT} n_j^{DMT}}{v_j^{RMT}}, j = 1, \ldots, n, \tag{5.37}$$

holds. Additionally, if n^{RMT} is sufficiently large, then $F_j(w_j)$ is stable and invertible.

Proof. From (5.35), (5.36), we get

$$F_j(w_j) = H_{jj}(w_j) + G_j \circ D_{jj}(w_j).$$

As $\mathbf{G} = (G_1, \ldots, G_n)$ are identity operators and H_{jj} are unimodular operators $H_{jj} = h_j \cdot w_j$ for $j = 1, \ldots, n$, for plant (5.34) we have that

$$\begin{aligned} F_j(w_j) &= H_{jj}(w_j) + D_{jj}(w_j) \\ &= (h_j - \frac{1}{v_j^{RMT}}) \cdot w_j - \frac{v_j^{DMT} n_j^{DMT}}{v_j^{RMT}}, j = 1, \ldots, n. \end{aligned}$$

As $h_j \neq \frac{1}{v_j^{RMT}}$, it is a linear operator. Additionally, considering n^{RMT} is sufficiently large, we obtain that F_j is invertible. Its norm is

$$\|F_j\| = |h_j - \frac{1}{v_j^{RMT}}|.$$

As $h_j < \infty$ and the production rate of RMTs v_j^{RMT} is a positive constant, we obtain $\|F_j\| < \infty$. Hence, from Definition 5.10 this operator is stable showing the assertion.

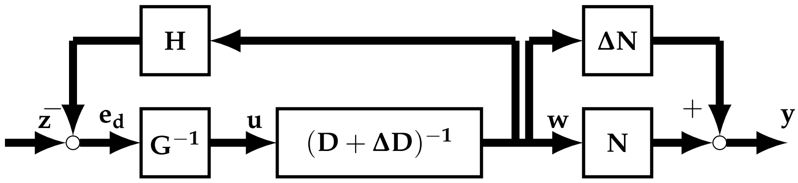

Figure 5.21.: Decoupling control of MIMO system

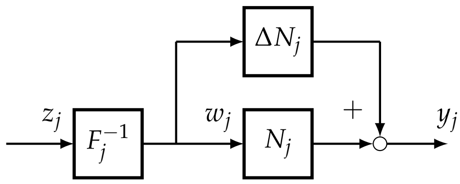

Figure 5.22.: Equivalent of Figure 5.21

□

After the decoupling, we can transform the capacity control of the complex MIMO system to multiple SISO systems. Therefore, we have similar theorems to the SISO system in the same three scenarios.

5.2.3.2. Capacity Control without Delays and Disturbances

In a nominal case without delays and disturbances, the model of the multi-workstation job shop system is given by

$$\begin{aligned} P_j : y_j(t) =& y_j(0) + \int_0^t x_{0j} + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(\tau) \cdot v_k^{RMT}) \\ & - (n_j^{DMT} \cdot v_j^{DMT} + u_j(\tau) \cdot v_j^{RMT}) d\tau. \end{aligned} \tag{5.38}$$

The RCF control of the system is displayed in Figure 5.23, for which the following theorem holds:

Theorem 5.23

Consider the MIMO system (5.38) *where each workstation* $j = 1, 2, \cdots, n$*, has its local RCF controller*

$$A_j(s(\cdot)) = (1 - \check{K}_j) \cdot s(\cdot)' \tag{5.39}$$

$$B_j^{-1}(s(\cdot)) = \frac{(h_j v_j^{RMT} - 1)s(\cdot)}{\check{K}_j v_j^{RMT}} - \frac{v_j^{DMT} n_j^{DMT}}{v_j^{RMT}} \tag{5.40}$$

with control parameters $\check{K}_j \in (0, 1)$*. Then the overall closed-loop system shown in Figure 5.23 is finite-gain input-output stable.*

Proof. According to the Proposition 5.22, system (5.38) can be decoupled into $y_j(t) = N_j F_j^{-1}$ for $j = 1, 2, \cdots, n$. From Definition 5.11, we choose

$$F_j^{-1}(s(\cdot)) = \frac{s(\cdot)v_j^{RMT} + v_j^{DMT} n_j^{DMT}}{h_j v_j^{RMT} - 1} \tag{5.41}$$

$$N_j(s(\cdot)) = \int (s(\cdot))dt. \tag{5.42}$$

Similar to Theorem 5.17, we can obtain that the Lipschitz semi-norm of the control system is

$$\|N_j\| := \sup_{s,\bar{s} \in D_s \& s \neq \bar{s}} \frac{\|N_j(s) - N_j(\bar{s})\|_{Y_s}}{\|s - \bar{s}\|_{U_s}} < 1 < \infty. \tag{5.43}$$

Hence, the conditions of Definition 5.10 hold and the feedback control system is finite-gain input-output stable.

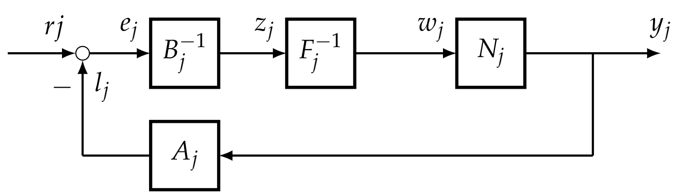

Figure 5.23.: RCF feedback control of MIMO system

□

Considering feedback tracking control of the system as shown in Figure 5.24, a result similar to Theorem 5.18 holds true:

Theorem 5.24

Consider a MIMO system (5.38) *where each workstation* $j = 1, 2, \cdots, n$*, has its local tracking controller of form* (5.28)*. Then the feedback tracking control system shown in Figure 5.24 is finite-gain input-output stable.*

Proof. The proof is identical to Theorem 5.16.

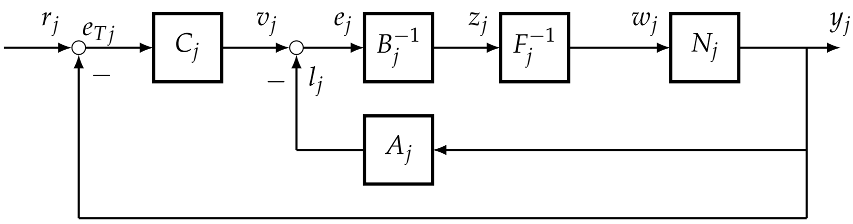

Figure 5.24.: Feedback tracking control of MIMO system

□

5.2.3.3. CAPACITY CONTROL WITH DISTURBANCES

Furthermore, when we include bounded disturbances $d_j(t)$ into the system, then the model reads

$$\begin{aligned} P_j : y_j(t) =& y_j(0) + \int_0^t x_{0j} + d_j(t) + \sum_{k=1}^{n} p_{kj} \cdot (n_k^{DMT} \cdot v_k^{DMT} + u_k(\tau) \cdot v_k^{RMT}) \\ & - (n_j^{DMT} \cdot v_j^{DMT} + u_j(\tau) \cdot v_j^{RMT}) d\tau. \end{aligned} \tag{5.44}$$

In light of Proposition 5.22, the system can be decoupled into $y_j(t) = (N_j + \Delta N_j)F_j^{-1}$ for $j = 1, 2, \cdots, n$. Similar to the SISO system case we have the following theorems for the RRCF and tracking control displayed in Figure 5.25 and 5.26 for the MIMO case:

Theorem 5.25

Consider a MIMO system with bounded disturbances (5.44) *where each workstation* $j = 1, 2, \cdots, n$*, has its local RRCF controllers* A_j *and* B_j *from* (5.39) *and* (5.40). *Then the closed-loop system shown in Figure 5.25 is finite-gain input-output stable.*

Proof. Completely analog to the proof of Theorem 5.23, where N_j is replaced by $(N_j + \Delta N_j)$.

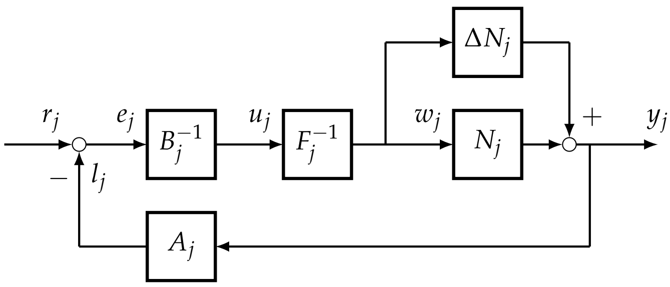

Figure 5.25.: RRCF feedback control of MIMO system with disturbances

□

Theorem 5.26
Consider a MIMO system with bounded disturbances (5.44) *where each workstation* $j = 1, 2, \cdots, n$, *has its local tracking controller* C_j *defined in* (5.28). *Then the feedback tracking control system shown in Figure 5.26 is finite-gain input-output stable.*

Proof. The proof is identical to Theorem 5.18.

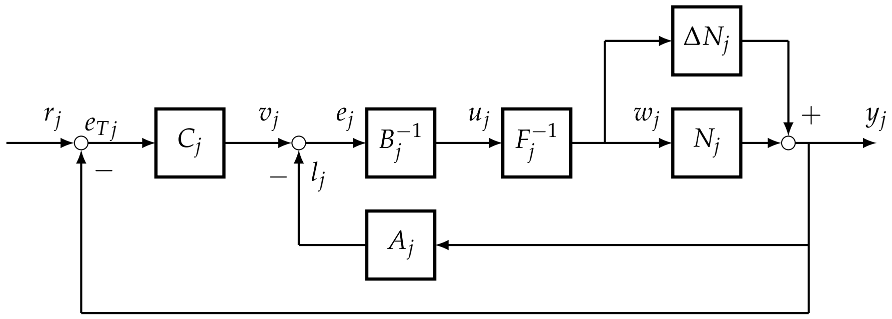

Figure 5.26.: Feedback tracking control of MIMO system with disturbances

□

5.2.3.4. CAPACITY CONTROL WITH DELAYS AND DISTURBANCES

With delays and bounded disturbances, the overall control system is shown in Figure 5.27.

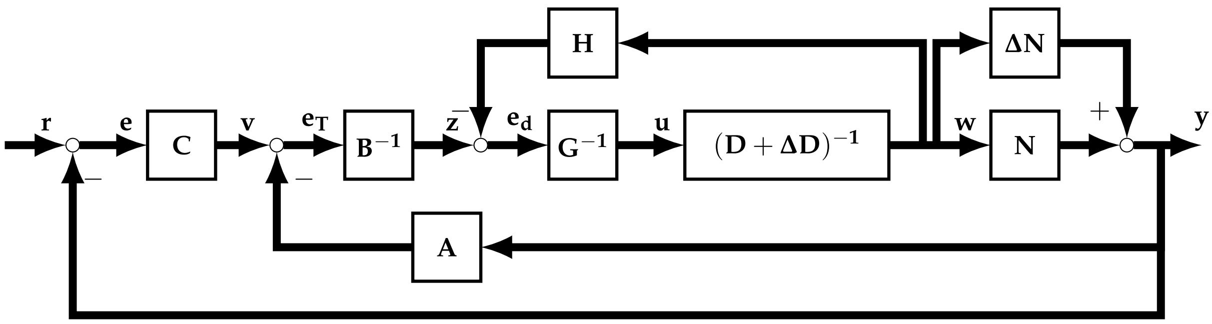

Figure 5.27.: Capacity control of MIMO system with delays and disturbances

Here, ΔD represents the effect of delays, which include reconfiguration delays and transportation delays. These delays are assumed to be fixed. In the decoupling control of the system, the delays are considered in the decoupling controller. Therefore, the disturbed and time-delayed system is equivalent to the one shown in Figure 5.26. Accordingly, similar results can be proven:

Theorem 5.27
Consider a MIMO system with delays and bounded disturbances (5.44) *where each workstation* $j = 1, 2, \cdots, n$*, is equipped with its own RRCF controllers* A_j *and* B_j *from* (5.39) *and* (5.40)*. Then the closed-loop system is finite-gain input-output stable.*

Proof. The proof is identical to Theorem 5.25. □

Theorem 5.28
Consider a MIMO system with delays and bounded disturbances (5.44) *where each workstation* $j = 1, 2, \cdots, n$*, has its own tracking controller* C_j *from* (5.28)*. Then the feedback tracking control system shown in Figure 5.27 is finite-gain input-output stable.*

Proof. The proof is identical to Theorem 5.26. □

To summarize, in the capacity control of a multi-workstation job shop system comprises of three stages. First, the decoupling controllers **H** and **G** are designed to transform the control of the MIMO system to multiple SISO systems. Then, for each SISO system, the RRCF controller A_j and B_j considering the orders input and output rate of each workstation are derived. Last, based on the RRCF control, the tracking controllers C_j are designed to ensure that the WIP level of each workstation is steered to a planned level. Considering delays and bounded disturbances, if the number of RMTs is sufficiently large, then the control system is finite-gain input-output stable.

5.3. DISCUSSION

In the above Sections 5.1 and 5.2, we discussed the design and stability analysis of PID and RRCF control methods for the capacity control of job shop systems. Both of these two control methods use a decentralized architecture, where each workstation has a local controller to control the capacity. The stability of these two control systems can be ensured when the number of RMTs is sufficiently large. However, the design and parametrization of both control methods are different.

In the PID case, the computation of the control parameters K_j^p, K_j^i and K_j^d as well as the evaluation of the feedback law are simple. Various tools, e.g., Routh-Hurwitz stability criterion and Nyquist stability criterion, can be used not only to analyse the stability but also to compute the possible stable range of the control parameters. However, in this setting the couplings between the workstations are considered to be disturbances, i.e., the input to workstation j is unknown to the controller and may lead to instability of the overall job shop system. Finding a good balance between the control parameters of all workstations could be done, e.g., via an optimization problem for a defined key performance index. Last, if all PID controllers together aim to assign more than the total number of RMTs n^{RMT}, then the truncation in (4.7) may not be optimal or even destabilizing.

Compared to the PID method, the computation of the RRCF control parameters is more involved. In this method, the complex MIMO system is firstly factorized to two stable operator $\mathbf{N} + \mathbf{\Delta N}$ and $\mathbf{D} + \mathbf{\Delta D}$. Considering the coupling between the workstations, the decoupling controllers $\mathbf{H}$ and $\mathbf{G}$ are designed to deduce the influence between each workstation. Then, the control of the MIMO system is transformed into multiple SISO systems. Thereafter, each SISO system has their local RRCF controller A_j and B_j and tracking controller C_j to control the capacity. The parameters may be computed through, e.g., PSO algorithm by minimizing $\|(I + NC)^{-1}\|$. Therefore, this method is designed to balance these parameters automatically and instabilities from the interaction of workstations are avoided. Once computed, the evaluation of the feedback law is cheap. Similar to PID, for the problem setting the truncation due to (4.7) needs to be accounted for in the computation of the control parameters. Again, if RRCF aims to assign more than n^{RMT} RMTs, then the truncation in (4.7) also may not be optimal and potentially destabilizing.

5.4. SUMMARY

This chapter concentrated on the implementation of PID and RRCF control methods on the design and theoretical stability analysis in the capacity control of job shop systems. The PID method as the benchmark for the RRCF method was firstly introduced. Different from the PID control method, RRCF is firstly applied for a SISO system. For the control of a complex MIMO system, a decoupling controller was designed to transform the MIMO system into multiple SISO systems. The stability of both the PID and RRCF control systems were analysed in three scenarios: (1) nominal case without delays and disturbances, (2) only with disturbances and (3) with delays and disturbances. After the design and analysis of these two control systems, we discussed and compared qualitatively these two control methods considering the design structure and parametrization of the controllers.

6 Numerical Simulation

In the previous Chapter 5, we introduced the controller design, theoretical stability analysis and qualitative comparison of proportional-integral-derivative (PID) and operator-based robust right coprime factorization (RRCF) methods in the capacity control of job shop manufacturing systems. In this chapter, we further analyse and compare the dynamics, stability and robustness of these two control systems from simulation perspective. We first introduce the design of an abstract interface for the comparison of these two control methods. Based on the interface, we further analyse and compare the performances of these control methods through simulation of a four-workstation three-product job shop system for the same three scenarios as in the theoretical analysis: (1) nominal case without delays and disturbances, (2) with disturbances and (3) with delays and disturbances. Furthermore, uncertainties, including external stochastic demands and internal transportation delays, are analysed for the robustness comparison.

6.1. Abstract Control Interface

In order to compare PID and RRCF in the capacity control at same cases, we adopt an abstract user interface based on Matlab software for a n-workstation m-product job shop system, which was designed in [7]. An abstract interface, as one type of interface model, provides a high-level description of the function and purpose without specifying how it is to be achieved. Therefore, this kind of interface is a useful expression of the design at the conceptual level, which is easy to edit and elaborate [262]. Generally, input and output are two essential components of the interface [263, Chapter 1]. In the abstract interface for PID and RRCF in the capacity control of job shop systems, the structure of the interface is given as in Figure 6.1. The input is the number of reconfigurable machine tools (RMTs) from respective controllers, the output is the current status of the system including, e.g., the input and output rates and work-in-process (WIP) levels.

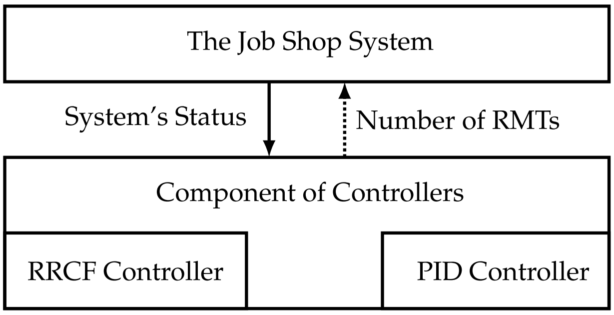

Figure 6.1.: Structure of the abstract interface

The software used for the interface design is another important factor [264]. Matlab is a powerful tool for simulation of control systems and interface design. It is a high-performance language for technical computing. In particular, it integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Here, we aim to create an abstract control interface for a multi-input multi-output (MIMO) job shop system, which allows us to compare all possible types of controllers and to analyse the behaviour of the model regarding different phenomena. The abstract interface for both PID and RRCF controllers is depicted in Figure 6.2. Here, the interface provides parameters as well as initial values of variables to the controllers, which are indicated by continuous lines. In turn, the controllers feedback the number of RMTs to the job shop model, which is indicated by dashed lines. Considering the job shop model from Chapter 4, the parameters and variables of a single workstation are the initial order input rate, orders input and output rates, initial, current and planned WIP levels, number and production rate of RMTs and dedicated machine tools (DMTs) as well as reconfiguration and transportation delays and disturbances. While the required data to compute the control input is dependent on the controller formulation, the feedback loop structure as sketched in Algorithm 1 remains identical for all controllers.

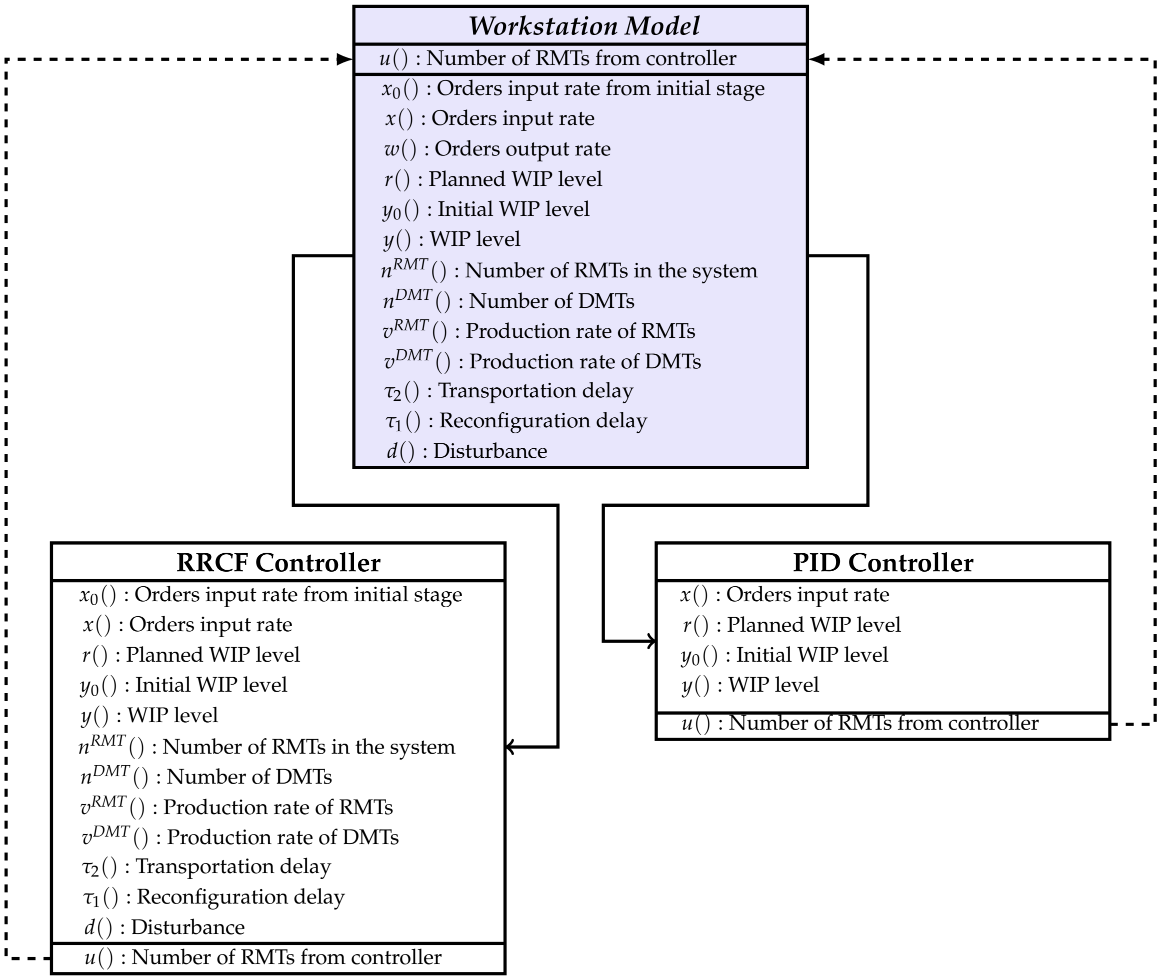

Figure 6.2.: Abstract interface for PID and RRCF methods in the job shop system, after [7]

Algorithm 1 Abstract closed-loop

1: **Given** initial WIP values $y_j(0)$ $j \in \{1, \ldots, n\}$.
2: **while** Termination criterion not met **do**
3: Measure input rates x_{kj}, $k, j \in \{0, 1 \ldots, n\}$
4: Compute control inputs $u_j(t)$ for all $j \in \{1, \ldots, n\}$
5: Apply controls to workstations
6: **end while**

6.2. Simulation of Capacity Control

With the abstract interface, we discuss PID and RRCF methods in the capacity control of a job shop system. Here, we consider a simulation setting instead of an experimental rig, as it allows the comparison of different control approaches more easily. We consider a four-workstation three-product job shop system presented in [259] using Matlab to evaluate the influence and efficiency of control methods as shown in Figure 6.3. The workstations operate for turning, milling, chamfering and drilling, respectively. Within the job shop system, a total of 10 RMTs is adopted. The respective parameter setting of the system is shown in Table 6.1. The probabilities of order flows between the workstations are dynamically changing with the dynamical order input and output rates [265]. The flow probability p^l_{jk} is the order flow of product l from workstation j to workstation k. In this case, $p^l_{jk} = p_{jk}$. Then we have following simulation results of the capacity control systems with three scenarios in Sections 6.2.1, 6.2.2 and 6.2.3.

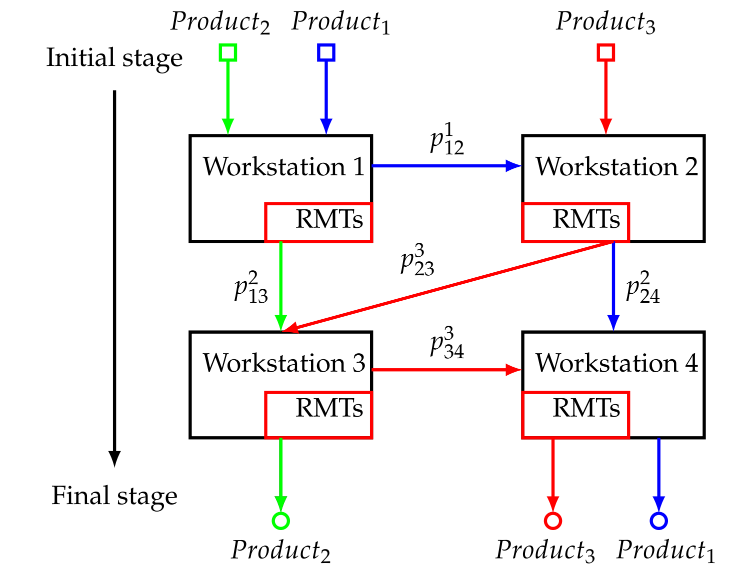

Figure 6.3.: A four-workstation three-product job shop system with RMTs

Table 6.1.: Parameters setting of the four-workstation three-product system

Workstation j	1	2	3	4
Initial WIP level $y_j(0)$	400	400	300	200
Planned WIP level r_j	240	400	400	240
Number of DMTs n_j^{DMT}	4	2	2	4
Production rate of DMTs v_j^{DMT}	20	40	40	20
Production rate of RMTs v_j^{RMT}	10	20	20	10

6.2.1. Simulation Results without Delays and Disturbances

Without delays and disturbances, the PID and RRCF control systems have been discussed in Section 5.1.2.1 and 5.2.3.2. In this scenario, we assume that the orders input rate of each product from the initial stage is fixed to 51 orders per hour. There is no reconfiguration delay and transportation delay. Based on the initial setting, we simulate these two control processes for 300 hours. The sampling time is 1 hour. The simulation results for the PID and RRCF control systems are shown in Figures 6.4 – 6.6.

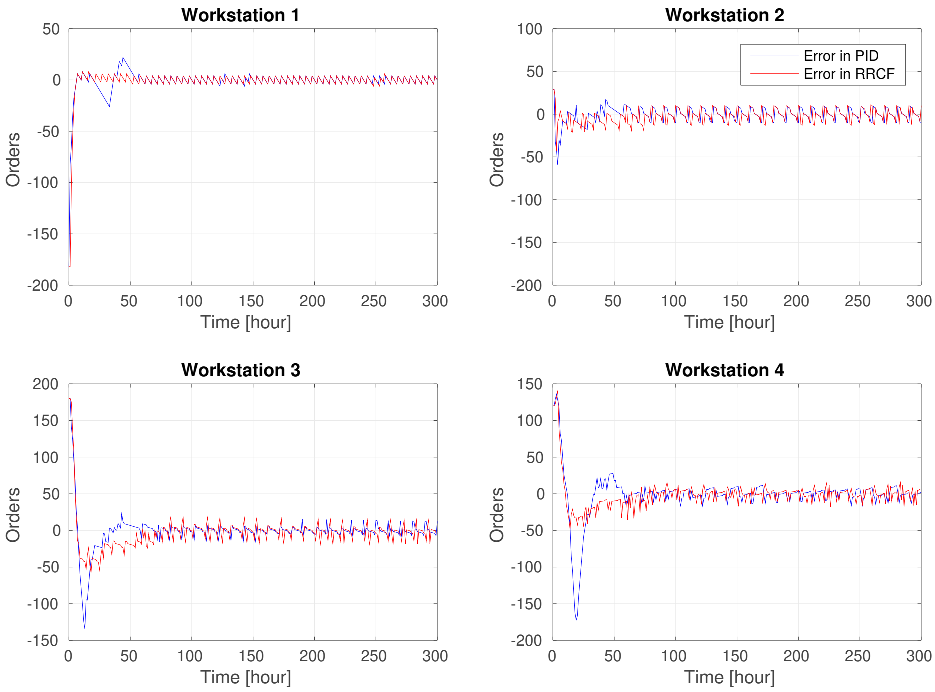

Figure 6.4.: Errors between planned and current WIP levels of workstations

In this case, as Product 1 and 2 are produced starting from Workstation 1, and Product 3 starting from Workstation 2, these two workstations may represent a bottleneck at the beginning of the simulation. Figure 6.4 illustrates the error between the planned and current WIP level of each workstation. The WIP levels of all workstations were practically stabilized (cf. [266, Chapter 2] for details) in the first 100 hours. The respective distribution of RMTs in the first 100 hours is shown in Figure 6.5. The blue and red lines present errors and number of RMTs within PID and RRCF control systems, respectively.

At Workstation 1, at the beginning of the simulation, due to input orders from the initial stage, the WIP level increased and induced a bottleneck, thus RMTs were assigned to this workstation at the first few hours in both control systems. The WIP level of RRCF was practically stabilized in 6 hours, while the PID took more than 50 hours. Thereafter, the respective number of RMTs were between 2 to 3 and the WIP level showed scattering but bounded behaviour. Additionally, the WIP level within the PID system showed higher overshoots, which indicated the degree of the bottleneck in the workstation.

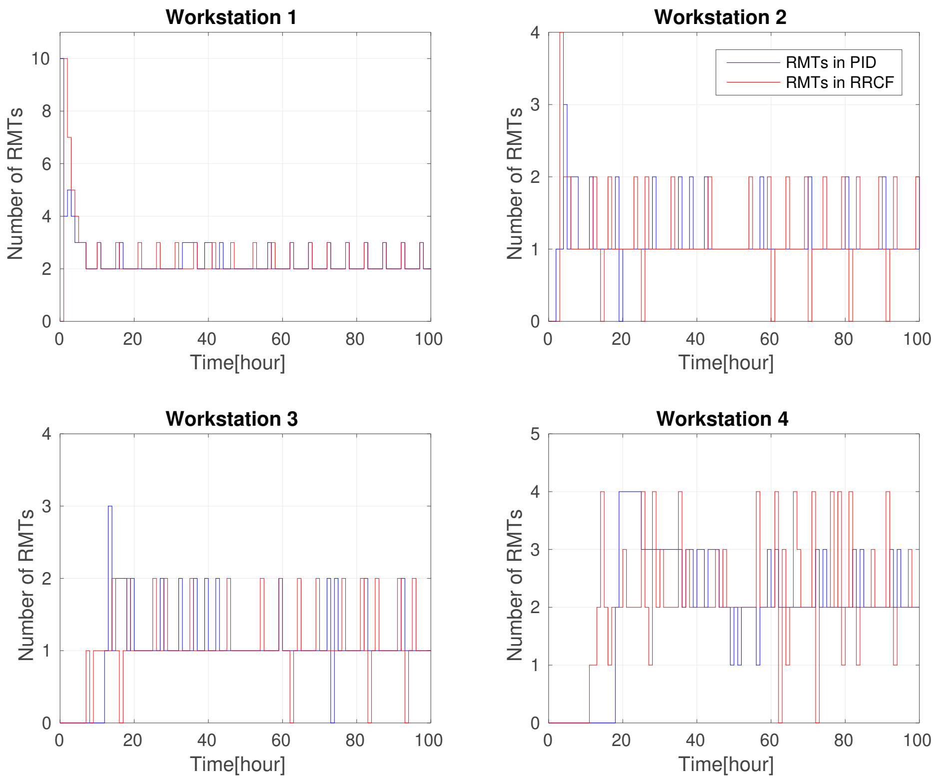

Figure 6.5.: Number of RMTs at each workstation

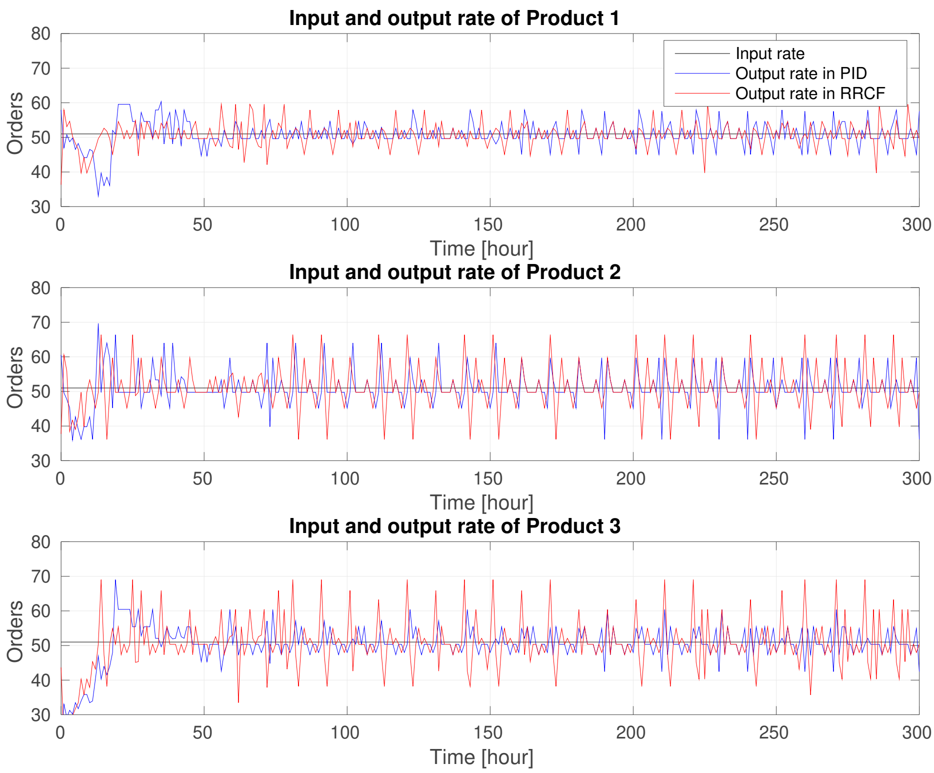

Figure 6.6.: Input and output rates of each product

At Workstation 2, owing to the order flows from the initial stage and Workstation 1 to this workstation, the WIP was quickly increased over the planned level and induced a bottleneck. At this time, both controllers started assigning RMTs to this workstation. The RRCF directly assigned 4 RMTs to this workstation and quickly solved the bottleneck problem. The WIP level was also practically stabilized in time. Here, PID firstly assigned 1 RMT to this workstation, which didn't solve the bottleneck. Thereafter, it assigned 2 and later 3 RMTs to this workstation, which resulted in a longer settling time than the RRCF.

At Workstation 3 and 4, after around 10 hours the bottleneck was shifted to these two workstations, the WIP levels were quickly increased over the planned level. Same as for Workstation 2, both control systems started assigned RMTs to these workstations, while the RRCF control system displayed quicker response to solve the bottlenecks. Moreover, the WIP levels of these two workstations within RRCF and PID tended to be practically stable after 50 hours, while PID showed higher overshoots and more oscillations.

From the Figures 6.4 and 6.5, we obtained that both PID and RRCF methods solved the bottlenecks and practically stabilized the system by controlling the distribution of RMTs. With the bottleneck issue solved, a constant configuration was reached, the WIP showed practically stable behaviour close to the planned level, which implied the orders input and output rates also coincided. However, RRCF showed a quicker response with shorter settling times and less overshoots than PID. More detailed information of each workstation is summarized in Table 6.2 including mean number of RMTs (MRMT), mean absolute error (MAE) and standard deviation of the absolute error (SDAE) between the planned and current WIP, and mean input rate (MIR) and mean output rate (MOR). We further obtained that the practically stabilized control systems shared almost the same mean utilization of RMTs, and the orders output rates also satisfied the input rates at all workstations. Nevertheless, the MAE and SDAE depicted the WIPs in RRCF were closer to the planned levels at most times during the control processes.

Table 6.2.: Performance measures of workstations

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.25	1.10	1.08	2.12	2.25	1.11	1.08	2.12
MAE	4.82	6.24	10.23	13.69	4.34	6.56	12.47	11.21
SDAE	12.60	6.50	24.55	29.01	16.14	5.72	22.11	18.45
MIR	102.00	102.10	101.89	101.39	102.00	102.10	101.91	101.32
MOR	102.52	102.13	101.53	101.23	102.52	102.13	101.53	101.16

After the analysis of each workstation, we further analysed the performance of each product. Figure 6.6 shows the orders input and output rates of each product. The orders input rate of each product in black lines is fixed to 51, while the output rate showed scattering but bounded behaviour for both PID and RRCF control systems. Corresponding to Figure 6.5, as RMTs were assigned to Workstation 1 and Workstation 2 at the first few hours, the capacity of Workstation 3 and Workstation 4 were lower. Due to all products were finished at Workstation 3 and 4, the output rates of all products were lower than the input rate. After about 15 hours, RMTs were assigned to the latter two workstations, which increased the output rates close to the input rate and were practically stabilized. Because RRCF assigned RMTs earlier than PID to the latter two workstations, the output rates of RRCF showed shorter settling times.

To summarize, we can conclude that both PID and RRCF can solve bottlenecks, ensure practical stability of the capacity control job shop system and satisfy fixed customer demand. Nonetheless, compared to PID, RRCF showed quicker response with shorter settling times and less overshoots.

6.2.2. SIMULATION RESULTS WITH DISTURBANCES

After the simulation of the nominal scenario without delays and disturbances, we further analysed the performance of this system with disturbances. In Sections 5.1.2.2 and 5.2.3.3, we theoretically analysed the stability of the disturbed system in PID and RRCF methods. In the simulation, rush orders are considered as a disturbance. Based on the nominal scenario simulation setting, each product had additional 29 orders rush to the system at 150 hour. The simulation results are shown in Figures 6.7 – 6.9, where the performance of the first 150 hours are identical to the nominal scenario in Figures 6.4 – 6.6, respectively. Here, we concentrate on the performance of the latter 150 hours for the rush orders.

The simulation result of the error between planned and current WIP of each workstation is shown in Figure 6.7. Before 100 hours, all workstations showed practically stable behaviour. At 150 hour, the rush orders destroyed the current stability but a few hours later, both PID and RRCF control systems were practically stabilized again. The errors and respective distribution of RMTs at each workstation from 150 to 200 hours are illustrated in Figure 6.7 and Figure 6.8.

At Workstation 1, additional 58 orders rushed to the workstation at 150 hour, with the result that the WIP was highly increased over the planned level, cf. Figure 6.7. At this time, PID and RRCF separately assigned another 2 and 3 RMTs to increase the output rate of the workstation, cf. Figure 6.8. RRCF took three hours to re-stabilize the WIP level, while PID took around 40 hours with overshoots. This denoted both PID and RRCF control systems could deal with rush orders, but the latter showed a

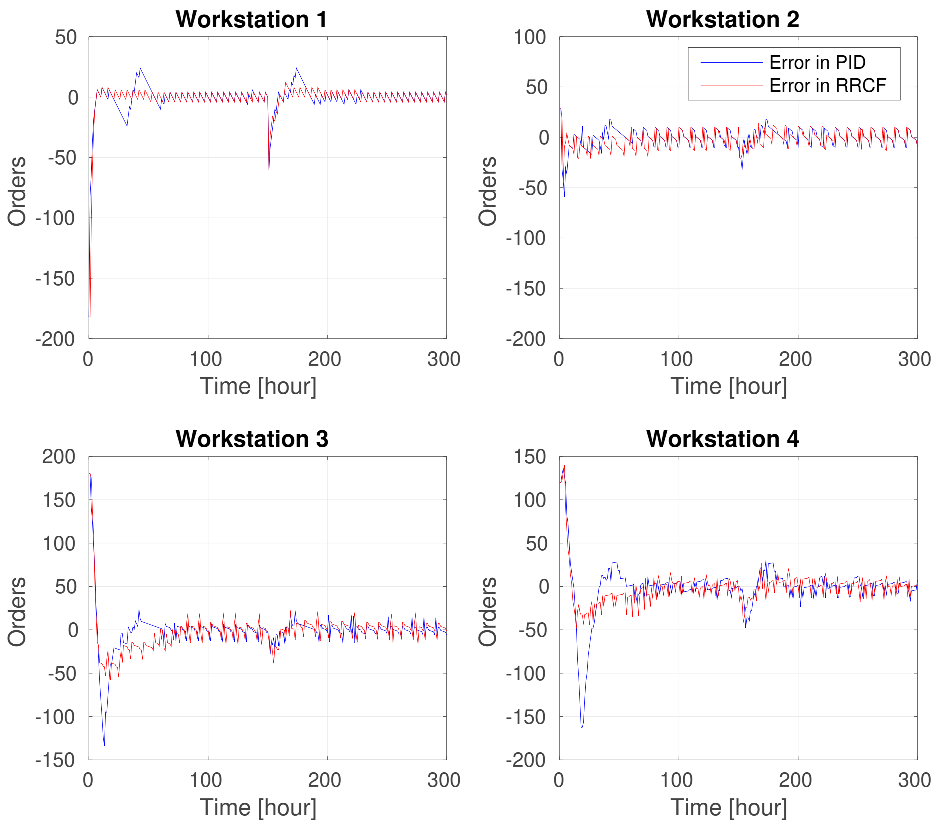

Figure 6.7.: Errors between planned WIP and current WIP levels of workstations with disturbances

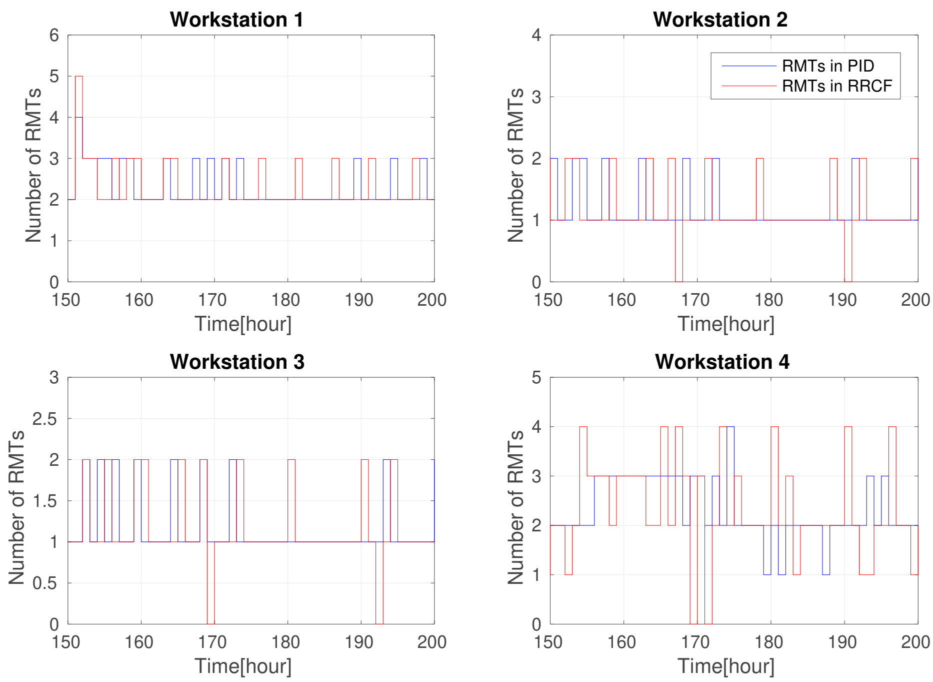

Figure 6.8.: Number of RMTs at each workstation with disturbances

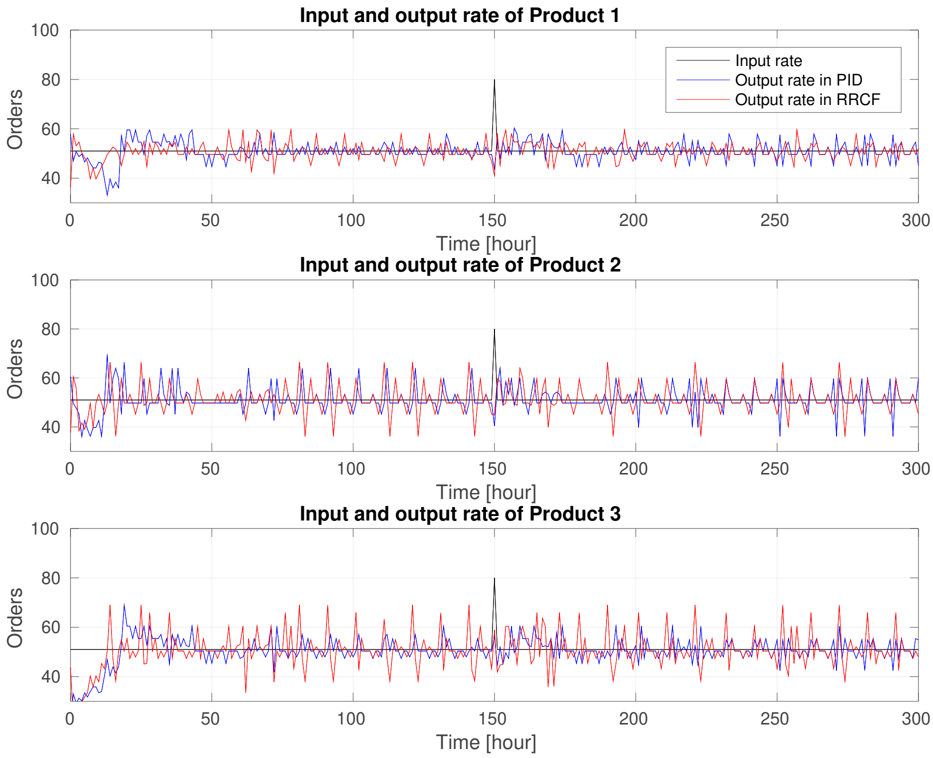

Figure 6.9.: Input and output rates of each product with disturbances

quicker response with shorter settling times and less overshoots than the PID system.

Workstation 2 also had additional rush orders from the initial stage and Workstation 1 at 150 hour. Therefore, the WIP was increased over the planned level result in bottleneck problem as shown in Figure 6.7. To deal with this problem, 2 RMTs were assigned to this workstation in both control systems, while the RRCF was relatively quicker, cf. Figure 6.8. In 20 hours, both control system was practically stabilized again. Due to the rush orders, the WIP levels of Workstation 3 and 4 were also increased and induced bottlenecks. Same to Workstation 2, both PID and RRCF also assigned additional RMTs to deal with the rush orders to ensure that the WIPs are close to the planned levels. This indicated that these two control systems could deal with rush orders to ensure the practical stability of the job shop system, but RRCF showed quicker response with shorter settling times and less overshoots.

The performance including MRMT, MAE, SDAE, MIR and MOR of all workstations are given in Table 6.3. We found that there was no big difference between PID and RRCF control systems in the MRMT, MIR and MOR. This also indicated both control systems could ensure the practical stability of the disturbed system. Whereas, owing to the settling times and overshoots differing, the MAE and especially the SDAE in the RRCF were smaller than for the PID system.

The orders input and output rates of each product is shown in Figure 6.9. At 150

Table 6.3.: Performance measures of workstations with disturbances

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.27	1.11	1.09	2.15	2.27	1.12	1.09	2.14
MAE	6.15	6.62	10.64	15.25	5.18	6.73	13.05	12.07
SDAE	13.50	6.82	24.56	28.78	16.63	5.83	21.98	18.48
MIR	102.19	102.29	102.08	101.57	102.19	102.29	102.07	101.52
MOR	102.72	102.26	101.79	101.46	102.72	102.33	101.73	101.40

hour, the input rate of each product in black line was increased to 80. Because the rush orders were produced from Workstation 1 and 2 and finished in Workstation 3 and 4, the output rates, were still practically stabilized but showed a slight increase compared to Figure 6.6.

In all, we conclude that both PID and RRCF control methods can deal with rush orders to retain the practical stability of the job shop system, while the RRCF control system has a quicker response and better transient performances on the settling times and overshoots.

6.2.3. Simulation Results with Delays and Disturbances

In Chapter 4, we introduced the modelling of job shop systems with RMTs, which comprised two delays: reconfiguration delay τ_1 and transportation delay τ_2. The former displays the time of an RMT changing the operation from one to another, which is assumed to be two hours. The latter delay is the time when orders flow from one to other workstations, which is fixed to 1 hour in this simulation. Based on the setting of the disturbed system in Section 6.2.2, we further include these two delays into the simulation. Then, we have the following simulation results for the disturbed and time-delayed system with PID and RRCF methods in Figures 6.10 – 6.12. Regarding the reconfiguration delay, we have the following rule for the implementation in Algorithm 2.

For each workstation, the error between planned and current WIP is shown in Figure 6.10. Compared to Figure 6.7, we obtained that the delays highly influenced the transient performance, such as higher overshoots and longer settling times in both PID and RRCF control systems. Compared to the PID system, the RRCF system still showed a quicker response with better transient performance on the settling times and overshoots. Both control systems were practically stabilized before 100 hours. The distribution of RMTs in the first 100 hours is illustrated in Figure 6.11. We obtained that due to the reconfiguration delays, there was no RMT working in the system at the beginning of the simulation. After two hours, RMTs started

Algorithm 2 Implementation of reconfiguration delay

Input initial variable u_{delay} for the number of RMTs at each workstation $j \in 1, 2, 3, 4$.
for $j = 1 : 4$ **do**
  if $t = 0$ **then**
    for $i = 1 : \tau_1$ **do**
      $u_{delay}(j, i) = 0$
    end for
  end if
end for
for $j = 1 : 4$ **do** ▷ Compared current u to previous $u_{previous}$
  if $u > u_{previous}$ **then**
    $u_{delay}(j, \tau_1 + 1) = u(j)$
  else
    for $i = 1 : \tau_1 + 1$ **do**
      $u_{delay}(j, i) = u(j)$
    end for
  end if
  $\hat{u}(j) = u_{delay}(j, 1)$ ▷ Obtained the real number of RMTs $\hat{u}$
  for $i = 1 : \tau_1$ **do** ▷ Shifted the variable
    $u_{delay}(j, i) = u_{delay}(j, i + 1)$
  end for
end for
Output the real number of RMTs to the system

working for Workstation 1 to deal with the bottleneck and later on to other workstations. Compared to PID, RRCF still displayed quicker response with shorter settling times and less overshoots. Regarding the rush orders at 150 hour, both control systems still showed ability to solve the bottleneck problems, but they took longer time compared to Figure 6.7. Then we concluded that both PID and RRCF can ensure the practical stability of the disturbed and time-delayed system, while RRCF still showed quicker response with shorter settling times and less overshoots.

We also calculated the MRMT, MAE, SDAE, MIR and MOR of each workstation within both control systems in Table 6.4. There also is no clear difference between PID and RRCF control systems about the MRMT, MIR and MOR, while the MAE and SDAE in RRCF were still obviously lower than the PID system. This indicated that RRCF was more effective than PID to deal with delays and disturbances to ensure the WIPs of workstations close to the planned levels.

Figure 6.12 presents the orders input and output rates of each product. The orders input rates of all product were also fixed to 51 orders per hour in black lines, and at 150 hour they rushed to 80. Compared to Figure 6.9, the output rates also showed longer settling times and higher overshoots in both PID and RRCF control

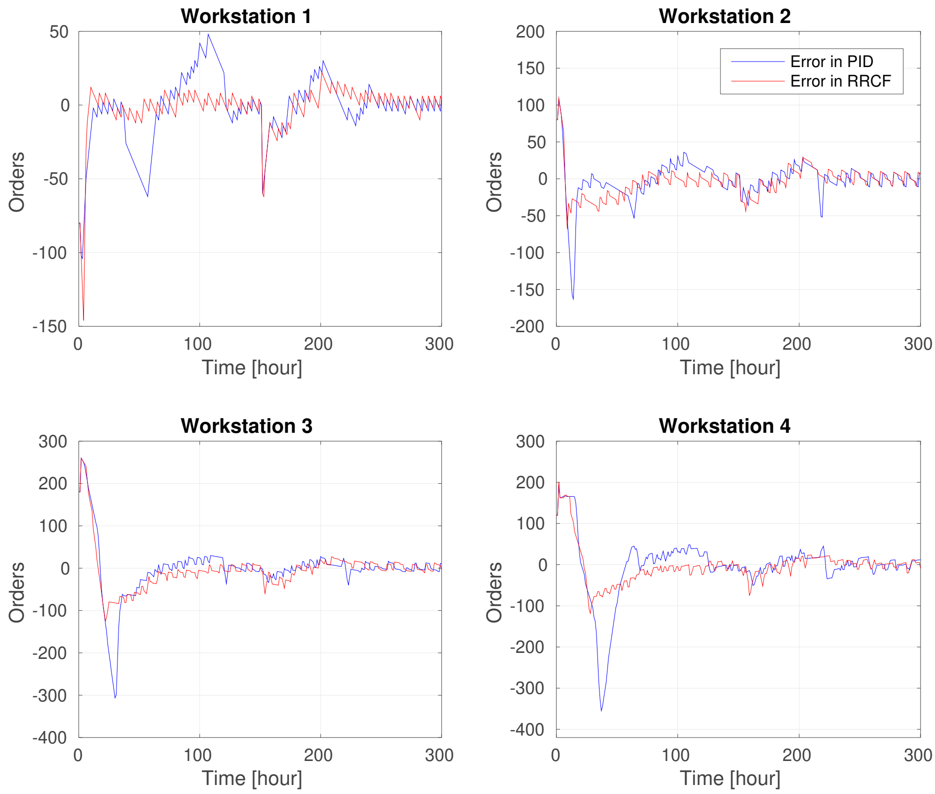

Figure 6.10.: Errors between planned and current WIP levels of workstations with delays and disturbances

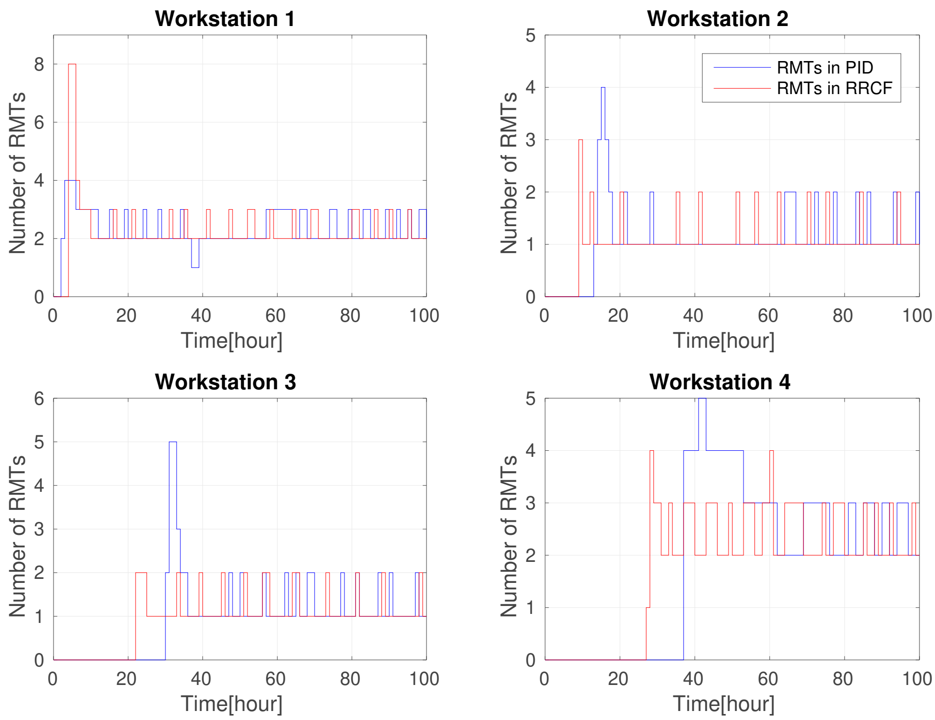

Figure 6.11.: Number of RMTs at each workstation with delays and disturbances

Table 6.4.: Performance measures of workstations with delays and disturbances

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.24	1.09	1.05	2.08	2.24	1.09	1.05	2.08
MAE	15.01	15.77	32.30	40.48	8.45	14.03	28.53	25.952
SDAE	17.97	21.93	58.91	64.19	15.82	16.05	43.63	36.37
MIR	101.85	101.77	101.40	100.59	101.85	101.79	101.42	100.64
MOR	102.39	101.79	101.06	100.41	102.39	101.79	101.06	100.48

systems. At the first 20 hours, there was no RMTs working for Workstation 3 and Workstation 4, so the output rates of the products were lower than the input rate. After about 20 hours, RMTs were assigned to the latter two workstations, then the output rates were increased and practically stabilized. The rush order didn't highly influence the output rates in the RRCF system but for the PID system.

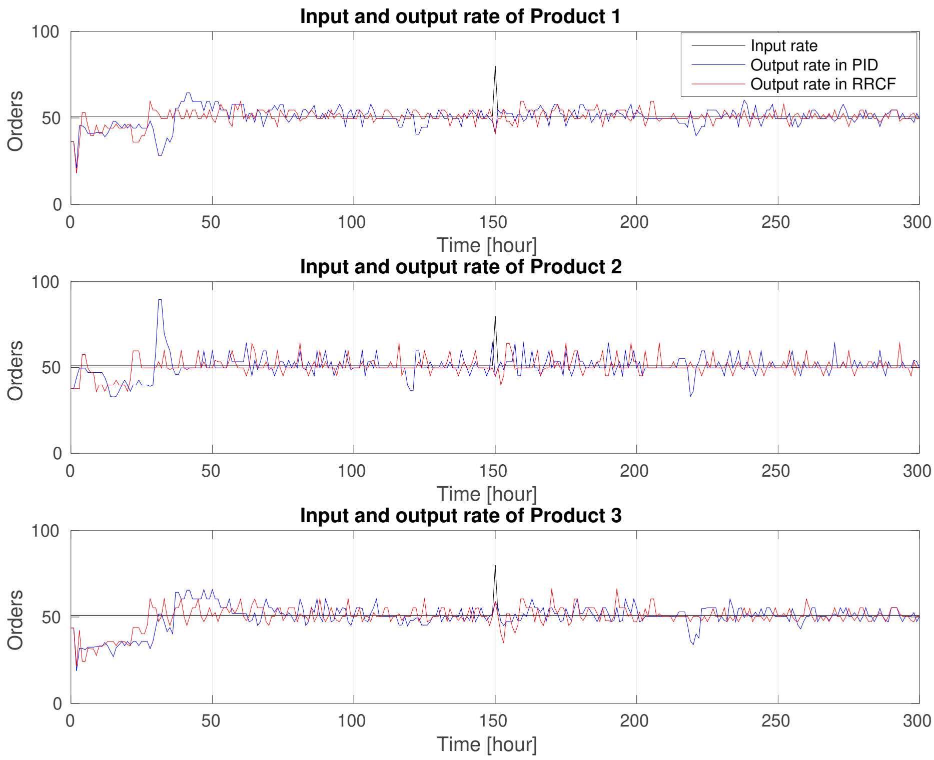

Figure 6.12.: Input and output rates of each product with delays and disturbances

From the simulation of the given three scenarios, we can conclude both PID and RRCF methods can ensure practical stability of the capacity control job shop system with RMTs. For each workstation, the WIP showed practically stable behaviour close to the planed level, which implied the orders output rates also could practically track the input rates. For each product, the output rate was also practically stabilized and close the input rate. Whereas, the RRCF control system displayed better transient performance on the settling times and overshoots than the PID system. This indicated that RRCF was more effective than PID on the capacity control of job shop systems to deal with delays and disturbances.

6.3. UNCERTAINTY ANALYSIS

In the above section, we focused on the transient and stability analysis of the capacity control job shop system with constant demand, where the transportation delay was assumed to be fixed. However, in practice, the latter are typically time-varying, and highly affect the performance of the capacity control systems. Therefore, we focused on robustness analysis and comparison of PID and RRCF control systems for these uncertainties. Here, the Monte-Carlo simulation is applied to analyse the robustness of these two control systems for external volatile customer demand and internal varying transportation delay, cf. Figure 6.13. This method is based on repeated random samples to get numerical results. It mainly includes the following steps: (1) generating a large number of input samples according to their distribution patterns, (2) estimating the output corresponding to each input sample through simulation, (3) analysing and aggregating the results [267]. In this simulation, we also use the case in Figure 6.3 and the basic setting in Table 6.1. Figure 6.13 illustrates the process of the uncertainty analysis within Matlab software.

Within the Monte-Carlo simulation, the first step is to generate a large number of random numbers. Here, we initially set the dimension (e.g., 3 types of products) and length (e.g., 301 sample points) of each control process, as well as the iteration times (e.g., 1000) of the simulation. Then, we generate the required (e.g., $3 \cdot 301 \cdot 1000$) random numbers with respective Gaussian distribution as a base for the uncertainty.

In the second step, we simulate the control processes and estimate the related output variables, such as the WIP levels and order output rates of workstations. The detailed process is identical to Section 6.2. Firstly, we initialize the setting of the job shop system and input one set of random numbers at each sample point. With the current status of the system, the controller (PID or RRCF) calculates the number of RMTs for the workstation. Considering the reconfiguration delay of RMTs, the system gets the real number of RMTs at each workstation, and then we calculate, shift and save the current values of variables of the system, such as the WIP levels, the orders input and output rates of each workstation and product. If the simulation length of the control process (e.g., 300 hours) is not finished, we input another set of random numbers to the system and repeat the calculation process. Otherwise, we check the iteration time of the simulation (e.g., 1000 times). If the iteration is not finished, we initialize the setting of the system again and repeat the simulation process for another set of random numbers.

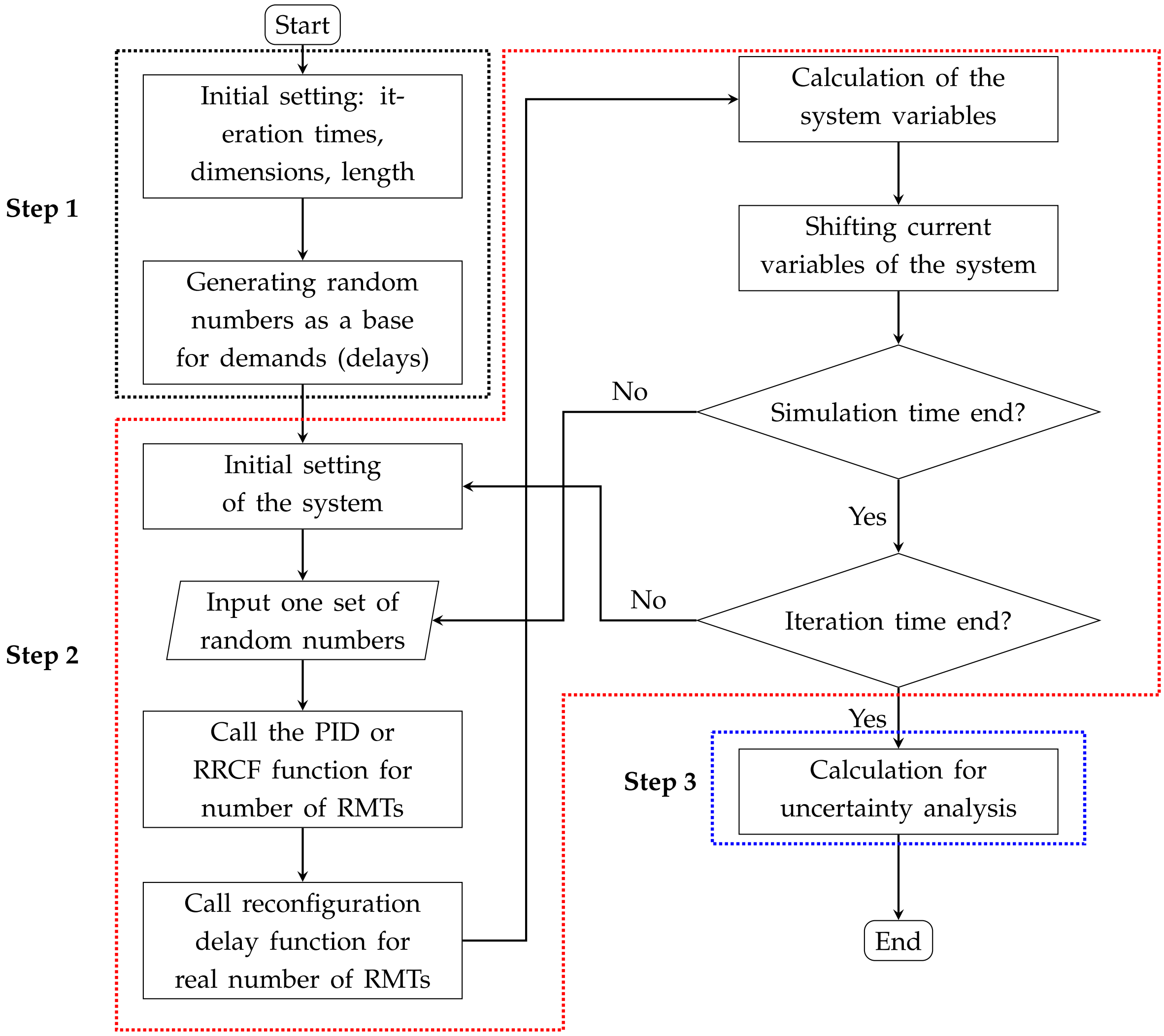

Figure 6.13.: Monte-Carlo simulation for uncertainty analysis

After all simulations, the next step is to calculate and analyse the performance of these two control systems, e.g., the distributions of errors between the current and planned WIP levels and orders output rates of products. For these distributions, the mean and standard deviation values of the absolute errors between the planned and current WIP levels of workstations are calculated to analyse and compare the robustness of the control systems. The mean and standard deviation of the distribution of RMTs are calculated as the robustness cost. Additionally, the mean transient performance of the system, such as the mean of settling times and overshoots, are also displayed.

Based on the method, we firstly analyse the performance of these two control systems for external uncertainty (i.e. volatile customer demand) in Section 6.3.1 and then for internal uncertainty (i.e. varying transportation delay) in Section 6.3.2.

6.3.1. ANALYSIS FOR STOCHASTIC DEMANDS

As known, volatile customer demand is a big challenge for manufacturers, which highly affects the stability of the capacity control system. The demand of each product was assumed to be bounded and satisfy a Gaussian distribution $N(\mu, \sigma^2)$ [268], where the mean value was $\mu = 51$ and identical to Section 6.2. We considered three scenarios with Gaussian distribution in (1) $N(51, 2.5^2)$, (2) $N(51, 5^2)$ and (3) $N(51, 10^2)$, where the mean value was fixed, and the standard deviations were increased with around the 5%, 10% and 20% of the mean value. We first focused on the analysis and comparison the mean transient performances and robustness of these two control systems in the Gaussian distribution $N(51, 2.5^2)$. Then, we focused on the robustness analysis and comparison of these three scenarios. In each scenario, the setting of each control process simulation was identical to Section 6.2.3 but with volatile demands. The simulation of the capacity control process was conducted 1000 times (i.e. iteration time). Then we got that the dimension (3 types of product) and length (301 sample points in the control process) are 3 and 301 respectively. The quantity of the random number was $3 \cdot 301 \cdot 1000$ for the Monte-Carlo simulation. Here, the transportation delay was fixed to 1 hour.

When the input rates of products satisfying the Gaussian distribution $N(51, 2.5^2)$ were limited between 40 to 60, cf. Figure A.4 in the Appendix, we obtained the following results for both PID and RRCF control systems displayed in Figures 6.14 – 6.16 and Tables 6.5 – 6.6. Figure 6.14 shows the mean errors between planned and current WIP levels of each workstation within both PID and RRCF control processes for 1000 simulations. The respective MRMT at each workstation is given in Figure 6.15. Different from the graphs in Section 6.2, the mean errors and number of RMTs showed stable behaviours in these two control systems. However, the transient performance including the settling times and overshoots were highly different in PID and RRCF. The red and blue lines represent the values within RRCF and PID, respectively.

At Workstation 1, the initial WIP was higher than the planned level and also there were additional input orders from the initial stage. This induced a bottleneck, so both controllers started assigning RMTs to the workstation. Due to the reconfiguration delay, no RMTs worked for the workstation at first two hours, therefore, the WIP was continuously increasing over the planned level (the mean error was decreasing). Two hours later, RMTs started working for the workstation, the WIPs were decreased quickly and less than the planned level. Then some RMTs were de-assigned and the WIP levels in both control systems were increased again. The RRCF control system were quickly stabilized in around 20 hours, while the PID system showed stable behaviours after 150 hours.

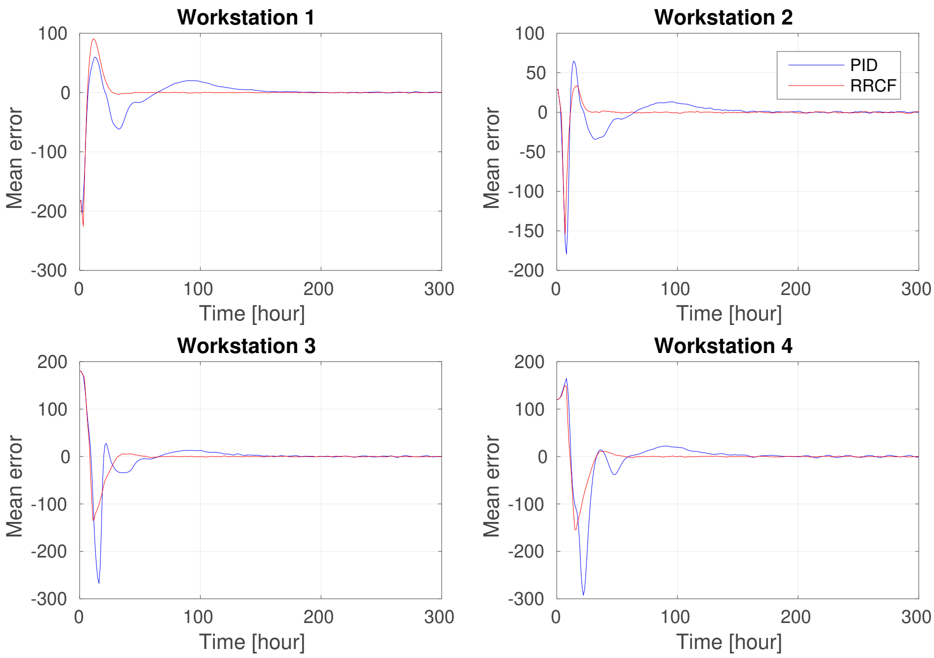

Figure 6.14.: Mean errors between planned and current WIP levels of workstations for stochastic demands with $N(51, 2.5^2)$

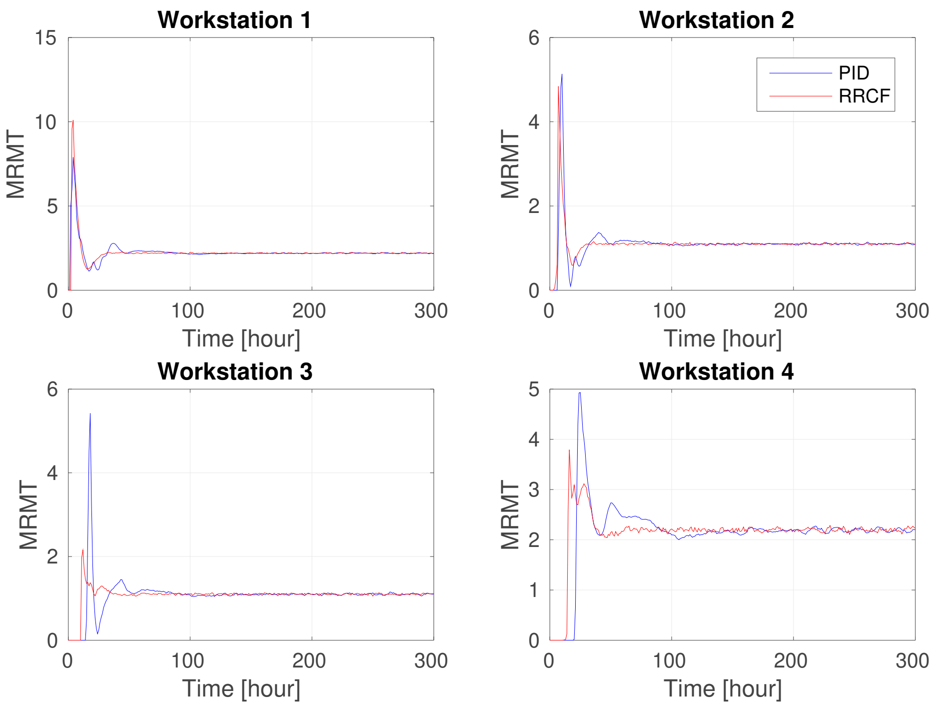

Figure 6.15.: Mean number of RMTs at each workstation for stochastic demands with $N(51, 2.5^2)$

At Workstation 2, the initial WIP was less than the planned level. Because of more input orders from Workstation 1 and from the initial stage, and less output due to no RMT working at the workstation at first few hours, the WIP was increased and over the planned level. This led to a bottleneck, then controllers started assigning RMTs to the workstation and the mean number of RMTs was increased, but the RRCF control system has a quicker response than the PID system. Later on, the mean error in RRCF was quickly stabilized in 20 hours, but 150 hours in PID. As the bottleneck shifted to Workstation 3 and 4, RMTs were also assigned to these two workstations, again RRCF also showed quicker response with shorter settling times and less overshoots than PID. Additionally, the standard deviations of the errors showed similar behaviours to the mean values of the error, cf. Figure A.5 in the Appendix. However, the values of the standard deviations in RRCF are less than PID. This illustrated that the WIP of each workstation could be robustly stabilized to the planned level, and the input and output rate could coincide in a bound facing the bounded stochastic demands.

To compare the robustness between PID and RRCF control systems, Table 6.5 summarized the key performance indexes of workstations in these two control systems. MAE and SDAE between planned and current WIP levels of workstations were calculated for the robustness measurement [63]. Here, RRCF showed lower MAE and SDAE than PID. This illustrated that the distribution of WIPs in RRCF were closer to the planned levels with higher robustness than PID. Additionally, the MIR and MOR of each workstation in both control systems were almost the same. To measure the cost of the robustness, the MRMT and standard deviation of the number of RMTs (SDRMT) at each workstation were also calculated. There was no difference on the MRMT in both control systems, while the SDRMT at Workstation 1 and 4 were higher in RRCF, which demonstrated there were more reconfigurations of RMTs at these two workstations. This indicated the cost of the high robustness of these two workstations within RRCF were higher than PID.

Table 6.5.: Performances of workstations for stochastic demands with $N(51, 2.5^2)$

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.25	1.10	1.08	2.12	2.25	1.10	1.08	2.12
SDRMT	0.77	0.62	0.68	1.03	1.01	0.56	0.56	1.31
MAE	20.07	17.88	25.97	37.57	13.55	12.74	19.85	23.73
SDAE	26.32	21.53	39.57	46.41	27.28	15.72	30.02	31.37
MIR	102.00	102.10	101.89	101.35	102.00	102.10	101.93	101.46
MOR	102.53	102.10	101.56	101.22	102.53	102.10	101.60	101.33

Furthermore, the MIR and MOR of each product were also computed in these two control processes after 1000 simulations. With same distribution of orders input rate of each product in $N(51, 2.5^2)$, the MIR in black and MOR in blue and red lines for PID and RRCF control systems are shown in Figure 6.16. The RRCF control system present a quicker response with short settling times and less overshoots than the PID system to track the input orders. This indicated that both PID and RRCF could ensure robust stability, but RRCF displayed better transient performances with shorter settling times and less overshoots in a statistic. The MOR and SDRMT of each product in the simulation of the control processes in 300 hours are given in Table 6.6. The MOR of each product in both control systems were almost close to the MIR, which indicated both control systems could satisfy customer demand. Yet, the standard deviations of orders output rates (SDOR) of Products 1 and 3 finished at Workstation 4 in RRCF were higher than PID, which corresponded to the high SDRMT of Workstation 4 in Table 6.5.

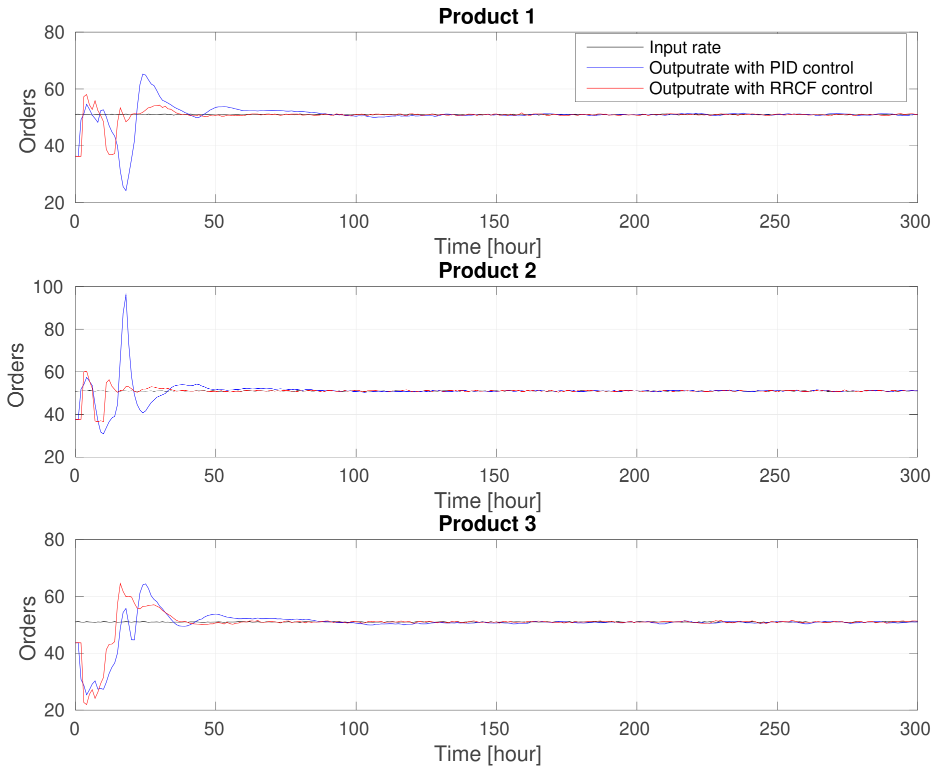

Figure 6.16.: Mean input and output rates of products for stochastic demands with $N(51, 2.5^2)$

Table 6.6.: Performances of products for stochastic demands with $N(51, 2.5^2)$

Controller	PID			RRCF		
Product	1	2	3	1	2	3
MIR	51	51	51	51	51	51
MOR	50.93	51.01	50.29	50.77	50.90	50.56
SDOR	6.24	7.57	7.06	6.67	6.37	8.84

From the above analysis, we conclude that both PID and RRCF can ensure the robust stability of the capacity control job shop system facing the stochastic demands.

However, the RRCF control system is more robust than PID due to the less MAE and SDAE of the distribution of errors between planned and current WIP levels. From the statistics of the control processes, the RRCF showed a quicker response than PID with shorter settling times and less overshoots on the control the WIP levels of workstations and orders output rates of products.

Based on the analysis of PID and RRCF methods in the capacity control systems for the stochastic demands with $N(51, 2.5^2)$, we further considered the robustness of these two control systems for the demands distributions in $N(51, 5^2)$ and $N(51, 10^2)$, respectively. The detail statistic simulation results are given in Appendix A.2.1.2 and A.2.1.3. In these two scenarios, both WIP levels of workstations and orders output rates of products still showed robust stable behaviours, and shorter settling times and less overshoots in RRCF. To compare the robustness of these two control systems with orders input rates of products satisfying $N(51, 2.5^2)$, $N(51, 5^2)$ and $N(51, 10^2)$, the distribution of the errors between planned and current WIP levels of workstations and orders output rates of products are displayed with boxplots in Figures 6.17 and 6.18, respectively. In Figure 6.17, the errors in these two control systems were distributed around 0 in the three scenarios, which indicated the WIPs were controlled around the planning WIP levels in both control systems. With the bound of orders input rates of products extending, the bound of errors of workstations were also extended, but RRCF showed smaller bounds in all scenarios. Also, the bounds of orders output rates of products were also extended but PID with slight smaller bounds, which is corresponding to the lower SDRMT at Workstations 3 and 4, cf. Figure 6.19.

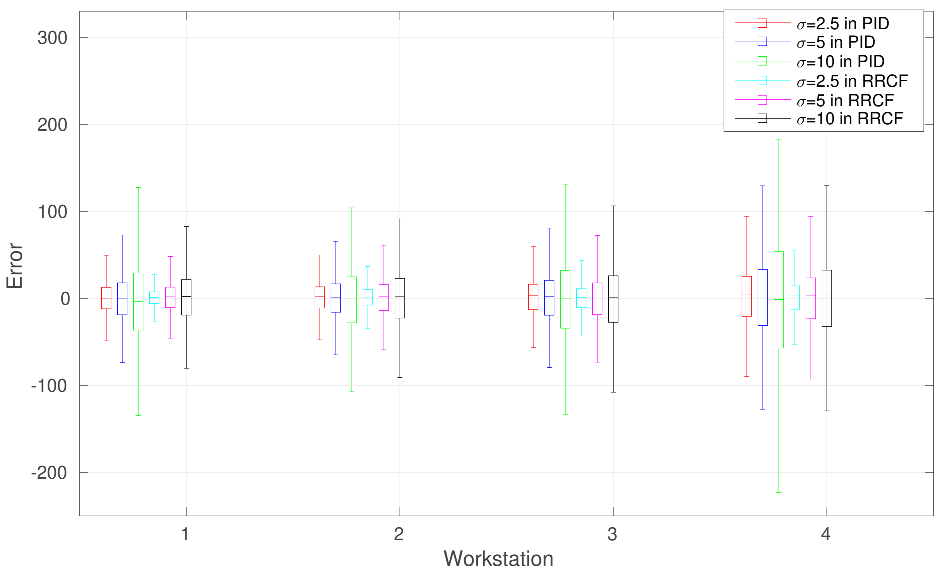

Figure 6.17.: Distribution of errors between planned and current WIP levels of workstations for stochastic demands

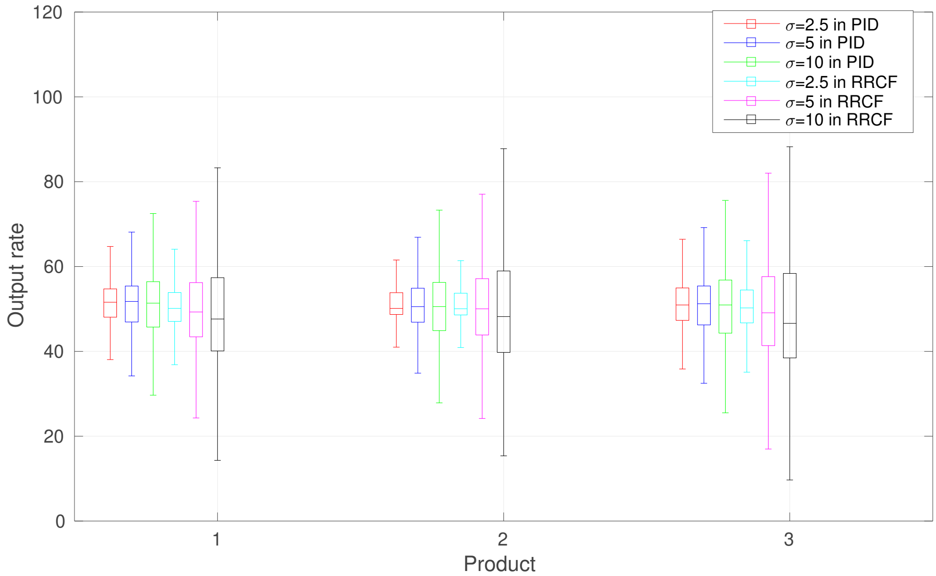

Figure 6.18.: Distribution of orders output rates of products for stochastic demands

Furthermore, to compare the robustness and cost of the robustness of these control systems, the MAE and SDAE between planned and current WIP, the MRMT and SDRMT of workstations are summarized in Figure 6.19. It displayed the MAE and SDAE in RRCF were less than the PID system in all scenarios. With the bound of demands increasing, the MRMT in both control systems almost identical, but the SDRMT was increased. Especially in RRCF, the values of SDRMT in the last two scenarios were highly greater than PID. This displayed more reconfiguration of RMTs in this control system. Then we obtained the RRCF control system was more robust than the PID, but it also took more reconfiguration of RMTs and might increase the cost. The MIR and MOR of each workstation and each product in both control systems were kept almost identical (cf. Figure A.16 in the Appendix), so both control systems could satisfy volatile customer demands within the three scenarios of $N(51, 2.5^2)$, $N(51, 5^2)$ and $N(51, 10^2)$.

In all, we conclude that both RRCF and PID have the ability to deal with stochastic demands and ensure robust stability for the capacity control of job shop manufacturing systems. Yet, the RRCF control system displayed better average transient performance with shorter settling times and less overshoots than PID. As the value of MAE and SDAE between planned and current WIP levels at workstations were less in the RRCF system, RRCF was more robust than PID facing the stochastic demands. Furthermore, with the bound of demands extending, the range of WIP levels of workstations and orders output rates of products in PID and RRCF control systems were also increased. Hence, we got that wider bounds of demand distributions would decrease the robustness of these two control systems, but RRCF displayed higher robustness in all scenarios.

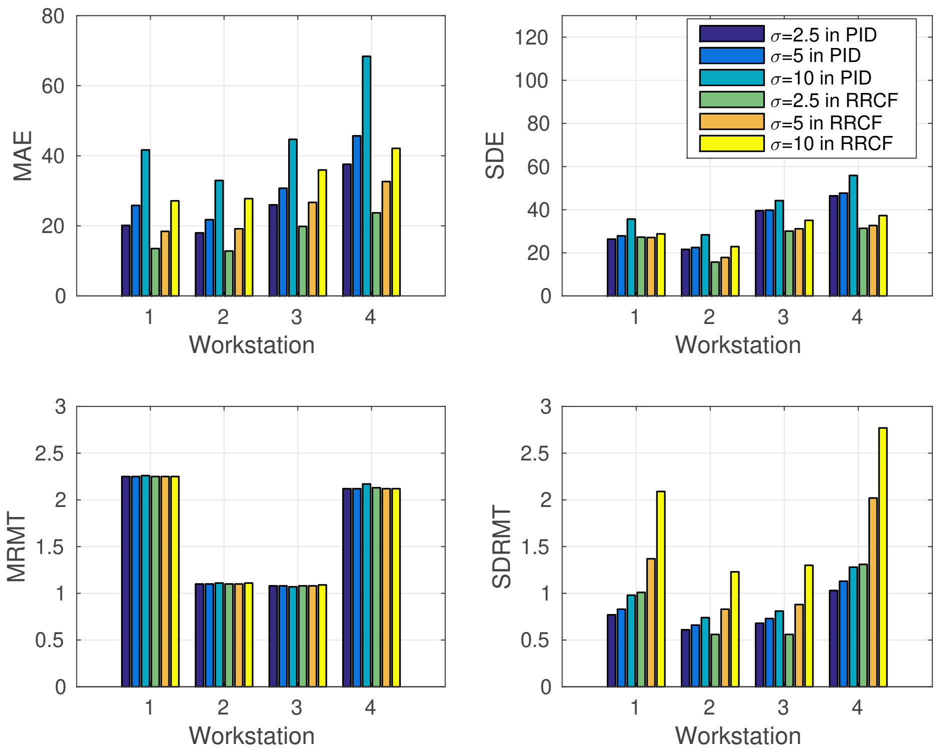

Figure 6.19.: Performance of workstations for stochastic demands

6.3.2. ANALYSIS FOR STOCHASTIC TRANSPORTATION DELAYS

After the external uncertainty analysis, we continue to analyse and compare the performance of PID and RRCF in the capacity control of the job shop system for internal stochastic transportation delays in the orders input rate of each workstation. We use the same setting to the external uncertainty analysis, but the input rate of each product is fixed to 51 and the transportation delay is bounded and follows a Gaussian distribution. We also considered three scenarios with the distribution of delays satisfying $N(1, 0.05^2)$, $N(1, 0.1^2)$ and $N(1, 0.2^2)$. For the four-workstation job shop system in Figure 6.3, the delays in the orders input rate of each workstation can be different. Therefore, we generated $4 \cdot 301 \cdot 1000$ random numbers in the Monte-Carlo simulation. As the sampling time of the simulation is 1 hour, but the random number of the delays have decimals, here it is assumed to be three decimals. Therefore, we have the solution in Algorithm 3 to compute the orders input rates with transportation delay. With the setting, we firstly focus on the performance comparison of PID and RRCF control systems for the same the scenario with transportation delay satisfying $N(1, 0.05^2)$. Then, we compare the robustness of these two control systems for the three scenarios with distribution in $N(1, 0.05^2)$, $N(1, 0.1^2)$ and $N(1, 0.2^2)$.

Considering the transportation delays satisfy the Gaussian distribution $N(1, 0.05^2)$ (cf. Figure A.17 in the Appendix), the Monte-Carlo simulation results are given in

Algorithm 3 Calculation of input rates $x(j)$ of workstation j with transportation delays $\tau_2(j)$ at time t

Input a initial global variable x^T, for the orders input rate without delay $\bar{x}(j)$ of workstation j for $j \in \{1, 2, 3, 4\}$ at time t.
for $i = (t/0.001 + 1) : 1 : (\tau_2(j) + t + 1)/0.001$ **do**
  if $(i <= (\tau_2(j) + t)/0.001)$ **then**
    $x^T(j, i) = x^T(j, i);$
  end if
  if $(i <= ((t + \tau_2(j) + 1)/0.001))$ **then**
    $x^T(j, i) = x^T(j, i) + \bar{x}(j, i) * 0.001;$
  end if
end for
for $i = (1 + (t/0.001)) : (t + 1)/0.001$ **do**
  $x(j) = x(j) + x^T(j, i);$
end for
Output the real orders input rates of workstations

Figures 6.20 – 6.22, and Tables 6.7 and 6.8. Figure 6.20 shows the mean error between planned and current WIP at each workstation in PID and RRCF control processes after 1000 simulations. We obtained the red and blue lines for the mean errors of RRCF and PID showed almost the same settling times, but the PID present more overshoots and oscillations. The corresponding mean number of RMTs at each workstation is displayed in Figure 6.21. The RRCF still showed a bit quicker response. The varying transportation delays may induce bottlenecks. Therefore, the mean number of RMTs in the control process also showed more oscillations.

More statistical data is summarized in Table 6.7, including MRMT and SDRMT, MAE and SDAE, as well as MIR and MOR. We obtained that the mean utilization of RMTs in both control systems was identical, and also the mean output rates could track the orders input rates of all workstations. However, MAE and SDAE for the robustness measurement and SDRMT for the cost of robustness were different. The MAEs in PID were a bit less at Workstation 1 and 2, but greater at Workstation 3 and 4. The overall MAE and SDAE in RRCF were less than PID, but the SDRMT was greater than PID. Then we obtained the RRCF control system was more robust than the PID system, but also required more reconfiguration cost.

Furthermore, the mean input and output rates of products in the control processes with 1000 simulations is displayed in Figure 6.22. When the orders input rate of each product in black lines were fixed, the MOR in PID and RRCF showed stable behaviours after 100 hours. The settling times of both control systems were almost the same, but PID showed greater overshoots and more oscillations. The overall MIR, MOR and SDOR of each product is listed in Table 6.8. The MOR and MIR of each product almost coincided in both control systems and the SDOR were similar.

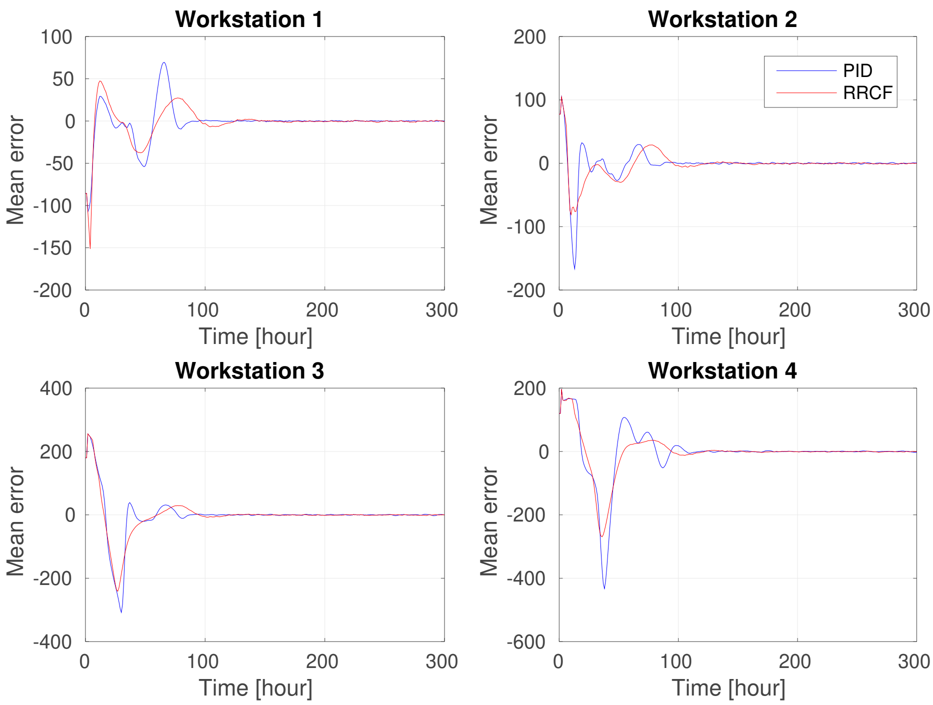

Figure 6.20.: Mean errors between planned and current WIP levels of workstations for stochastic delays with $N(1, 0.05^2)$

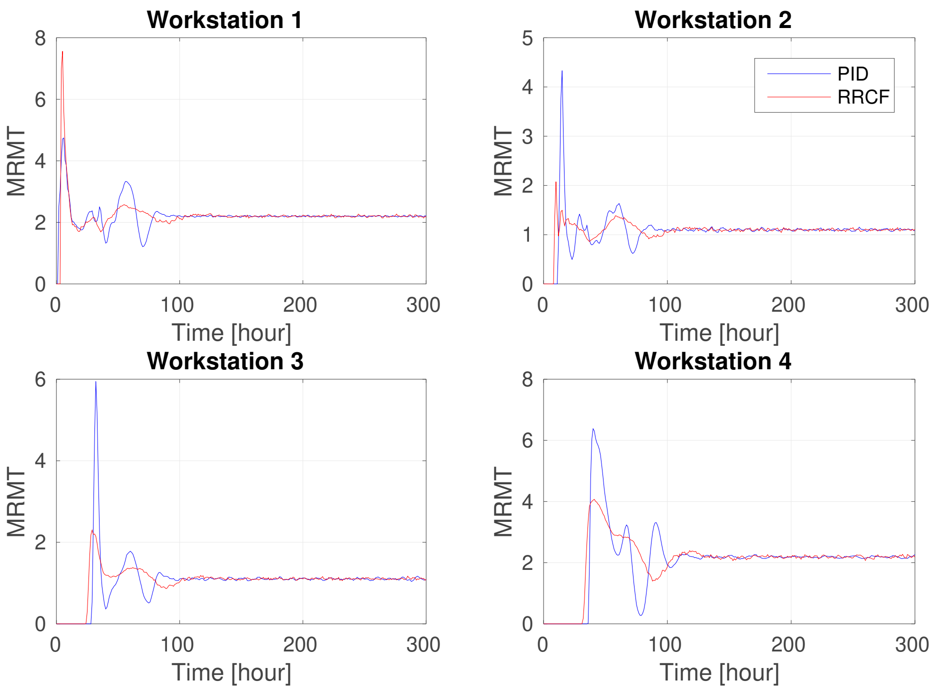

Figure 6.21.: Mean number of RMTs at each workstation for stochastic delays with $N(1, 0.05^2)$

This indicated both PID and RRCF control systems could satisfy customer demand facing stochastic transportation delays.

Table 6.7.: Performances of workstations for stochastic delays with $N(1, 0.05^2)$

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.22	1.08	1.05	2.06	2.22	1.08	1.05	2.05
SDRMT	0.59	0.60	0.83	1.35	1.06	0.69	0.73	1.46
MAE	14.05	18.18	36.74	48.65	18.22	21.74	36.18	41.77
SDAE	18.41	23.20	58.67	68.86	18.90	19.81	52.20	53.27
MIR	101.68	101.61	101.25	100.33	101.68	101.61	101.35	100.39
MOR	102.21	101.61	100.91	100.20	102.21	101.61	101.01	100.25

Table 6.8.: Performances of products for stochastic delays with $N(1, 0.05^2)$

Controller	PID			RRCF		
Product	1	2	3	1	2	3
MIR	51	51	51	51	51	51
MOR	50.51	50.74	49.69	50.29	50.67	49.97
SDOR	7.80	8.93	8.59	7.95	8.49	9.99

Facing the stochastic transportation delays with $N(1, 0.05^2)$, we conclude that both PID and RRCF can ensure the robust stability of the capacity control job shop system to ensure the WIPs distributed around the planned levels of workstations and also satisfy customer demand. Though they showed almost identical settling times of the mean errors between planned and current WIP in both control systems, RRCF displayed less overshoots. Additionally, RRCF had less MAE and SDAE between planned and current WIP levels of the overall system and indicated high robustness in RRCF. Still, it also took more reconfiguration of RMTs to retain the robustness.

Similar to the analysis for stochastic demands, we extended the bound of transportation delays distribution with $N(1, 0.1^2)$ and $N(1, 0.2^2)$, which are 10% and 20% of the mean value, respectively. The detail performances of these control systems with delays satisfying $N(1, 0.1^2)$ and $N(1, 0.2^2)$ distributions were enclosed in Appendix A.2.2. To compare the robustness of PID and RRCF control systems, the distribution of errors between planned and current WIP of workstations and orders output rates of products are shown in Figures 6.23 and 6.24. In Figure 6.23, the errors of all workstations were distributed close to 0, which implied the WIPs were also distributed close to the planned levels. Especially, with σ of delays distribution increasing, the bound of errors distribution in both control systems were also extended. At the same scenario, the errors in PID were distributed closer at Workstations 1 and 2 but not at Workstations 3 and 4. Regarding the distribution of orders output rates of products in Figure 6.24, we obtained that in all scenarios of both PID

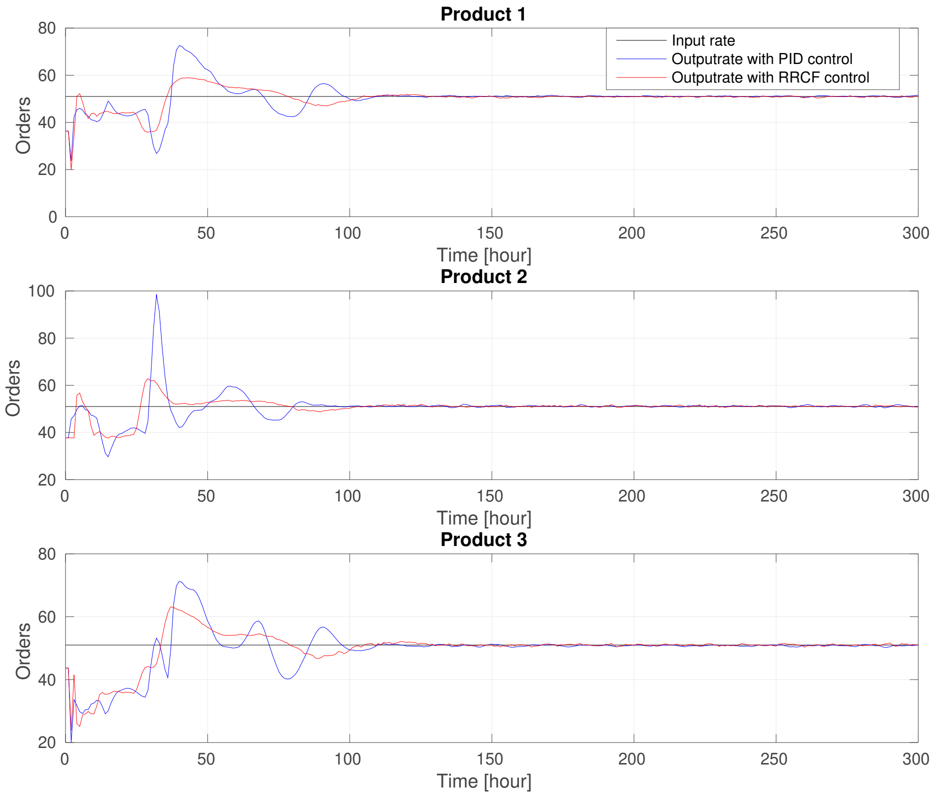

Figure 6.22.: Mean input and output rates of products for stochastic delays with $N(1, 0.05^2)$

and RRCF control systems, the orders output rates were distributed close to the input rates. The bounds of the distribution in the orders output rates of all products were increased in PID, while the bounds of Product 1 and 2 almost did not change and of Product 3 even went to decrease in RRCF, which were corresponding to the SDRMT at Workstation 4, cf. Figure A.29 in Appendix A.2.2. Then we conclude that the stochastic transportation delays had less influence on the orders output rates of products in RRCF.

To measure the robustness of these two control systems, the MAE and SDAE for the distribution of errors between planned and current WIP levels (cf. Figure 6.23) are given in Figure 6.25. Also, MRMT and SDRMT of each workstation are given to measure the robustness cost in this Figure. Similar to Figure 6.23, with σ of delays distribution increasing, the trend of the MAE also went to increase in both control systems. In RRCF, the SDAE displayed an increasing tendency, but relatively stable in PID. This illustrated that with the changing range increasing, the robustness of both control systems were decreased, while the reconfiguration frequency of RMTs was increased. The MIR and MOR of workstations and products were still remained to be balanced and able to satisfy customer demands, cf. Figure A.29 in Appendix A.2.2. In all scenarios, RRCF displayed relatively higher robustness than PID.

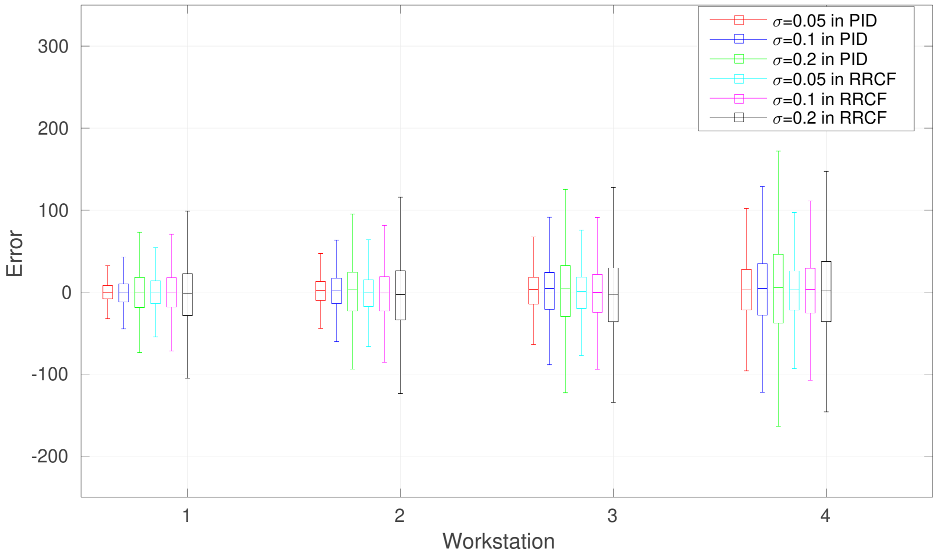

Figure 6.23.: Distribution of errors between planned and current WIP levels of workstations for stochastic transportation delays

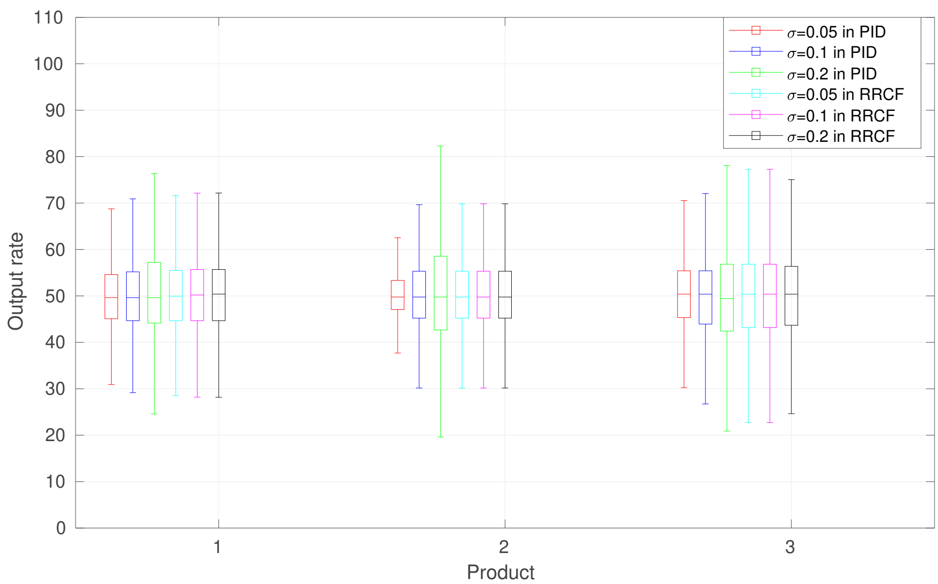

Figure 6.24.: Distribution of orders output rates of products for stochastic transportation delays

From the above analysis of stochastic transportation delays in the capacity control job shop system, we obtain that both PID and RRCF can ensure the robust stability of the job shop system to guarantee the WIPs of all workstations around the planned levels and satisfy customer demands. Different from the influence of stochastic demands, the delays highly influence the transient performances including the settling times and overshoots. The RRCF showed relatively high robustness than PID but also took more reconfiguration cost of RMTs. With the range of delays increasing, the robustness of both control systems also showed a decreasing tendency but rela-

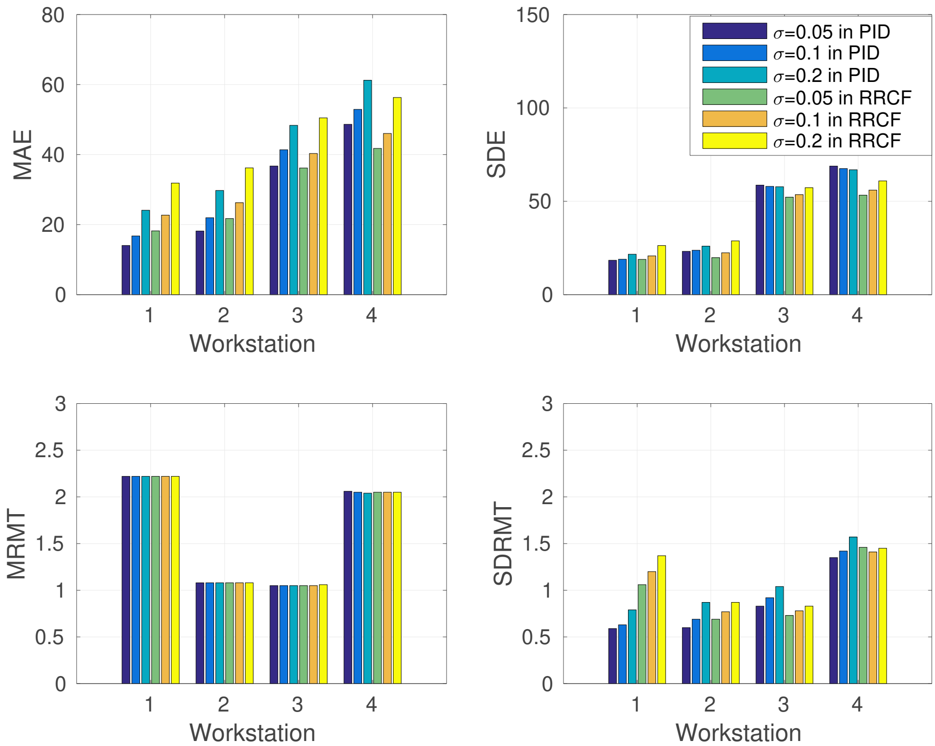

Figure 6.25.: Performance of workstations for stochastic delays

tively slow. We can predict that if the bound of the delays is wide enough, both PID and RRCF may also lose the robust stability.

6.4. SUMMARY

In this chapter, we concentrated on the quantitative analysis and comparison of PID and RRCF in the capacity control of a four-workstation three-product job shop system by simulation. Firstly, we introduced an abstract interface for the comparison of these two control systems in Section 6.1. Then, we analysed and compared their performances including the transient and practical stability within three scenarios for: (1) nominal case without delays and disturbances, (2) only with disturbances and (3) with delays and disturbances in Section 6.2. The simulation results showed that both control systems were able to deal with reconfiguration delay, transportation delay and rush orders to ensure the practical stability and solve bottleneck problems. In all scenarios, the WIPs of all workstations could be practically stabilized to the planned levels and satisfy customer demand within RRCF and PID control systems. However, RRCF displayed quicker response with shorter settling times and less overshoots. Based on the simulation, we further analysed and compared the performance, especially robustness, of these two control systems for various uncertainties by using the Monte-Carlo simulation. Here, volatile customer demands and varying transportation delays were considered as external and internal uncertainties, respectively. They were assumed to satisfy a Gaussian distribution. Volatile customer demands as the external uncertainty were analysed firstly in Section 6.3.1. The statistic results indicated that both two control systems were still able to ensure robust stability to deal with the stochastic demands. Yet, RRCF showed a quicker response with shorter settling times and less overshoots on the mean transient performances. Additionally, the MAE and SDAE between the planned and current WIP levels of workstations were calculated to measure the robustness. The results showed that the RRCF had high robustness than PID, but it also required more reconfigurations of RMTs. Thereafter, we investigated the robustness of these control systems when the range of the uncertainty was extended in three scenarios: (1) $N(51, 2.5^2)$, (2) $N(51, 5^2)$ and (3) $N(51, 10^2)$. The results demonstrated that the wider the changing range of demands, the worst the robustness of systems, but RRCF still exhibited higher robustness. Because the minimum bound of demand is limited 0, but the maximum bound can be infinite, then we predict when σ is increased enough, these control systems will be unstable. Later on, we analysed and compared the performance of these two control systems for the internal uncertainty – varying transportation delays in Section 6.3.2. The simulation results indicated that both control systems could deal with the varying transportation delays to ensure the robust stabilities of the capacity control systems. The statistic results indicated that RRCF had a relatively quicker response with less overshoots, and the overall robustness was higher than PID but not for all workstations, for example, Workstation 1. Also, we investigated the robustness of these control systems when the bound of delays distribution was extended in three scenarios: (1) $N(1, 0.05^2)$, (2) $N(1, 0.1^2)$ and (3) $N(1, 0.2^2)$. The results indicated that the robustness in both control systems were decreased slowly. Because the minimum bound of the delay is 0, but the maximum may be infinite, so when the range is extended large enough, these two control systems may also be unstable. Still, for bounded uncertainties, both PID and RRCF could ensure robust stability of the capacity control system and RRCF performed relatively quicker response and higher robustness. The above simulation results and comparisons serve as indicator for the effectiveness of RRCF in the capacity control of job shop systems with RMTs.

7 Conclusion and Outlook

In this dissertation, we introduced the research on the capacity control of job shop manufacturing systems with reconfigurable machine tools (RMTs). In this chapter, we summarize the main results of the dissertation, introduce the conclusions and contributions and point out the limitations and more possible research directions.

7.1. Conclusion

In this research, we focused on developing an effective machinery-oriented capacity control method for the manufacturers to deal with customer demand fluctuations (e.g., quantities, types of products and delivery dates) and complex manufacturing problems (e.g., bottlenecks and unbalanced capacities). A capacity control strategy, which uses RMTs together with advanced operator-based robust right coprime factorization (RRCF), was proposed for job shop manufacturing systems. In this strategy, all workstations have their local controllers to respond quickly for various delays (reconfiguration delay and transportation delay) and disturbances (e.g., rush order, uncertainties) with less involvement with other workstations. Considering the conflict on economic and operational perspective on the work-in-process (WIP) level, the goal of the capacity control system was designed to ensure that the WIP of each workstation remains close to a planned level, which was the key quantitative performance indicator. Stability and robustness as the key qualitative performance indicators of the capacity control system were achieved within a decentralized architecture. The main contributions and conclusions of the dissertation are summarized as followings.

Firstly, we developed a mathematical model of job shop systems by integrating the flexibility of RMTs and developed the application degree of RMTs. Due to the high productivity of dedicated machine tools (DMTs), we also included these machine tools in the model. Every workstation had a fixed number of DMTs and a varying number of RMTs. We also included some complex properties into the model, such as reconfiguration delays, transportation delays and disturbances. In this model, we assumed that when the job shop system is working on high WIP levels, then the output rates of each workstation is equal to the maximum capacity, which could be controlled by adjusting the number of RMTs of workstations. Here, customer demands were assumed to be bounded and satisfy a Gaussian distribution. The sequence policy of input orders was given in a first-in first-out (FIFO) manner.

Based on the model, we concentrated on the implementation of capacity control for job shop systems by using RRCF. The proportional integral derivation (PID) control method was adopted as the benchmark to evaluate the effectiveness of RRCF, which was also implemented in this dissertation. We firstly designed controllers for general job shop systems by using RRCF and PID methods and analysed the stability of these two control systems for three scenarios: (1) nominal case without delays and disturbances, (2) only with disturbances and (3) with delays and disturbances. Then we compared these two methods in a qualitative perspective. We concluded that both RRCF and PID control methods were applicable in the capacity control of job shop systems with reconfiguration delays, transportation delays and disturbances. The design of PID controller as well as the computation of the control parameters and the evaluation of the feedback law were simple. Nonetheless, in the setting, the orders input rates from other workstations were considered as a disturbance, which was unknown to the controller and may lead to instability of the overall job shop system. Compared to the PID control algorithm, the design of the RRCF controller was complex and involved to compute more control parameters, but it was designed to balance these parameters automatically. Hence, instabilities from the interaction of workstations can be avoided. Once computed, the evaluation of the feedback law was cheap.

Furthermore, we implemented the capacity control methods from the simulation perspective and compared RRCF and PID quantitatively. The performances of these two control systems were evaluated in the same three scenarios as in the qualitative comparison. We concluded that both control systems could be practically stabilized to ensure that the WIPs of all workstations are close to the planned levels, solve bottlenecks and satisfy customer demands. However, the RRCF control system showed quicker response with shorter settling times and less overshoots than the PID system. Thereafter, a Monte-Carlo simulation was used to analyse and compare the robustness of these two control systems for external and internal uncertainties on the stochastic demands and transportation delays. The mean values and standard deviations of the absolute errors between planned and current WIP levels of workstations were calculated to measure and compare the robustness of these two control systems. Additionally, the mean values and standard deviations of the number of RMTs were considered as the cost for the robustness. We concluded that both PID and RRCF could ensure the robustness of the job shop system for customer demand fluctuations and varying transportation delays. But RRCF still displayed quicker response and higher robustness. Later on, we compared the robustness of these two control systems for three scenarios with the mean value μ fixed but standard deviation σ in 5%, 10% and 20% of the mean value. The results indicated that with the standard deviation increased, the robustness of these two control systems were decreased, but RRCF still presented higher robustness in most cases. Therefore, we conclude that using RMTs cooperating with RRCF is an effective approach for the capacity adjustment of job shop manufacturing systems to deal with volatile customer demands and varying transportation delays.

7.2. OUTLOOK

From the above research, we concluded that combining RMTs with respective control methods is an effective approach for the capacity control of job shop manufacturing systems in short or medium terms. But there are some limitations, which point out more open research directions in the future:

Firstly, the proposed mathematical model is based on the funnel model. The effectiveness of this model on the capacity control has been proven in the literature. This model can be further extended and integrated with more performance indicators, e.g., backlog and inventory. Additionally, this research is focused on achieving the WIPs of workstations on the planned levels. We can extend the model by integrating the WIP levels of products. Additionally, considering different products, the production rates at the same workstation can be varying. More uncertainties, such as the machine breakdown or worker absence can also be included in the model. As the proposed mathematical model is available for the systems of high WIP levels with bounded disturbances, for low WIP systems (e.g., some flow shops), this model may not be suitable. Therefore, another research direction can be to develop a mathematical model integrating more complex problems for various perspectives.

As we discussed before, the proposed capacity control approach is applicable for systems with bounded demands. If the demands are out of bound, the system may lose stability. Moreover, the reconfiguration rules for RMTs can be optimized, for example, a priority rule for the assignment of RMTs when the required RMTs exceed constraints. The proposed capacity control approach is designed from the customer perspective, so there is a high frequency of reconfigurations of RMTs. Therefore, another work can be to develop an effective reconfiguration rule by minimizing the cost at the same time satisfying the demands.

Additionally, the design of the RRCF controller is relatively complex, it involved many parameters for the decoupling control, which have great influence on the performance. Therefore, another work can be the sensitivity analysis of these control parameters on the capacity control of job shop systems. We can also analyse the robustness of the control system for more uncertainties, such as varying reconfiguration delay of RMTs.

The research on improving the RRCF control methods can be another direction. RRCF is a relative novel control method, which still needs to be developed on the design of controllers for more perspective or complex problems, such as constraints in the capacity control model. Currently, a great number of improved PID methods have been proposed, such as incorporating with fuzzy algorithm [204], which can also be considered in the capacity control. Therefore, another direction can be to develop more advanced control methods in the capacity control systems and compare their performance for various perspectives.

Since RMTs have not been widely applied by manufacturing companies, the settings in the simulations was arbitrarily given through literature review. In the future work, we will try to collect real data and implement this approach for a practical case. From the planning perspective, the definition of planned WIP levels and bounds of the practical and robust stability can be another topic.

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A Appendix

A.1. Simulation Results of Capacity Control

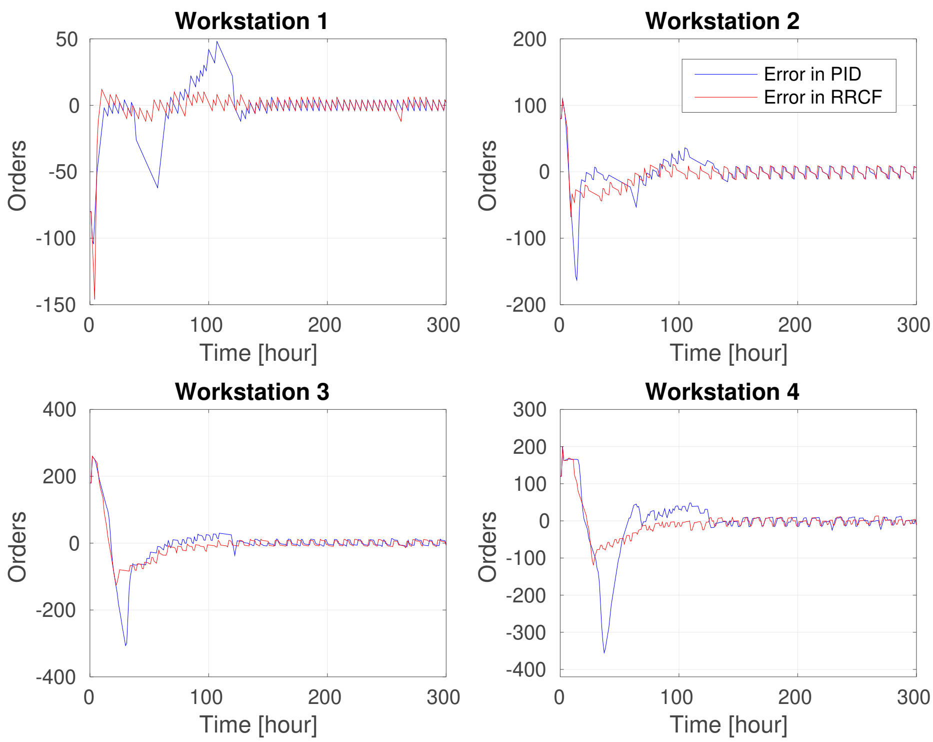

Figure A.1.: Errors between planned and current WIP levels of workstations with delays and without disturbances

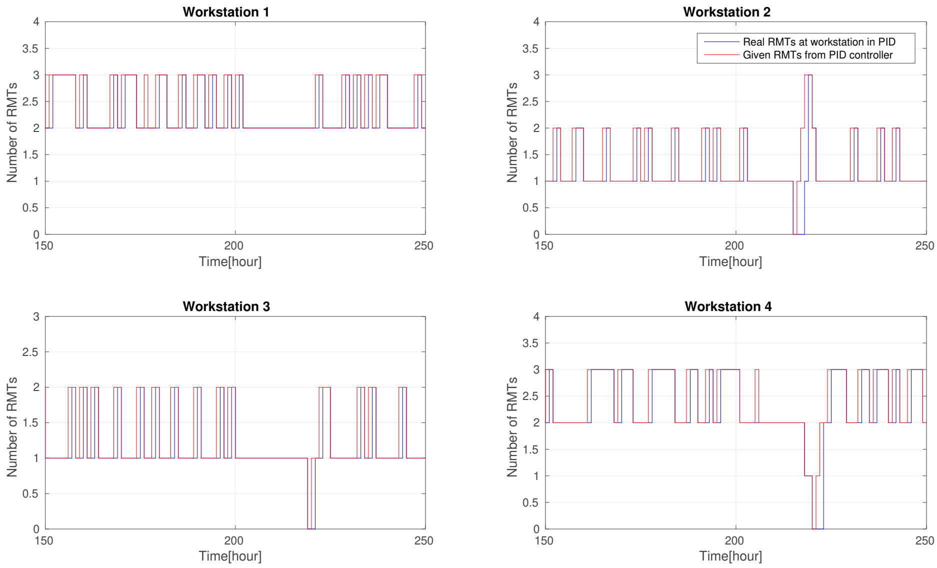

Figure A.2.: Distribution of RMTs of the disturbed and time-delayed system with PID control

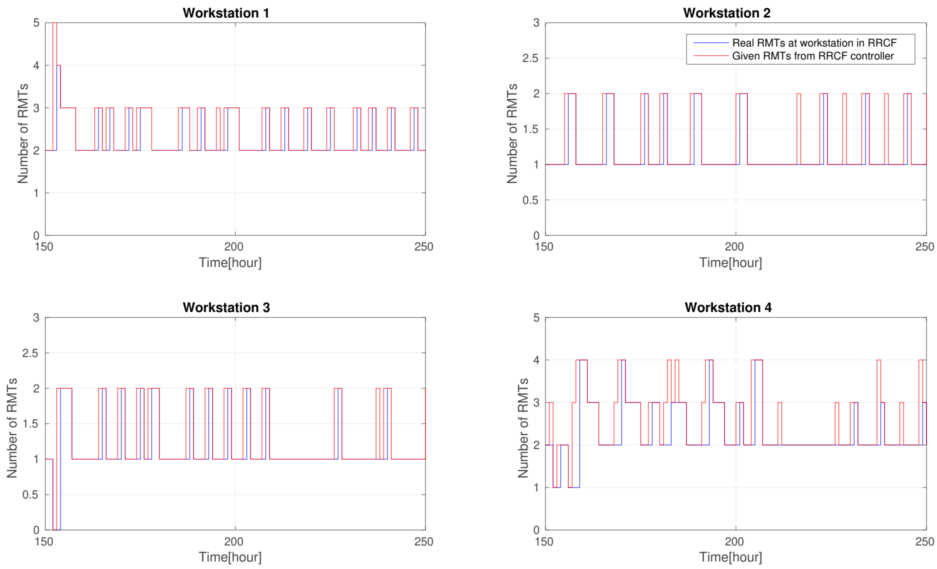

Figure A.3.: Distribution of RMTs of the disturbed and time-delayed system with RRCF control

A.2. SIMULATION RESULTS OF UNCERTAINTY ANALYSIS

A.2.1. SIMULATION RESULTS FOR STOCHASTIC DEMAND

A.2.1.1. FOR $\sigma = 2.5$

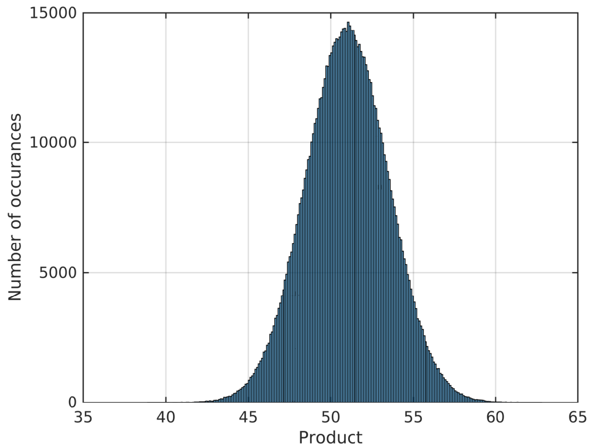

Figure A.4.: Distribution of stochastic demands with $N(51, 2.5^2)$

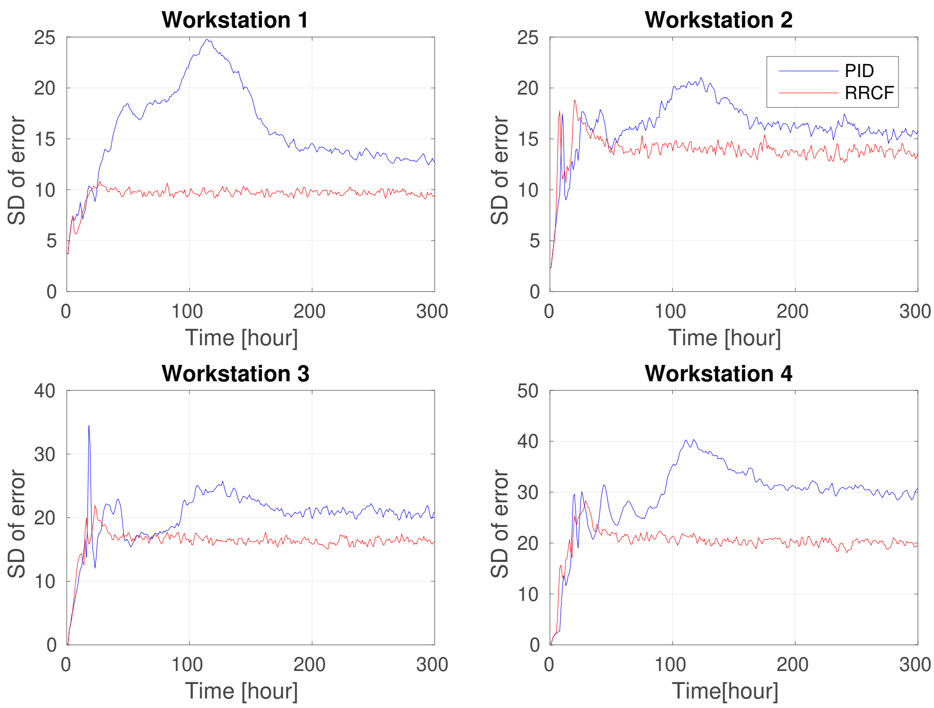

Figure A.5.: Standard deviations of errors between planned and current WIP levels of workstations for stochastic demands with $N(51, 2.5^2)$

A.2.1.2. FOR $\sigma = 5$

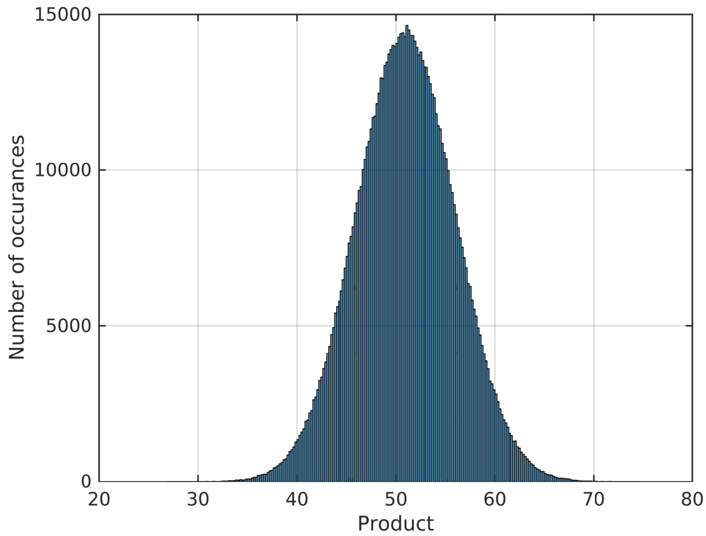

Figure A.6.: Distribution of stochastic demands with $N(51, 5^2)$

Table A.1.: Performances of workstations for stochastic demands with $N(51, 5^2)$

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.25	1.10	1.08	2.12	2.25	1.10	1.08	2.12
SDRMT	0.83	0.66	0.73	1.13	1.37	0.83	0.88	2.02
MAE	25.83	21.77	30.75	45.69	18.43	19.16	26.69	32.65
SDE	27.88	22.47	39.79	47.70	27.09	17.82	31.14	32.65
MIR	102.00	102.08	101.83	101.33	102.00	102.08	101.99	101.37
MOR	102.53	102.09	101.50	101.19	102.53	102.08	101.65	101.24

Table A.2.: Performances of products for stochastic demands with $N(51, 5^2)$

Controller	PID			RRCF		
Product	1	2	3	1	2	3
MIR	51	51	51	51	51	51
MOR	50.93	51.02	50.26	50.65	50.97	50.59
SDOR	7.02	8.32	7.91	10.50	10.37	13.40

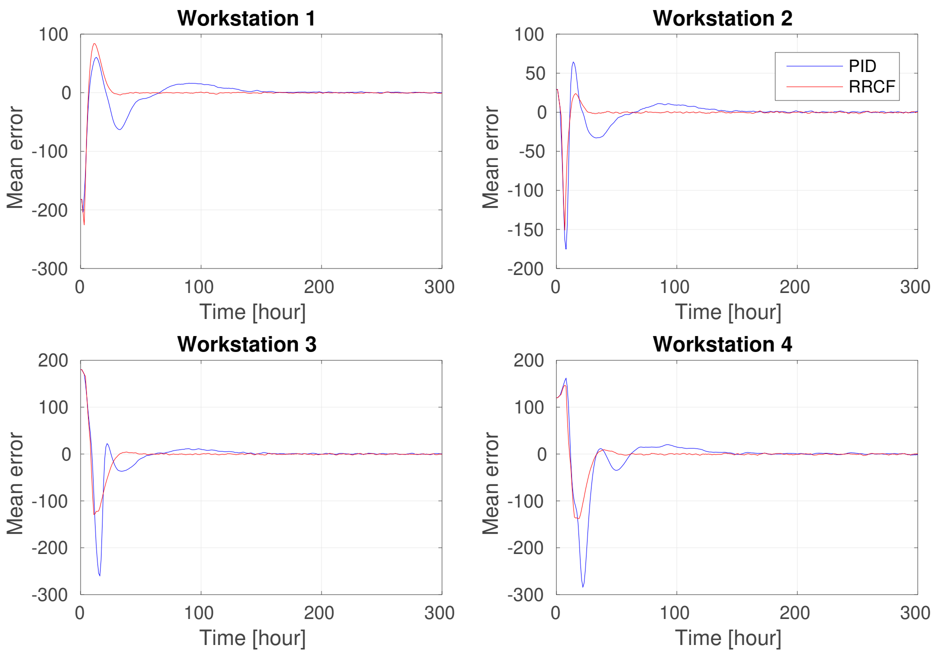

Figure A.7.: Mean errors of between planned and current WIP levels of workstations for stochastic demands with $N(51, 5^2)$

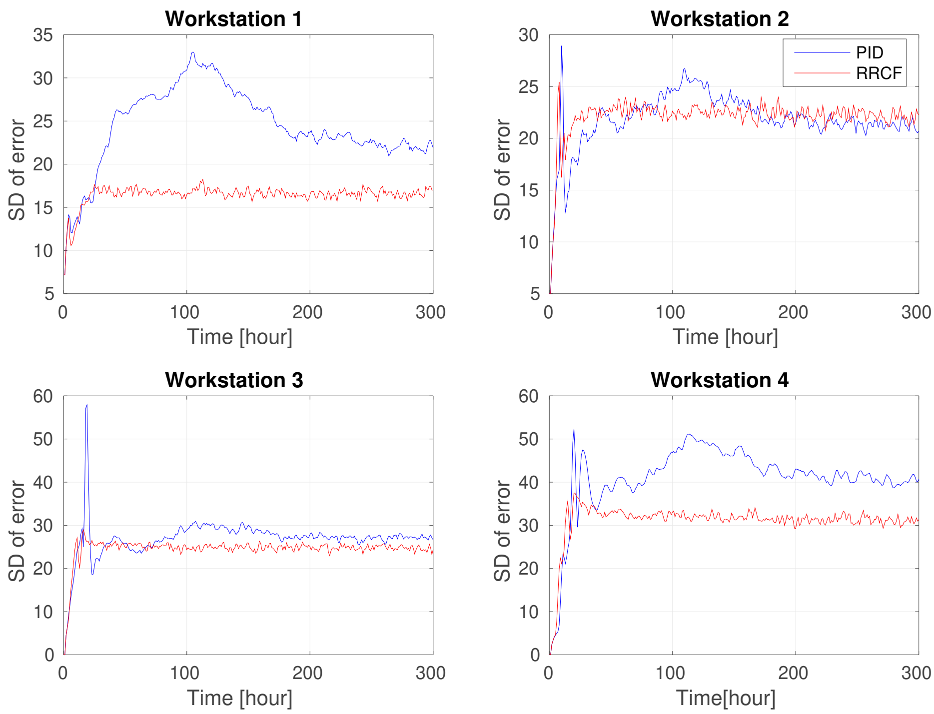

Figure A.8.: Standard deviation of errors in the control process for stochastic demands with $N(51, 5^2)$

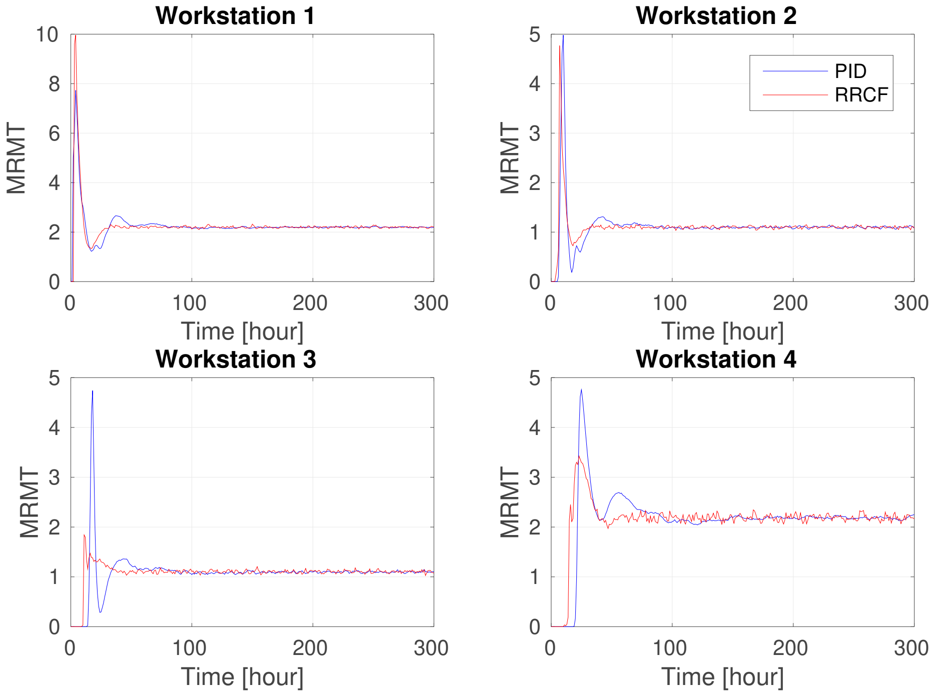

Figure A.9.: Mean number of RMTs at workstations for stochastic demands with $N(51, 5^2)$

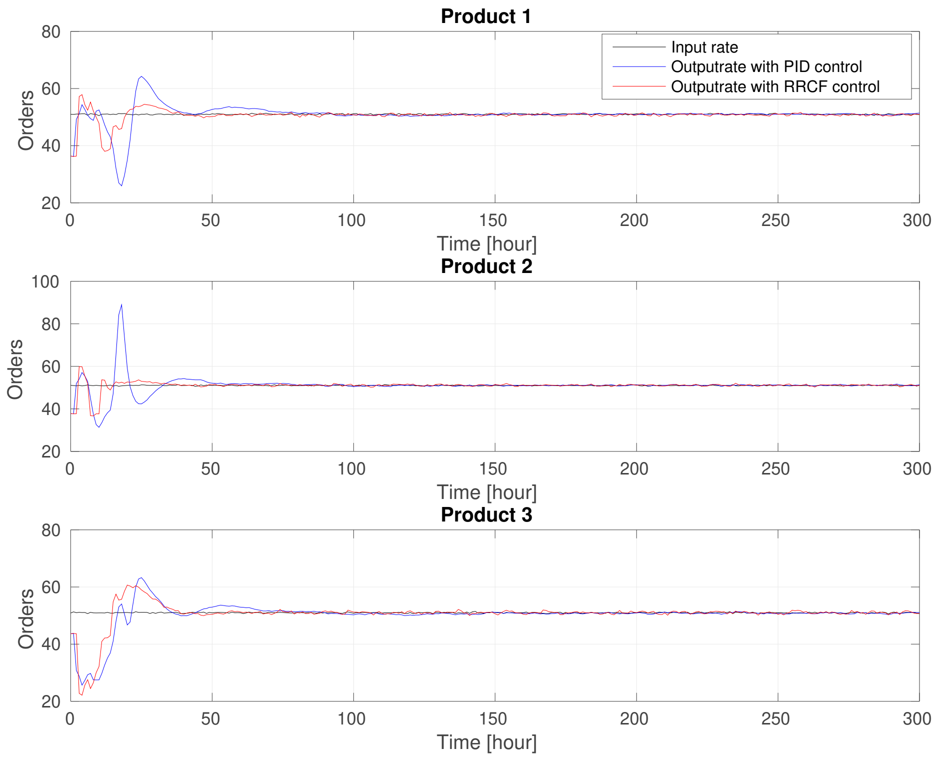

Figure A.10.: Mean input and output rates of products for stochastic demands with $N(51, 5^2)$

A.2.1.3. FOR $\sigma = 10$

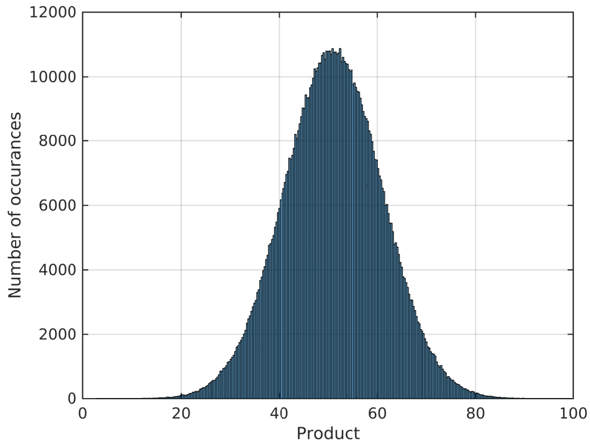

Figure A.11.: Distribution of stochastic demands with $N(51, 10^2)$

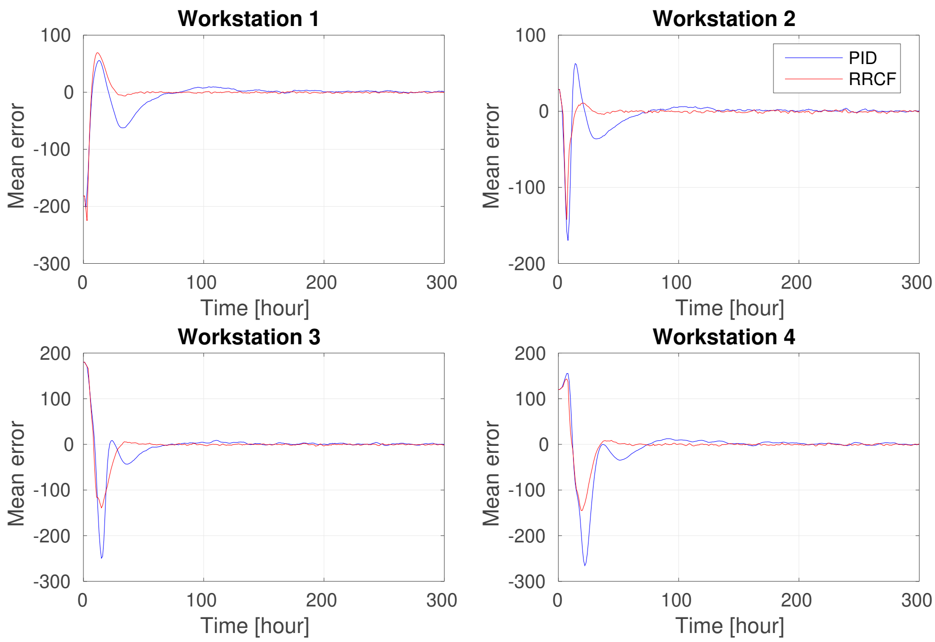

Figure A.12.: Mean errors between planed and current WIP levels of workstations for stochastic demands with $N(51, 10^2)$

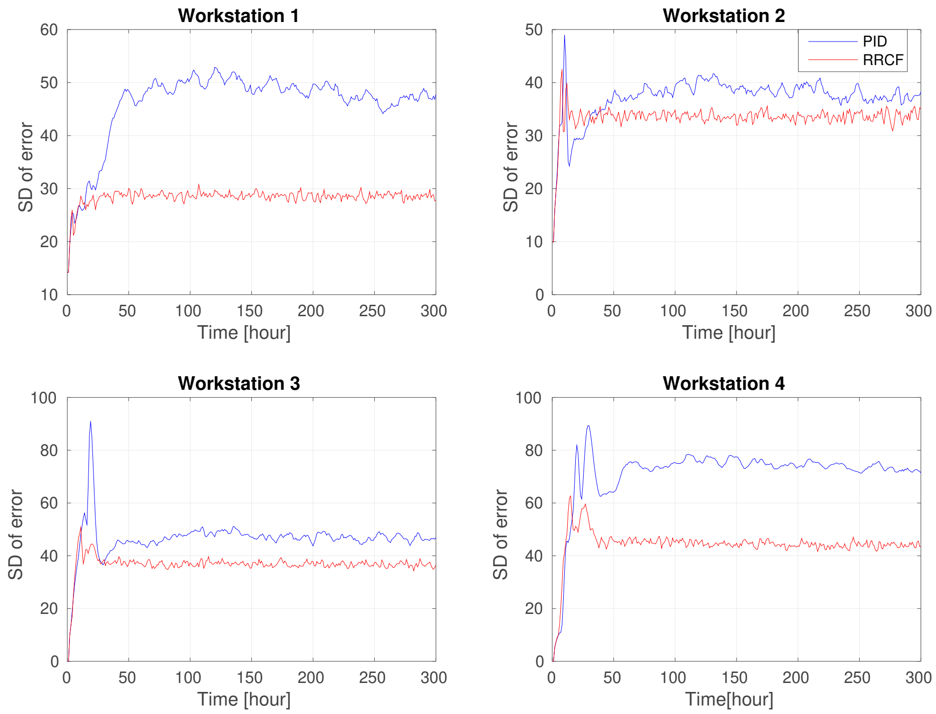

Figure A.13.: Standard deviations of errors between planned and current WIP levels of workstations for stochastic demands with $N(51, 10^2)$

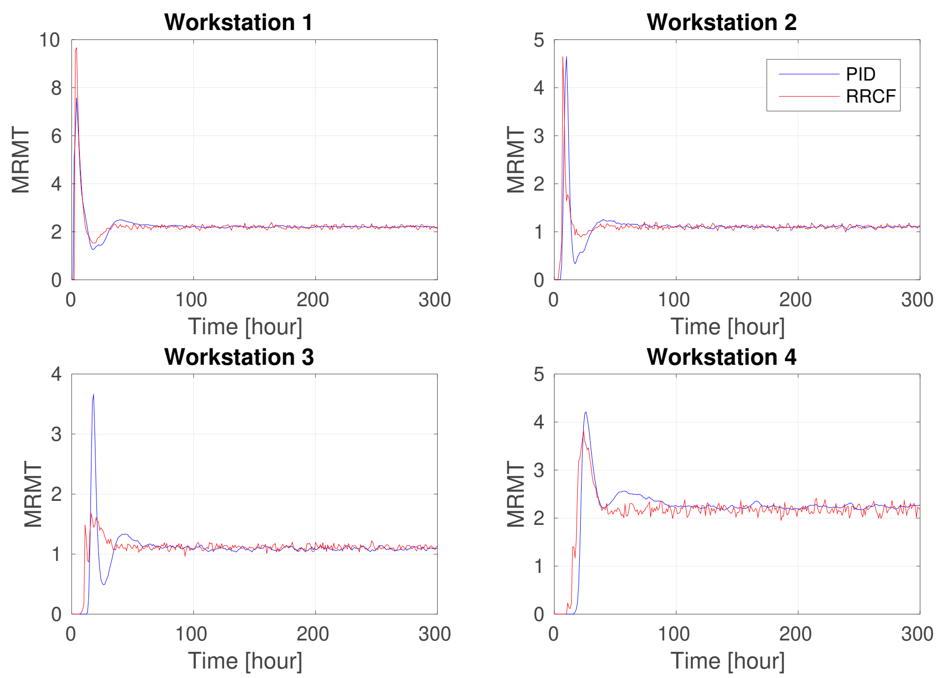

Figure A.14.: Mean number of RMTs at workstations for stochastic demands with $N(51, 10^2)$

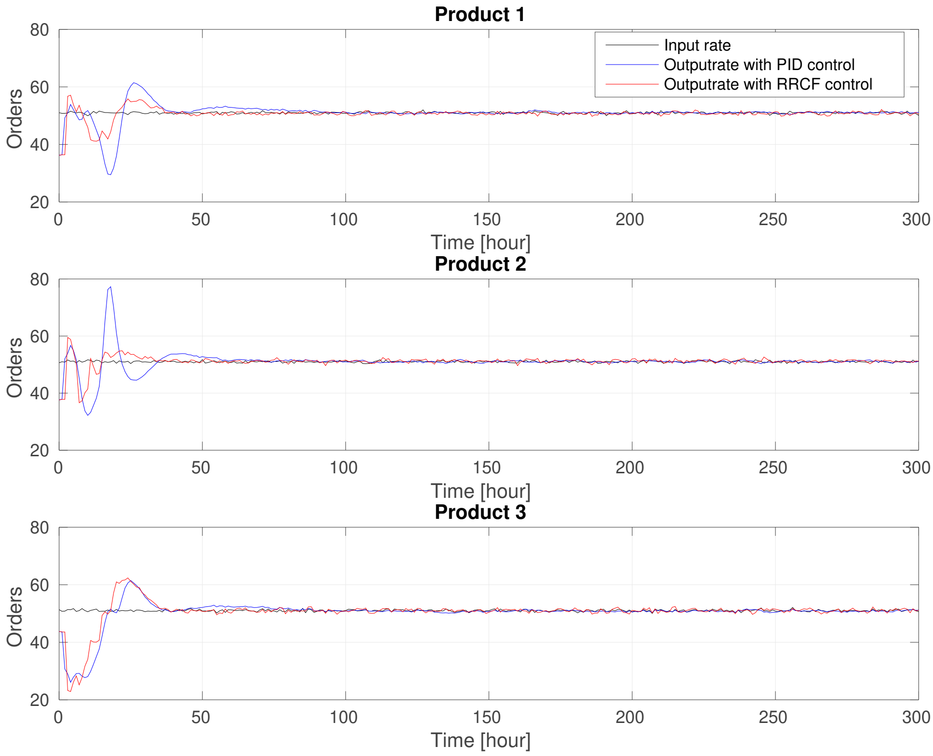

Figure A.15.: Mean input and output rates of products for stochastic demands with $N(51, 10^2)$

Table A.3.: Performances of workstations for stochastic demands with $N(51, 10^2)$

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.26	1.11	1.07	2.17	2.25	1.11	1.09	2.12
SDRMT	0.97	0.74	0.81	1.28	2.09	1.23	1.30	2.77
MAE	41.67	32.95	44.69	68.39	27.14	27.77	35.95	42.12
SDE	35.66	28.36	44.22	55.88	28.77	22.88	35.05	37.27
MIR	102.01	102.12	101.72	101.40	102.01	102.12	101.16	101.30
MOR	102.54	102.12	101.38	101.27	102.12	101.12	101.82	101.17

Table A.4.: Performances of products for stochastic demands with $N(51, 10^2)$

Controller	PID			RRCF		
Product	1	2	3	1	2	3
MIR	51	51	51	51	51	51
MOR	50.96	50.99	50.31	50.62	51.08	50.55
SDOR	8.55	9.70	9.80	15.93	16.11	18.26

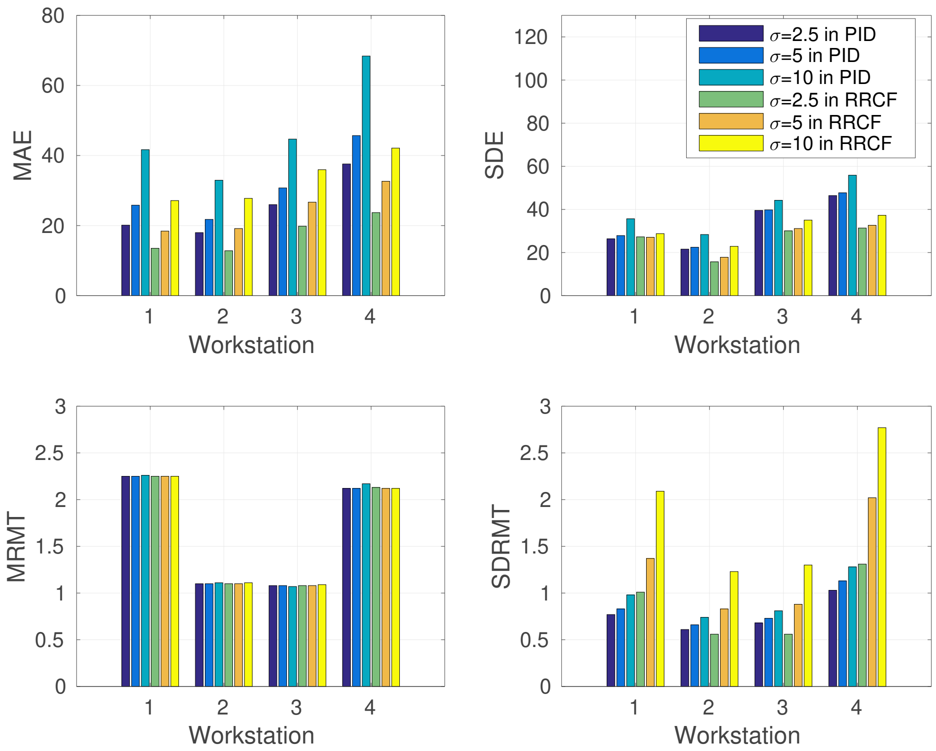

Figure A.16.: Statistics of MIR and MOR of workstations and products for stochastic demands

A.2.2. SIMULATION RESULTS FOR STOCHASTIC DELAY

A.2.2.1. FOR $\sigma = 0.05$

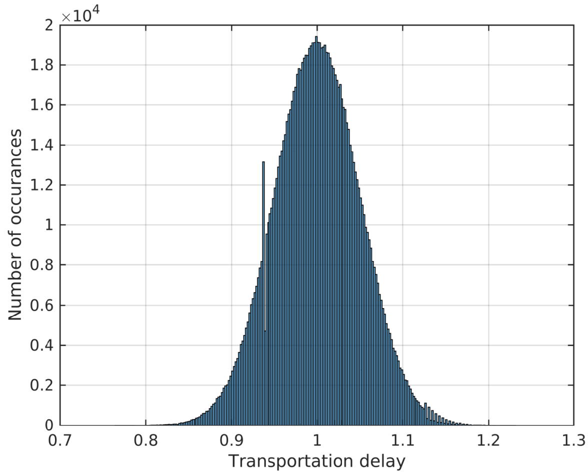

Figure A.17.: Distribution of transportation delays with $N(1, 0.05^2)$

A.2.2.2. FOR $\sigma = 0.1$

Table A.5.: Performances of workstations for stochastic delays with $N(1, 0.1^2)$

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.22	1.08	1.05	2.05	2.22	1.08	1.05	2.05
SDRMT	0.63	0.69	0.92	1.43	1.20	0.77	0.78	1.47
MAE	16.77	21.97	41.38	52.92	22.71	26.26	40.32	46.04
SDE	18.97	23.78	57.98	67.53	20.77	22.43	53.55	56.00
MIR	101.68	101.61	101.25	100.24	101.68	101.61	101.39	100.37
MOR	102.21	101.62	100.92	100.10	102.21	101.61	101.06	100.23

Table A.6.: Performances of products for stochastic delays with $N(1, 0.1^2)$

Controller	PID			RRCF		
Product	1	2	3	1	2	3
MIR	51	51	51	51	51	51
MOR	50.52	50.83	49.58	50.26	50.69	49.97
SDOR	8.49	10.24	9.26	8.32	9.16	10.20

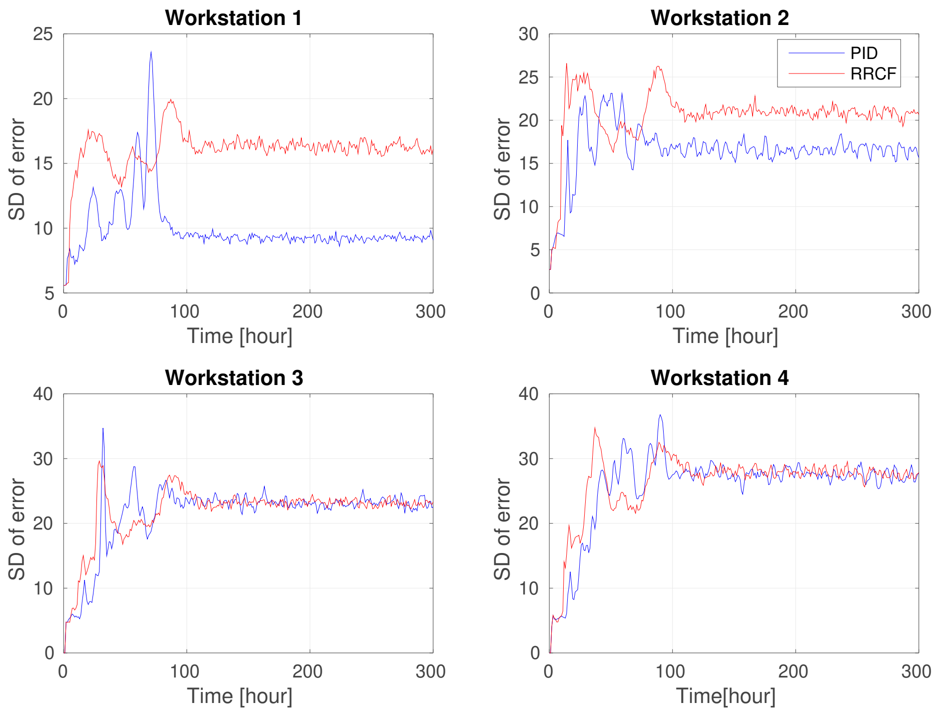

Figure A.18.: Standard deviations of errors between planned and current WIP levels of workstations for stochastic delays with $N(1, 0.05^2)$

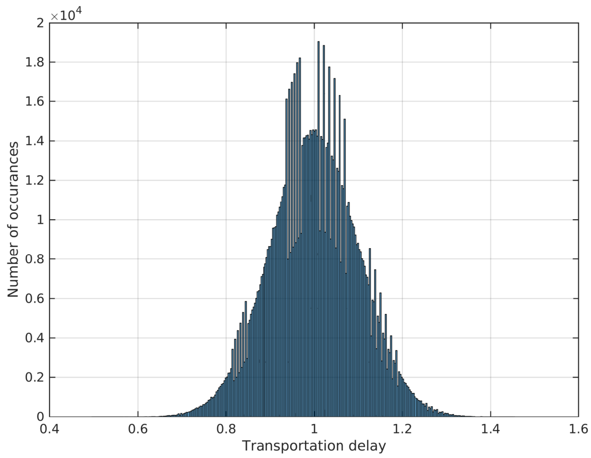

Figure A.19.: Distribution of transportation delays with $N(1, 0.1^2)$

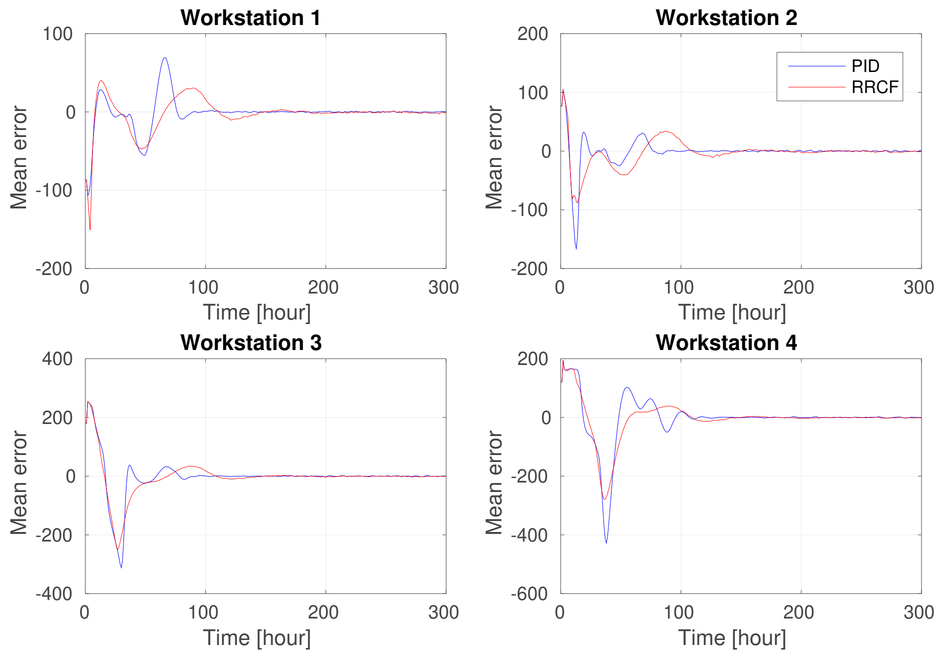

Figure A.20.: Mean errors between planed and current WIP levels of workstations for stochastic delays with $N(1, 0.1^2)$

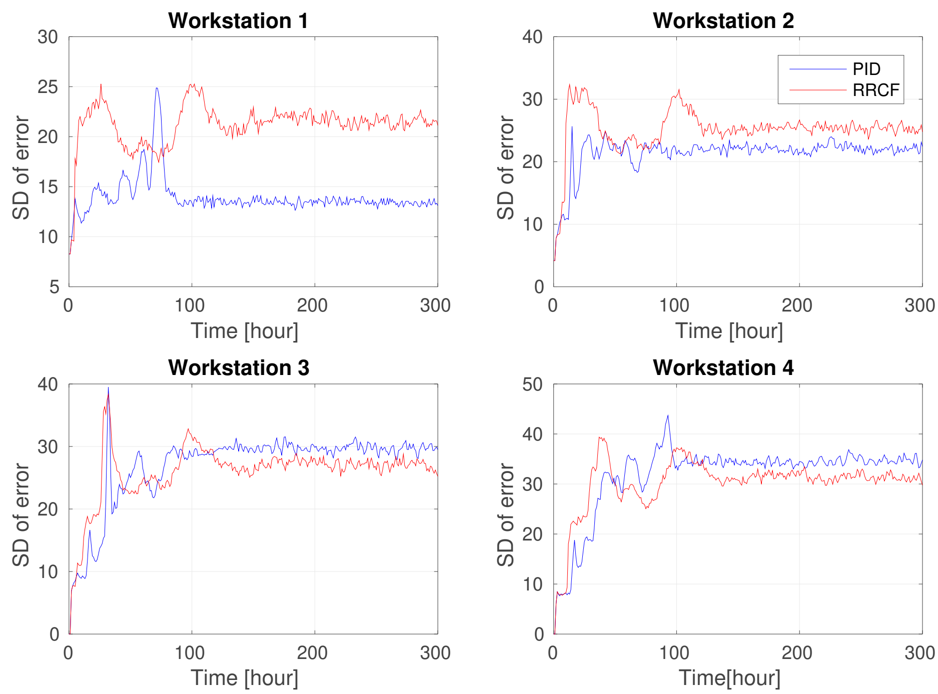

Figure A.21.: Standard deviations of errors between planned and current WIP levels of workstations for stochastic delays with $N(1, 0.1^2)$

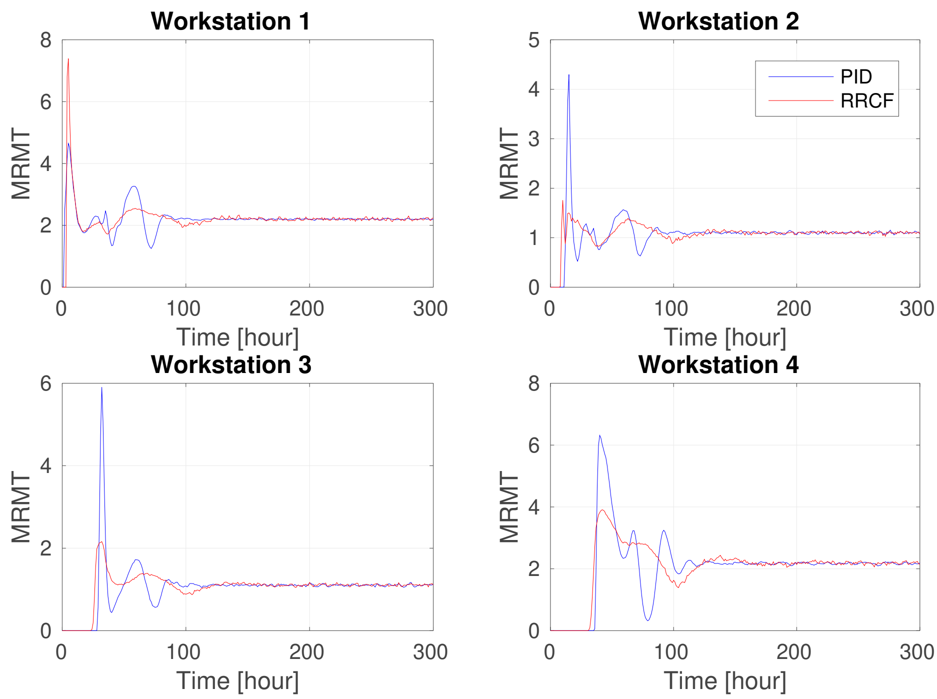

Figure A.22.: Mean number of RMTs at workstations for stochastic delays with $N(1, 0.1^2)$

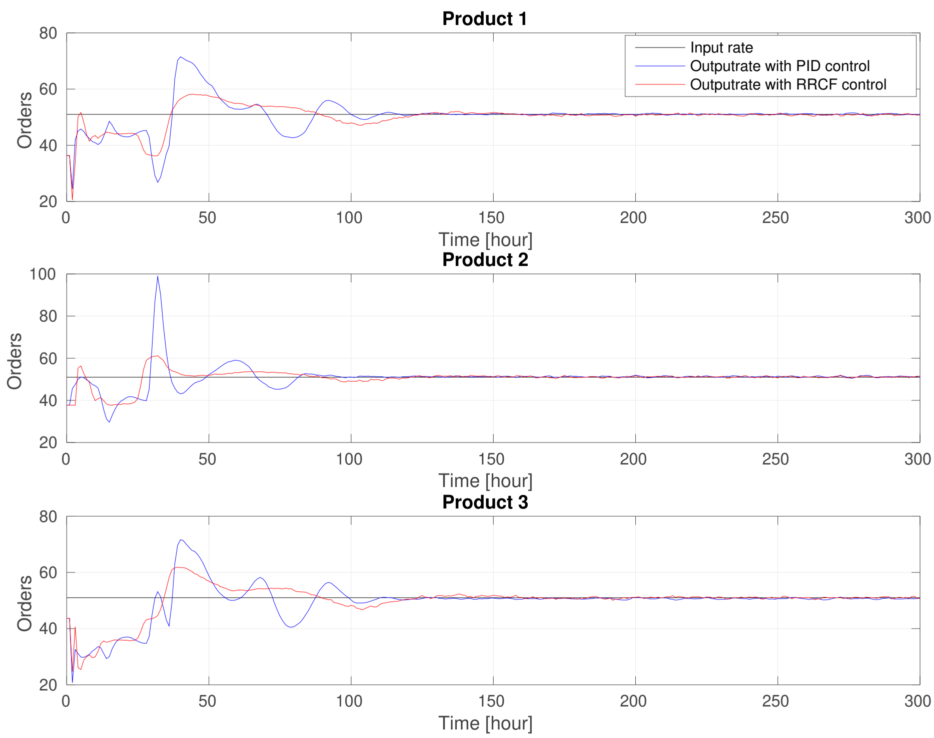

Figure A.23.: Mean input and output rates of products for stochastic delays with $N(1, 0.1^2)$

A.2.2.3. For $\sigma = 0.2$

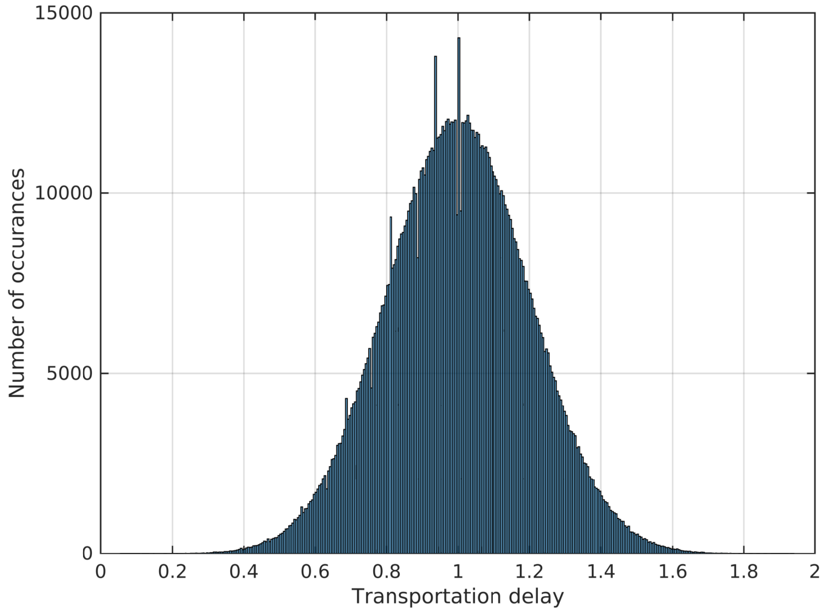

Figure A.24.: Distribution of transportation delays with $N(1, 0.2^2)$

Table A.7.: Performances of workstations for stochastic delays with $N(1, 0.2^2)$

Controller	PID				RRCF			
Workstation	1	2	3	4	1	2	3	4
MRMT	2.22	1.08	1.05	2.04	2.22	1.08	1.06	2.05
SDRMT	0.79	0.87	1.04	1.57	1.37	0.87	0.83	1.45
MAE	24.11	29.76	48.36	61.23	31.87	36.21	50.49	56.31
SDE	21.65	25.96	57.79	66.88	26.29	28.81	57.27	60.92
MIR	101.68	101.61	101.28	100.11	101.68	101.61	101.44	100.34
MOR	102.21	101.62	100.96	99.97	102.21	101.60	101.11	100.19

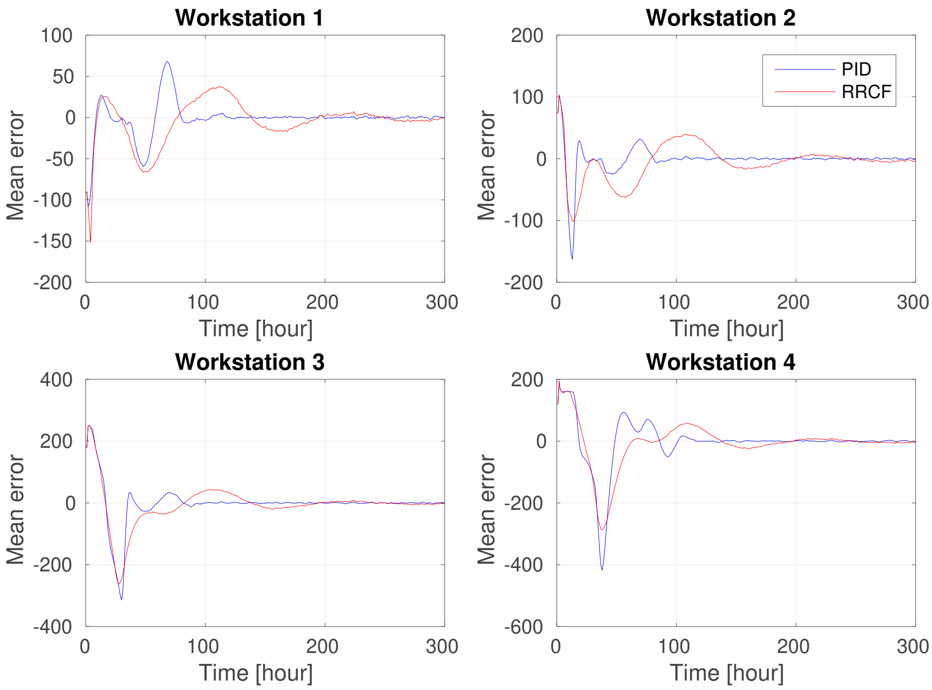

Figure A.25.: Mean errors between planed and current WIP levels of workstations for stochastic delays with $N(1, 0.2^2)$

Table A.8.: Performances of products for stochastic delays with $N(1, 0.2^2)$

Controller	PID			RRCF		
Product	1	2	3	1	2	3
MIR	51	51	51	51	51	51
MOR	50.47	50.96	49.50	50.23	50.70	49.97
SDOR	9.56	11.84	10.47	8.66	9.87	10.22

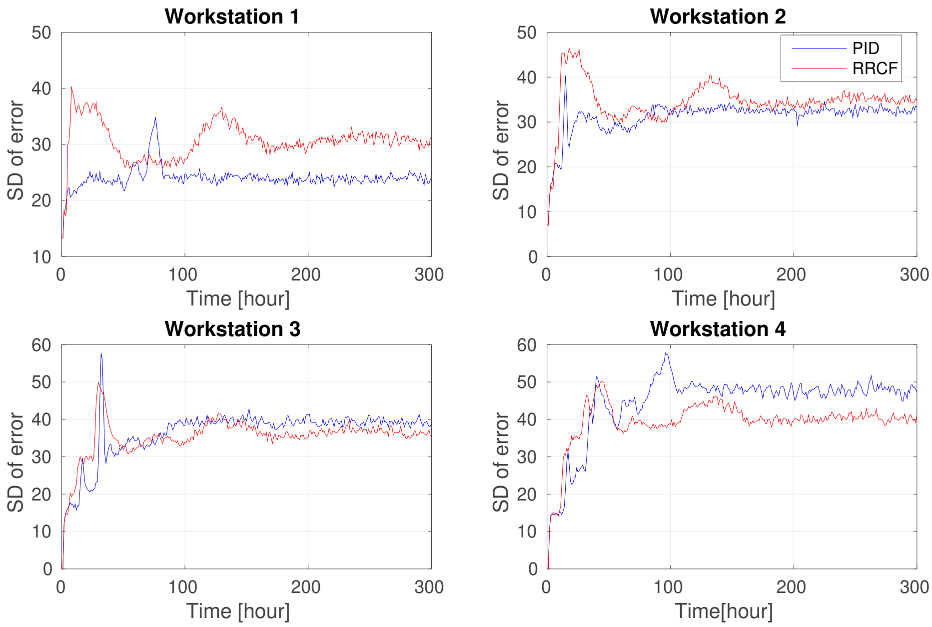

Figure A.26.: Standard deviations of errors between planned and current WIP levels of workstations for stochastic delays with $N(1, 0.2^2)$

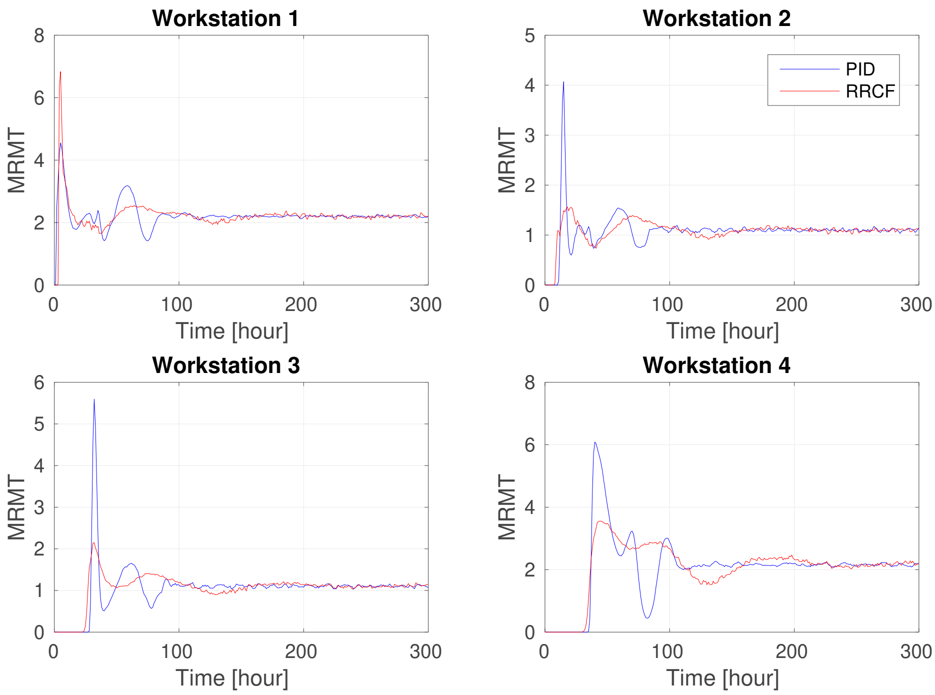

Figure A.27.: Mean number of RMTs at workstations for stochastic delays with $N(1, 0.2^2)$

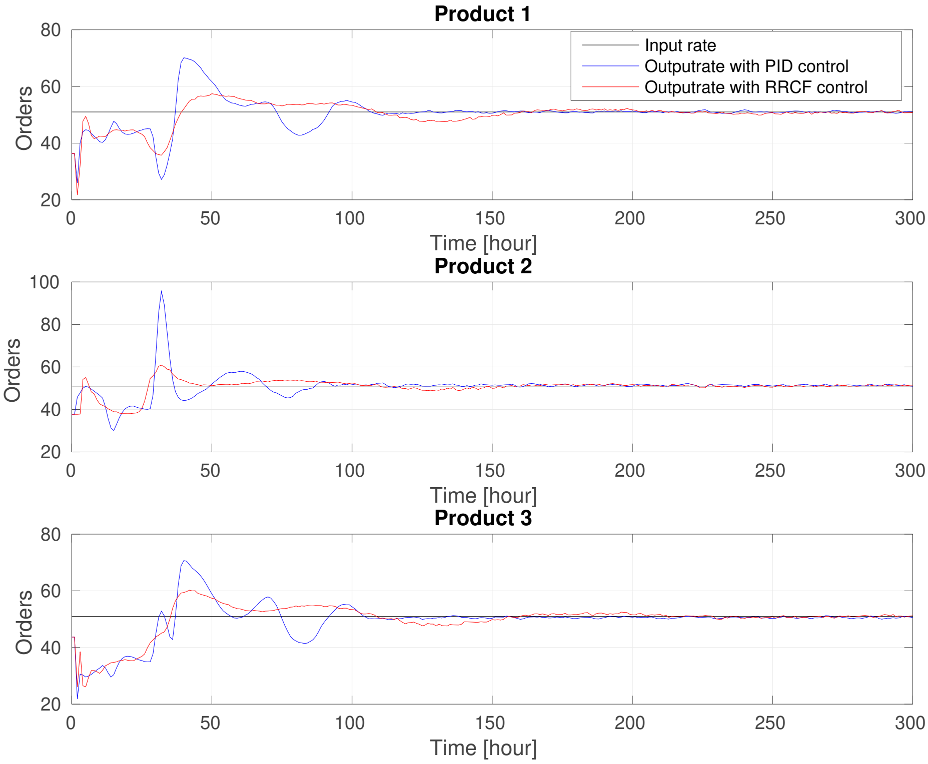

Figure A.28.: Mean input and output rates of products for stochastic delays with $N(1, 0.2^2)$

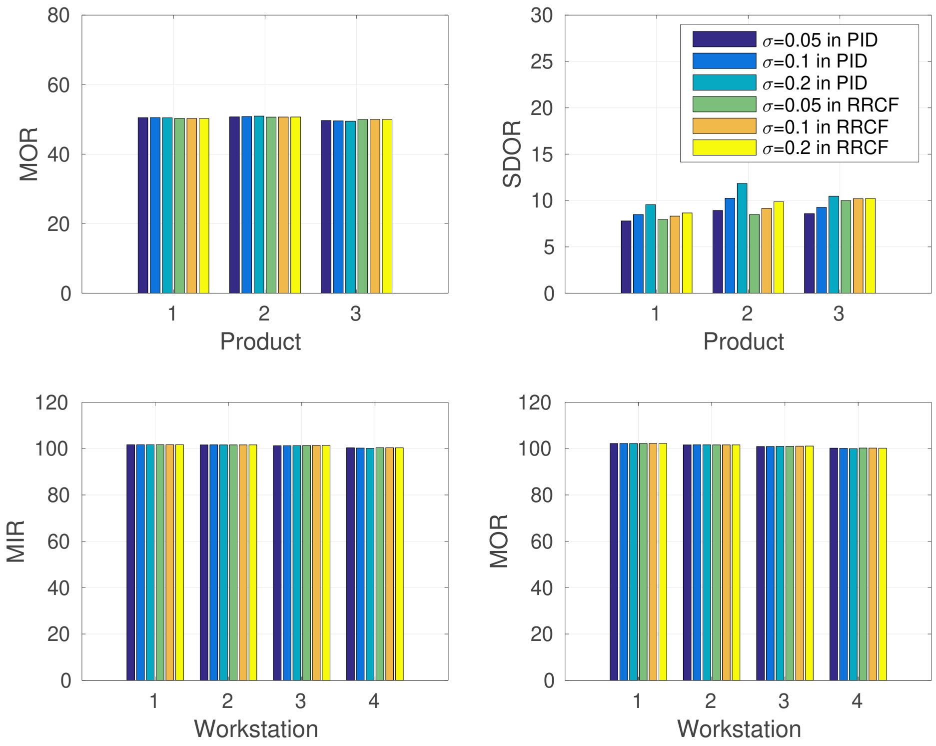

Figure A.29.: Statistics of MIR and MOR of workstations and products for stochastic transportation delays

B List of Publications

- P. Liu, Q. Zhang and J. Pannek. Development of operator theory in the capacity adjustment of job shop manufacturing systems. *Applied Science*. 9(11), 2019
- P. Liu, Q. Zhang and J. Pannek. Application of reconfigurable machine tools in the capacity control of job shop systems. *International Journal of Agile Systems and Management*. 11 (3): 206–221, 2018.
- P. Liu, Q. Zhang and J. Pannek. Evaluation of control approaches for capacity adjustment in job shop systems. *Proceedings of the 9th IFAC Conference MIM 2019 on Manufacturing Modeling, Management, and Control*. (2019)
- P. Liu, U. Chinges, Q. Zhang and J. Pannek. Capacity control in disturbed and time-delayed job shop manufacturing systems with RMTs. *Proceedings of the 9th Vienna International Conference on Mathematical Modelling*. 51 (2):807–812, 2018.
- P. Liu and J. Pannek. Operator-based capacity control of job shop manufacturing systems with RMTs. *Proceedings of the 6th International Conference on Dynamics in Logistics*. 264–272, 2018.
- P. Liu and J. Pannek. Modelling and controlling of multi-workstation job shop manufacturing systems with RMTs. *Proceedings of the 6th CUST International Business Research Conference*. LPM-07, 2017.
- P. Liu, Q. Zhang and J. Pannek. Capacity adjustment of job shop manufacturing systems with RMTs. *Proceedings of the 10th International Conference on Software, Knowledge, Information Management and Application*. 175–180, 2016
- Q. Zhang, P. Liu and J. Pannek. Combining MPC and integer operators for capacity adjustment in job shop systems with RMTs. *International Journal of Production Research*. 1–16, 2018. doi: 10.1080/00207543.2018.1521022

- Q. Zhang and P. Liu and J. Pannek. Modeling and predictive capacity adjustment for job shop systems with RMTs. *Proceedings of the 25th Mediterranean Conference on Control and Automation.* 310-315, 2017.

- U. Chinges, P. Liu, Q. Zhang, I. Rügge and J. Pannek. Abstract control interface for job shop manufacturing systems with RMTs. *Proceedings of the 11th International Conference on Software, Knowledge, Information Management and Application.* 1-6, 2017.