STOCHASTIC PLANNING AND SCHEDULING FOR RECONFIGURABLE JOB SHOPS AND FLOW LINES

by

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To my mother and father

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ABSTRACT

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The uncertain and competitive market is leading manufacturers to look for fast and effective technological solutions to manage their production systems and make them highly responsive to market needs. Moreover, customers are requesting customized, high-quality products quickly and at low costs. Utilizing rigid manufacturing systems such as dedicated manufacturing systems (DMSs) or flexible manufacturing systems (FMSs) limits manufacturers' responsiveness. Reconfigurable manufacturing systems (RMSs) were introduced to cope with these challenges. These systems are built around modularity and reconfigurability and use reconfigurable machine tools (RMTs) as their main component. The adjustable structure of RMT allows the system to adapt to market requirements. However, production management in RMSs is a particularly challenging task compared to traditional systems, which makes manufacturers skeptical about adopting these systems.

To address this issue, this dissertation presents novel methodologies to manage production activities within RMSs regarding planning, scheduling, and control. The research was conducted in two main parts based on the system type (i.e., job shop or flow line). A novel mixed-integer linear programming (MILP) model for planning and scheduling is formulated for the former. Then, it was extended to a two-stage stochastic (TSS) formulation to incorporate the uncertainties in volume and machines' productivity. A data-driven controller with predictive capabilities was developed for the latter. It collects real-time data to reschedule raw material injection time and control the inner-stage movement of work-in-process (WIP) units to optimize their levels. The applicability of the proposed models was validated using case studies adopted from the literature. The result of this dissertation showed the cost-benefits of utilizing RMSs and the effectiveness of adopting the proposed methodologies to manage RMSs.

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LIST OF ABBREVIATIONS

ABS	agent-based simulation
ANOVA	analysis of variances
CNC	computer numerical control
CPPS	cyber-physical production system
CRM	customer relationship management
DMS	dedicated manufacturing system
DNC	direct numerical controlled
EEV	expected results of using the EV problem
ERP	enterprise resource planning
EV	expected value problem
EVPI	expected value of perfect information
FFL	flexible flow line
FFLSP	flexible flow line scheduling problem
FJS	flexible job shop
FJSSP	flexible job shop scheduling problem
FLSP	flow line scheduling problem
FMS	flexible manufacturing system
HMI	human-machine interface
IMS	information management system
IOT	internet of things

IPPS	integrated process planning and scheduling
JSSP	job shop scheduling problem
KPI	key performance indicators
LME	large manufacturing enterprises
MAD	mean absolute deviation
MILP	mixed-integer linear programming
MMPS	max-min-plus-scaling
MPA	max-plus algebra
MPC	model predictive control
MPL	max-plus-linear system
OEE	overall equipment effectiveness
PCB	printed circuit board
PDF	probability density function
PIM	production information management
PSO	particle swarm optimization
RFL	reconfigurable flow line
RFSCP	reconfigurable flow line scheduling and control problem
RIM	reconfigurable inspection machine
RJS	reconfigurable job shop
RJSSP	reconfigurable job shop scheduling problem

RMS	reconfigurable manufacturing system
RMT	reconfigurable machine tool
RP	recourse problem
RPFL	reconfigurable parallel flow line
RSFL	reconfigurable serial flow line
SME	small and medium enterprise
TSS	two-stage stochastic
VSS	value of stochastic solution
WIP	work-in-process
WS	wait and see solution

NOMENCLATURE

Decision Variables

$b_{o,k,l}$	WIP inventory level of order k after operation o
$c_{o,k,m,l}$	Completion time of operation o for order k on machine m at period l
$d_{o,k,i,m,l}$	Production capacity for operation o of order k on configuration i for machine m at period l
$g_{o,o',k,l}$	Binary variable to show if operation o for order k precedes operation $o\prime$ at period l
$h_{k,l}$	Inventory level of product k at period l
$p_{o,k,o',k',m,l}$	Binary variable to show if operation o for order k precedes operation o' for order k' on machine m at period l
$s_{o,k,m,l}$	Starting time of operation o for order k on machine m at period l
$t_{o,k,m,l}$	Total production time for operation o for order k on machine m at period l
$u_{k,l}$	Backorder level for order k at period l
$u_p^{RFL}(k_p)$	Time instance when unit K_p enters the system
$v_{o,k,m,l}$	Binary variable if operation o for order k is assigned to machine m at period l
$w_{k,l}$	Delivery of order k at period l
$y_{m,i,l}$	Binary variable to show if configuration i is selected for machine m at period l
x_m	Binary variable to show if machine m is selected
$z_{m,i',i,l}$	Binary variable to track reconfiguration from i' to i on machine m at period l
z_{p,m,i,o_p}^{RFL}	Binary variable to show if i of m is selected to perform o_p of p

General Variables

$\sigma^{RFL}_{p,m,i,o_p}(K_p)$	processing time for o_p for K_p, using RMT m in configuration i
$w^{RFL}_{o_p}(k_p)$	Processing time for o_p of K_p
d^{RFL}_{q,s_p}	Arrival time for raw material s_p for product p from supplier q
$x^{RFL}_{o_p}(k_p)$	Starting time to operation o_p for k_p
$y^{RFL}_{p}(k_p)$	Time instance at unit k_p leaves the system

Parameters

$\alpha_{o,k}$	Binary value to show if operation o is required for product k
$\beta_{m,i,o}$	Production rate of machine m in configuration i to perform operation o
δ	Reconfiguration cost parameter ($/hour)
$\gamma_{m,i,o}$	Calibration rate for operation o when machine m is in configuration i
$BigM$	A very large number
CB_o	Penalty cost for holding WIP units for operation o
CH_k	Inventory holding cost for order k
$CO_{o,m}$	operation costs for operation o on machine m
CP_k	Production cost (raw material) for order k
$CT_{m,i,i'}$	Reconfiguration time between configurations i and i' for machine m
CU_k	penalty cost for backorders for order k
N^{RFL}_q	Buffer B_b capacity
P_j	Probability of scenario j
$Q_{k,l}$	Order Quantity for order k at production run l
$r^{RFL}_p(k_p)$	Due dates for unit K_p
T_l	Available production time at production run l
T^{RFL}_{q,s_p}	Lead time for raw material s_p for product p from supplier q

U	Storage capacity for WIP and finished products

Sets and Indexes

I	Total possible configurations
i, i'	Configuration index
j	Scenario Index
K	Total orders
k, k'	Order/product index
k_p	a unit of product p at current time step k
k_p^-	a unit of product p at previous time step k
L	Production period
l, l'	Production run index
M	Total number of machines
m	Machine index
O	Total possible operations
o, o'	operation index
o_p^{RFL}	operation o for product p, $1 \le o_p \le O_p$
q	suppler index, $q = 1, 2, ..Q$

Other Symbols

ε	Negative infinity
e	Zero

CHAPTER ONE

Introduction

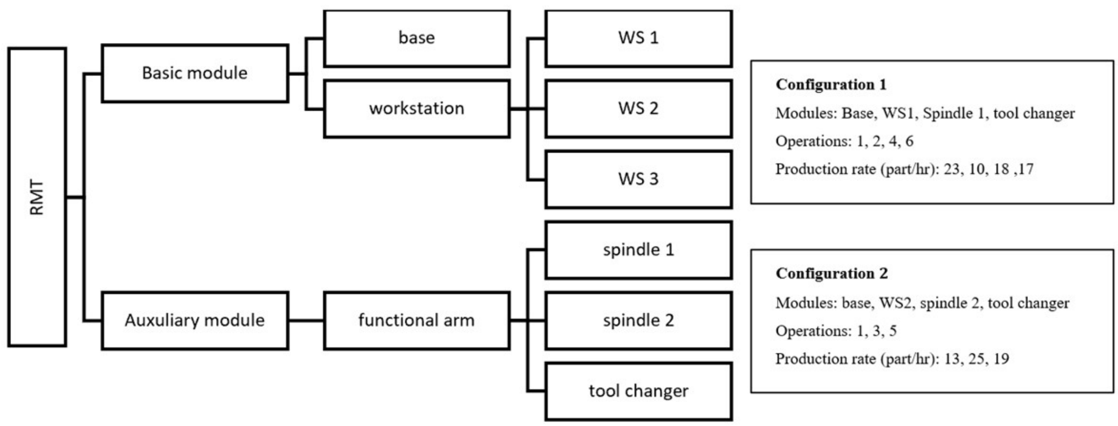
1.1 Research Background

Reconfigurable manufacturing systems (RMSs), as an advanced manufacturing system, joins high reconfigurability and responsiveness to address many challenges facing modern manufacturing firms (Khan, 2022). The current manufacturing era is characterized by a great degree of customized products, cost reduction, and demand volatility (Bortolini et al., 2018). The exclusivity of RMS is that it gives manufacturing firms an edge over others by rearranging the system's hardware and software modules quickly and cost-effectively. This approach reduces the prospect of production system obsolescence and provides the required functionality and capacity for the system at the exact time as needed. The system's open-ended nature allows manufacturing firms to continuously utilize and integrate new technologies. In addition, it ensures continuous system performance improvement and enables the production of new products and product customization (Andersen et al., 2020; Dotoli et al., 2019). There will be no need to replace the entire system with a new system when using this manufacturing strategy.

The main component of acRMS is the reconfigurable machine tools (RMTs). These machines can be configured into multiple configurations (Landers et al., 2001). Each has its production capabilities and functionality and is composed of different machining modules (Fan et al., 2022). Basic and auxiliary modules characterize RMTs as shown in Figure 1.1. Essential modules are fixed units such as columns and machine base. Auxiliary modules are changeable units such as spindle unit heads. They play an essential role in performing various operations, enabling RMTs to quickly change their functionality and capacity according to the production needs. These machines are arranged

Figure 1.1

The Tsypical Modular Structure of Reconfigurable Machine Tool (RMT)



in a certain way, and their layout defines the type of manufacturing system, whose choice is a significant decision that influences the subsequent decisions in managing these systems (Koren, 2010). Their arrangement determines the system as reconfigurable job shops (RJSs) or reconfigurable flow lines (RFLs); each operates differently with different goals and decisions (Mahmoodjanloo et al., 2021; Yelles-Chaouche et al., 2020).

By contracts to traditional manufacturing systems, RMS joins the following six core features (Morgan et al., 2021):

- Modularity: use of modular equipment which can be used in different production settings
- Integrability: use of software and hardware interfaces to allow a plug-and-play use of the resources
- Diagnosability: real-time monitoring to identify sources of quality and reliability problems
- Convertibility: possibility to change the functionality of some resources to produce
- Customizability: system capability and flexibility to meet product family varieties.

- Scalability: ability to expand overall system capacity, the counterpart to convertibility

Each character is specialized in enhancing the efficiency and usefulness of an RMS. Due to such advantages, it has been an active field and attracted the focus of researchers and practitioners. Nonetheless, some limitations are associated with a RMS that delay their extensive utilization in the real world (Carpanzano & Jovane, 2007). First, it offers several manufacturing routes (process plans) to produce the same part, making it challenging to evaluate the system performance in each route (Maksane, 2019). Second, it requires extensive process planning and scheduling knowledge to produce parts effectively (X. Li & Gao, 2020). Third, its productivity can be affected by changing the layout, configuration, tools, modules, etc (Sabioni et al., 2021b). Fourth, production plans must be frequently reworked in RMSs because manufacturing equipment and products are constantly changing (ElMaraghy, 2007). Unlike in dedicated manufacturing systems (DMSs), where they are done once or once in a while as in flexible manufacturing systems (FMSs). As a result, manufacturing firms working with the existing knowledge base may become skeptical of its adoption, partly due to its dynamic nature (Khan, 2022).

1.2 Motivation

Concerning the above thoughts, the motivation for this research is based on the fact that responsiveness and reconfigurability are essential for manufacturers to cope with the current market dynamics and globalization (Yazdani et al., 2022). RMS maintains the rapid addition, removal, or modification of process controls, functions, and/or operations, through reconfigurable hardware and software to alter production capability and capacity (Mehrabi, Ulsoy, et al., 2000). From an industry perspective, the world market has increased the demand for product diversity and customization, creating a competitive need to provide and scale product types and production volumes rapidly (Ateekh-Ur-Rehman &

Babu, 2012). This demand is experienced by small and medium enterprises (SMEs) and large manufacturing enterprisess (LMEs). The demand for LMEs represents a shift from mass production to mass customization and individualization (Koren, Gu, et al., 2017). Historically, LMEs have hesitated to adopt RMS because of its high investment costs and lower throughput capabilities. As a result, LMEs primarily rely on DMS and the general flexibility of FMS (Koren & Shpitalni, 2010). However, the emergence of customized or individualized products has seen a shift in LME focus toward research and development of RMS within moveable factories and cloud manufacturing (Morgan et al., 2021).

Support SMEs with agile manufacturing approaches is fundamental to their sustainability in this volatile market. It has long been known that SMEs are fundamentally different from large enterprises in terms of strategy, operations, etc (Westkämper, n.d.). Manufacturing methods that are helpful in the context of LMEs may not necessarily be as helpful in SMEs. Even if they are helpful, they most likely are adapted and implemented differently in (Brunoe et al., 2016). SMEs do not have resources equal to LMEs and can be excluded from modern and advanced automation due to many reseasons. For example, the high technical learning curve associated with RMS design, integration, operation, and maintenance (Abele et al., 2017). SMEs still widely adopt manual manufacturing processes to support the diversity of their products and small batch sizes (Zheng et al., 2019). Manual manufacturing processes are a significant disadvantage to SMEs to adjust, grow, and stay competitive dynamically.

For both SMEs and LMEs, RMSs have the potential to provide new abilities beyond traditional design methodologies and potentially provide adaptability and resilience to the market. While the benefits of RMS are well documented in the literature, some barriers limit industry adoption, such as higher costs, complexity, and lower speeds. Furthermore, some academics state that the most significant barrier is an enterprise’s resistance to change (Bortolini et al., 2018).

One solution to encourage the adoption of RMS is to propose production management approaches that adapt to operational and strategic environments and complex customer requirements (Bueno et al., 2020; Wiendahl et al., 2005). Numerous studies have laid the foundation for justifying the adoption of RMS and proposing optimization models for production management. However, these studies have focused on relatively slow-paced models with deterministic parameters. This body of theory presents a problem for manufacturers who face a rapidly changing market. Measuring a new system's effectiveness is based not only on understanding it but on how it will maintain the firm's competitiveness. The classical goal of manufacturing is to produce the required quantity cost-effectively at the required time. This generic aim needs improvement in the context of integration, automation, and responsiveness (F. et al., 2014). With integration, decision-makers can ensure consistency between the three significant decisions; what, how much, and when to produce the parts. Using automation, fast and intelligent decisions can be made to coordinate tasks in real-time (Valente & Carpanzano, 2011). Implementing these two concepts in production management can increase decision-making efficiency for configuration selection and response to customer needs. Otherwise, manufacturing firms are ill-equipped with concurrent strategies and approaches, and RMS may spend several more years in the concept-development stage.

1.3 Problem Statement

In the last decade, RMSs production management has received significant scientific attention. More than 60% of the scientific research was published between 2010 and 2018, according to (Bortolini et al., 2018). In these studies, optimization had a central role in assessing the performance of these systems. Different mathematical models and solving techniques have been used to analyze several criteria, such as cost, responsiveness, fault detection, and energy concerns. Literature review analyses show that most existing models assumed traditional management approaches, did not specifically consider the RMS type, lacked real-time capabilities and control techniques, and focused on deterministic cases (Bensmaine et al., 2014; Khan, 2022; Sabioni et al., 2021b; Yelles-Chaouche et al., 2020).

The traditional strategy for solving production management problems follows a hierarchical approach in which the planning problem is solved first to define the production targets. The scheduling problem is solved next within a shorter time horizon to specify what happens, where, and when to meet these targets. Then the production control problem is solved for monitoring and ensuring proper real-time implementation. This traditional strategy has several disadvantages: it does not guarantee consistency between management decisions, does not consider the interaction between decision variables, and neglects the effect of changeovers and daily inventories (Z. Li & Ierapetritou, 2009).

Developing an applicable mathematical model relies on emphasizing its primary goals. For example, RJS main goals are flexibility while considering the routing of parts, sequence of operations, and RMT configurations. On the other hand, RFL main goals are high productivity and scalability, considering work-in-process (WIP) levels. In these systems, all parts move in the same direction; therefore, routing and sequencing are not the main focus. Existing models mainly focus on process plan generation and machine selection without considering or assuming the machines' layouts (Sabioni et al., 2021a).

Adding stochasticity and real-time capabilities did not receive significant attention. Even though optimization was the primary approach in optimizing RMSs, real-time optimization was not widely considered. As described above, RMS is developed to cope with stochastic environments internally or externally. Carrying out scheduling and control in real-time helps to cope with system uncertainty effectively. In addition, it enables operators to monitor the production progress through visualization and display target performance measures, especially when incorporated with a simulation environment.

Therefore, there is a need to develop methodologies that can effectively integrate some of the production management problems. The objective of integrated methods is to obtain feasible and optimal planning decisions (production targets) for detailed scheduling operations and feasible and optimal scheduling decisions (routing and sequencing or raw material injection) for proper implementation, especially in a stochastic environment. Based on that, the research problem can be summarized as follows:

- A majority of developed models did not explicitly specify the system type for the developed model and focused only on machine selection without considering RMS type or layout.
- The literature focused on studying RMS in deterministic cases even though these systems are developed to cope with stochastic environments. Therefore, there is a need to integrate stochastic aspects in developing RMSs optimization models
- Hierarchical production management approach was assumed in most of the proposed models.
- Incorporating real-time capabilities and providing production monitoring in optimization models

1.4 Research Objectives

This research aims to develop integrated production management formulations under stochasticity that address different system structures; RJSs and RFLs. The goal is to analyze some of the key performance indicatorss (KPIs) for each type. For example, cost, time, and demand fulfillment for RJSs. For RFLs, WIP, tardiness, and flow time. In order to obtain results that provide extensive information to operate and reconfigure RMS in stochastic market environments. The following are the objectives of conducting this research:

- Propose mathematical optimization formulations focusing on integrated production management and ensuring consistency between management functions.
- Develop mathematical optimization that matches the operational goals of the selected system type and its sub-problems. For example, flexibility in RJSs and productivity in RFLs.
- Incorporate real-time capabilities and production traceability in the developed approaches.
- Quantitively analyzes different RMS structures' performance using different KPIs. Productivity, demand satisfaction, tardiness, flow time, WIP levels.

1.5 Research Significance

As previously mentioned, RMSs were introduced as an effective technology to achieve responsiveness in a dynamic market with changing functionality and capacity. Some limitations halt the adoption of these systems. For example, most currently developed approaches assume a traditional management and deterministic environment. Therefore, continuous efforts should be devoted to developing optimization methods. This research was conducted to encourage the use of new and different techniques in developing RMS optimization models. For example, integrated management models, real-time capabilities, controlling techniques, and system type. This research contributes to the knowledge base in the following aspects:

- Proposing novel methodologies for planning, scheduling, and controlling RJS and RFL systems that are utilizing RMTs as their manufacturing equipment.
- Developing planning and scheduling mixed-integer linear programming (MILP) models for dynamic and stochastic RMS. The models integrate the decisions for

machines configurations selection with their production planning and scheduling. The first model is deterministic, which was extended to a two-stage stochastic (TSS) model. These models consider new aspects such as the number of products, quantity and complexity, calibration rate, WIP, and inventory management. In addition, uncertainties in demand and production rates.

- Investigating the effects of different production parameters on the overall performance of flexible job shops (FJSs) in terms of cost, time, and productivity, using sensitivity analysis and analysis of variances (ANOVA).
- Formulating a data-drive controller to optimize output tardiness and select machines' configurations. The controller utilizes real-time shop floor updates such as raw material arrivals and completion times of operations to control the levels of WIP for the RFL system. This controller considered parallel and serial system layouts with supply chain aspects.
- Developing a faster and more efficient approach to model parallel RFL to control the inter-stage movements of parts.

1.6 Research Methodology and Tools

Planning, scheduling, and control were investigated in two parts based on the common system types used in manufacturing industries (i.e., job shop and flow line) To alleviate RMS production management problems. This research considers these forms as RJS and RFL, respectively. For each type, an appropriate methodology was chosen. The methodology selection criterion is based on the nature of the problem and its goals, as discussed in Chapter 2. First, an Industry 4.0-focused optimization methodology was chosen for RJS systems. This methodology is based on MILP formulation for volume-product mix production. The MILP formulation was developed to generate a cost-optimized production and scheduling plan. This problem was investigated in three parts. The first part focuses on developing a comprehensive MILP formulation that reflects new aspects of production planning and scheduling for RMSs. The second part provides a new discussion on the reconfigurability feature and encourages the transition to RMS. The third part is to extend this formulation to a two-stage stochastic formulation to incorporate the uncertainties in volume and machines' productivity. For more details, refer to Chapter 3. The required research tools to implement this methodology are:

- DOcplex (IBM Decision Optimization CPLEX Modelling for Python) optimization software package.
- Benders decomposition algorithm for modeling and solving the TSS problem

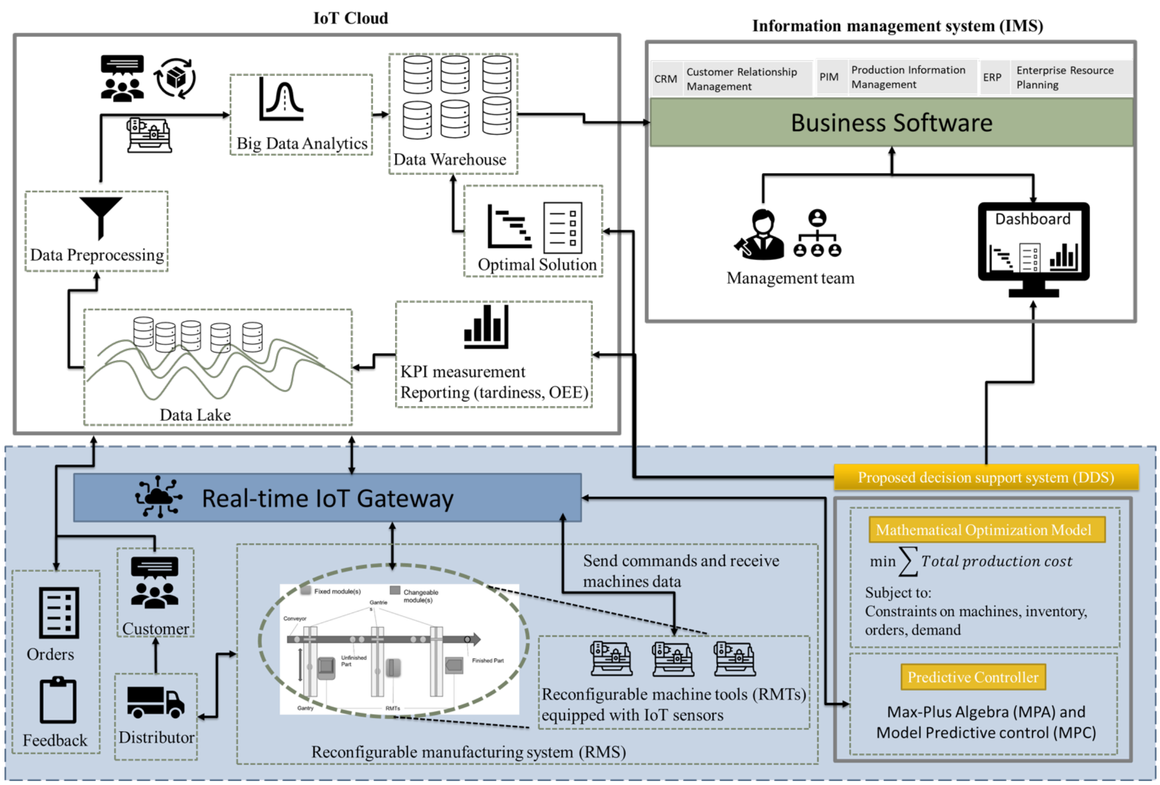
Second, a data-driven model-based controller for real-time scheduling of RFL systems. This methodology utilized the collected data from an agent-based simulation (ABS) model to optimize and monitor production activities in real time. The data collected from the system is fed into the decision module, where reconfiguration and production decisions are optimized. The controlling algorithm is based on max-plus algebra (MPA) and model predictive control (MPC). MPA is a mathematical technique to model discrete manufacturing systems using only maximization (max) and addition (plus) operations (De Schutter et al., 2020; Heidergott et al., 2014). MPC is an advanced control methodology characterized by ease of use and the ability to add constraints on the inputs, states, and outputs. For more details, refer to Chapter 4. The required research tools to implement this methodology are:

- YALMIP MATLAB optimization toolbox (Lofberg, 2004).
- An ABS software – AnyLogic.

The developed framework can be integrated with any organization's

Figure 1.2

General Overview of the Proposed Production Management Framework and its Integration with the Organization Elements



decision-support system elements, as shown in Figure 1.2. Figure 1.3 shows a flowchart to implement the proposed framework for managing RMSs.

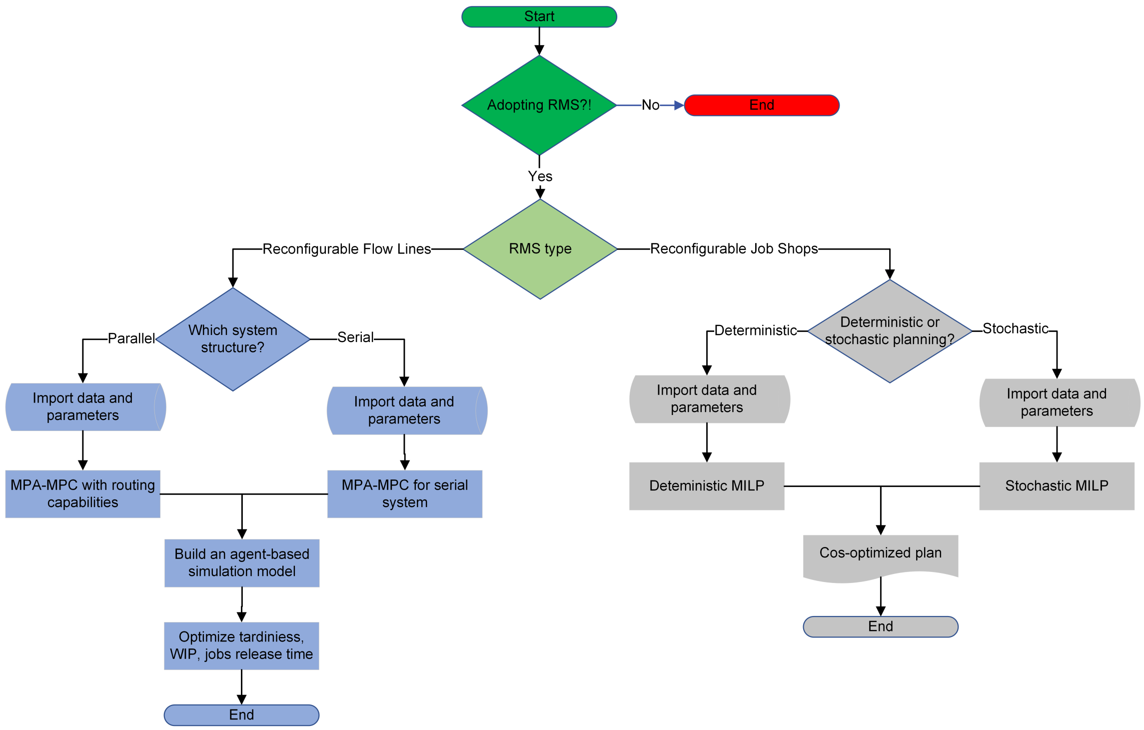
1.7 Research Assumptions

In conducting this study, the following assumptions were made. It was assumed that:

- As described above, the main focus of RMS is to support SMEs with agile manufacturing approaches. Therefore, this study focused on small to medium problem size.

Figure 1.3

Flowchart for Implementing the Proposed Framework



- The product grouping is a deep topic driving a path of the product-process subject. Thus, this topic is just covered to the extent required in developing the methodologies.

- Selecting RMS structure is done at the managerial level based on the producible parts and their operational requirements.

- The design of the available RMTs is optimal. It provides customizability within the part family under production.

- Technical machining details such as type of tools, machining axis, and cutting angles are considered breadthwise as most other studies.

1.8 Research Limitations

The research limitations are summarized as follows:

- Due to the lack of industrial application, the proposed methodologies were evaluated using theoretical examples adopted from the literature. This is a general limitation is RMS optimization literature (Khan, 2022).
- The development of the proposed model was conducted using low computational power, which limited the problem size. However, computational experiments were conducted to investigate the applicability of the proposed models. Results show that the models are suitable for small to medium size production.
- This research did not consider all RMS, such as reconfigurable assembly and cellular systems, due to the limited research timeline.

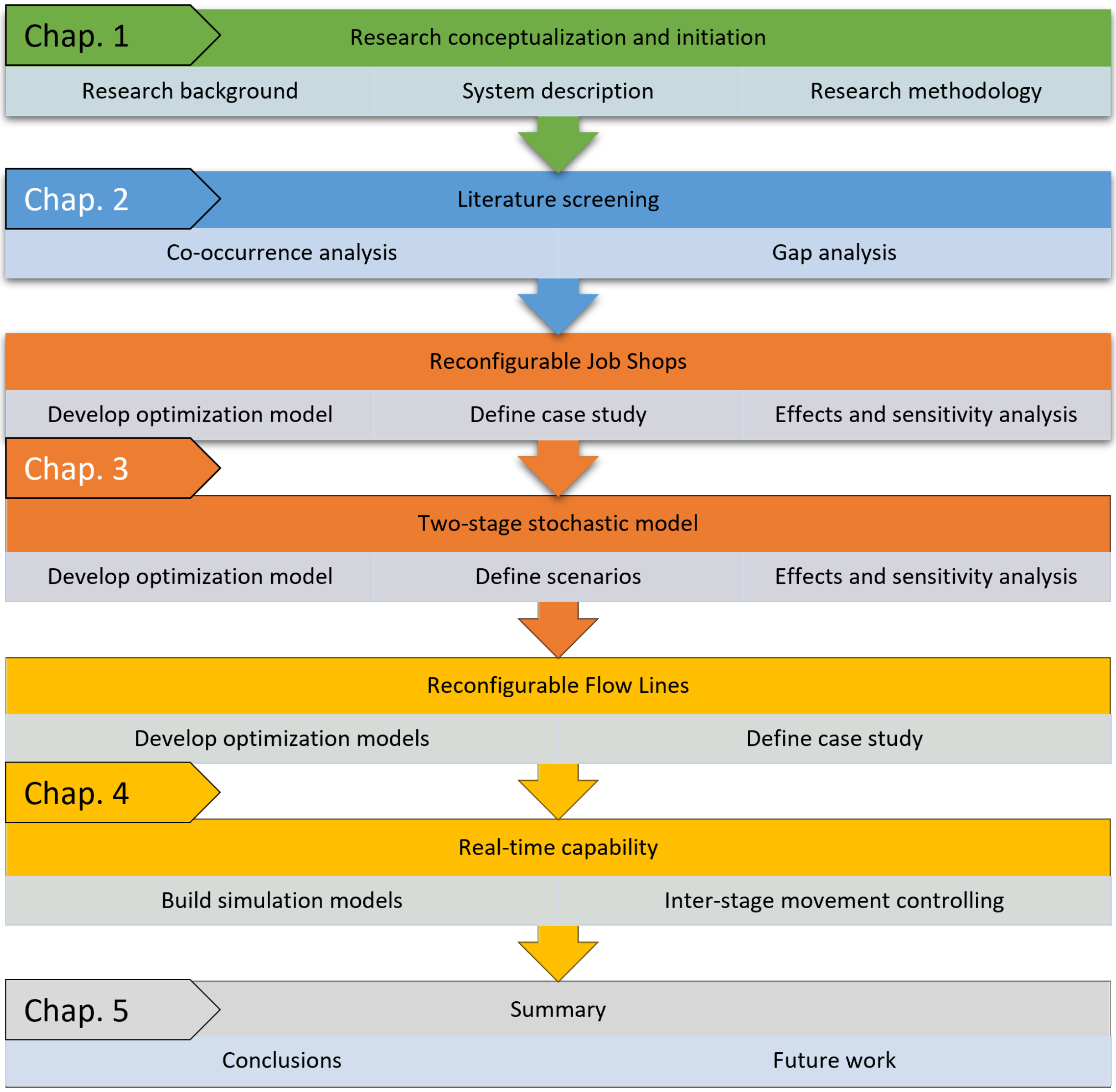
1.9 Research Overview

The remainder of this dissertation is organized as follows and shown in Figure 1.4:

- Chapter 2 introduces the reader to traditional manufacturing systems and their limitations in coping the current market. Then, highlights the main scope of RMS and the characteristics and structure of its main components. A comparison of RMS with traditional systems is also presented. To better understand the production management in RMS, The main elements of production management in RMS are explained. Existing RMS optimization models and their limitations and research gaps were analyzed. First, a network analyses was performed to pinpoint the current focus and research opportunities.
- Chapter 3 discusses production management in terms of planning and scheduling of RMSs in the form of RJS. A deterministic MILP model was formulated to model

Figure 1.4

Research Outlines



RJS and optimize their planning and scheduling simultaneously. Then, effects analyses for influencing internal and external factors were conducted. To address uncertainties in demand and machines production rate, the MILP model was extended to a TSS model. Then, TSS model was evaluated and its applicability is presented

- Chapter 4 discusses production management in terms of scheduling and controlling of RMSs in the form of RFL. A real-time controller is developed for two system structures: serial and parallel. The developed controller was evaluated using simulation experiments. In addition, the efficiency of the developed algorithm for controlling WIP inner-stage movements in parallel systems was evaluated.

- Chapter 5 summarizes the dissertation conclusions and discusses the promising directions for future research.

CHAPTER TWO

A Review of the Literature

2.1 Traditional Manufacturing Systems

Current manufacturing systems, mainly operated as dedicated or flexible systems, do not possess the reconfigurability feature that supports manufacturers' responsiveness to meet the market at a reasonable cost in a short time. Due to globalization, product customization, and demand fluctuations, their use in modern production is declining. DMSs rely on fixed automation and high-volume production of one standard product, which defines the mass production concept. When there is mass production, the cost per part is rather cheap. DMSs are considered a cost-effective solution when the market demand and supply are balanced. However, there are numerous instances where dedicated lines do not run at their maximum capacity, resulting in losses.

On the other hand, FMSs consist of computer numerical control (CNC) or direct numerical controlled (DNC) machines and other programmable automation solutions which can create a range of goods on the same platform (Maksane, 2019). Despite this benefit, flexible systems have not yet gained widespread adoption due to their higher investment cost and complexity (Koren, 2010). Because CNC machines only operate with a single tool, their production rates are much lower than those used in DMSs (Koren, 2006). Additionally, FMSs often have lesser production capacities than DMS and are not flexible enough to adapt quickly to changes in capacity. Table 2.1 compares the two systems by showing their main attributes.

Production facilities may come into two forms; job shop or flow line (Cheng et al., 2022). Job shops are one of the primary production systems adopted by manufacturers worldwide, which produce products in high volume. The flow of the material is

Table 2.1

Comparison of Dedicated Manufacturing Systems (DMSs) And Flexible Manufacturing Systems (FMSs)

Criteria	DMSs	FMSs
Machines types	Dedicated	CNC or DNC
Example	Canned goods	Apparel
Advantages	• Short lead-time • Low cost	• General flexibility • Scalable capacity
Limitations	• No customization • No scalability	• High investment cost • Slow

intermittent, meaning they are not continuous or steady. Most job shop items need a lengthy setup period between each machine's operation. Similar machines are placed next to one another to create a workshop, which results in a process layout (Groover, 2020). A practical example of these systems can be seen in the production of glasses (Khalife et al., 2010). On the other hand, flow lines come in two types; serial and parallel. In these forms, the product flow is unidirectional and processed in ordered operations at only one machine in each stage for one or more stages (Lee & Loong, 2019). In other words, a part enters the system and moves from an upstream machine to a downstream machine through a buffer or conveyor. One of the main problems in flow lines is controlling the WIP flow to prevent the overflowing of intermediate buffers. A practical example of a flow line is in multi-layer printed circuit board (PCB) fabrication (Laisupannawong et al., 2021). Table 2.2 compares these two types. Figure 2.1 shows a typical structure of both types. In this research, the job shops are extended to RJS, and flow lines are extended to RFL since the manufacturing equipment that is to be used is RMTs. RJSs are studied in Chapter 3 and RJSs are studied in Chapter 4.

Table 2.2

Comparison of Flow Lines and Job Shops

Criteria	Flow lines	Job shops
Layout	Product layout	Process layout
Material Flow	Unidirectional	Nonuniform
Advantages	• Short lead-time • Low inventory • Short transportation distances	• High-quality products • High customization • Ease of supervision
Limitations	• Blockage and starving phenomena • High setup cost • low customization	• Long lead time • Scheduling complexity • High Investment
Example	PCB fabrication, automobiles	Glasses, tailoring

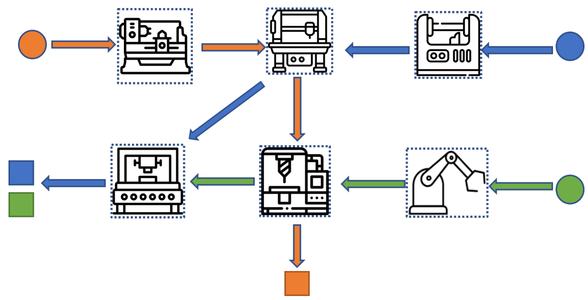
2.2 Reconfigurable Manufacturing Systems

Koren et al. (1999) introduced RMSs as an intermediate solution that combines the advantages of DMSs and FMSs (Benyoucef, 2020; Koren & Shpitalni, 2010). Their main objective is to join high reconfigurability and responsiveness to the dynamic market changes (Bortolini et al., 2018). The reconfigurability of RMS combines flexibility and productivity by prolonging the production system through rearrangement and reuse of the manufacturing equipment and processes (Andersen et al., 2020; Dotoli et al., 2019). Reconfigurations can be done at different levels: physical rearrangement of machines, adding new machines/manufacturing resources, removing existing machines/manufacturing resources, redesign/reconfiguration of machine/manufacturing resources, and allocation and assigning a new role to human resources in different workstations (Khanna & Kumar, 2019). With a such design, the system's capabilities and functionalities can be changed over time in response to market changes. Responsiveness is a manufacturing systems ability that allows them to introduce new products to current systems easily and to react rapidly and cost-effectively to (Koren, 2006):

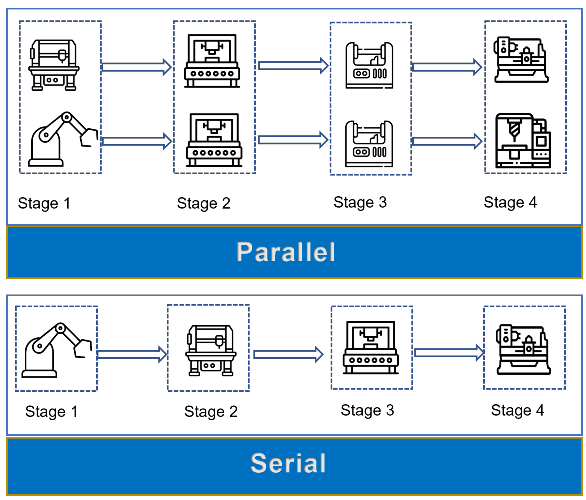
- Market changes

Figure 2.1

The Manufacturing Process Flow in (a) Job Shops and (b) Flow Lines



(a)



(b)

Note: Machines icons made by Freepik and Smashicons from www.flaticon.com

- Customers' orders
- Government regulations in terms of safety and environment
- System failures and reduce downtimes

Market changes include:

- Changes in product demand
- Changes in current products

Table 2.3

Comparison of Reconfigurable Manufacturing Systems With Dedicated and Flexible Manufacturing Systems

Criteria	DMSs	FMSs	RMSs
Cost per item	Low	Medium	Reasonable
Demand	Stable	Variables	Variable
Productivity	Very high	Low	High
Flexibility	No	General	Customized
Machine structure	Fixed	Fixed	Changeable
System focus	Part	Machine	Part family

- Introducing new products

The challenges mentioned earlier cannot be addressed using DMSs and FMSs. They can be addressed by a manufacturing system that is designed with flexibility in changing production capacity as the market grows and functionality as products are introduced or changed. Based on that, RMSs can be defined as manufacturing systems that are designed for rapid adjustment in production capacity and functionality, in response to new circumstances, by rearrangement or change of its components in both hardware and software levels within a part family. They consist of multiple RMTs, which come in multiple configurations. In addition, reconfigurable inspection machines (RIMs) can be added to the system to inspect the produced parts in real time.

To better understand the differences between RMSs, DMSs and FMSs, Table 2.3 compares the main attributes of these systems.

2.2.1 Reconfigurable Machines

RMS is a system generally designed around a product part family. It allows quick architecture reconfiguring in both hardware and software resources to match the required functionality and capacity (Eguia et al., 2016). A typical RMS consists of multiple RMTs which offer this reconfigurability feature due to their modular and adjustable structure (Bortolini et al., 2021). The production capacity and functionality of each RMT are altered by rearranging or changing the RMT basic modules (i.e., base, structural elements) and auxiliary modules (i.e., functional arm). The combinations of these modules are called configurations, each having its operational capability and productional capacity. Operational capability represents the variety (i.e., number) of operations a machine can perform in one of its configurations (Ashraf & Hasan, 2018). Figure 1.1 depicts a typical RMT modular structure and its configurations properties. The RMT is set up in a configuration that best matches the production requirement and configuration properties. For example, assume a part requires operations 1, 4, and 6 to produce a finished unit, then configuration 1 should be selected and its modules installed on that RMT. When the production requirements are changed, and the existing configuration does not match these requirements, the RMT is reconfigured to another configuration. On the other hand, traditional systems such as FMSs are generally comprised of CNC machines with fixed hardware and software and a limited tool magazine. These machines produce various parts and are designed before operational requirements are known. Thus, they often have high capital waste as many companies produce only a few product models.

Additionally, rapid and cost-efficient inspection tools may be required for measuring geometrical and dimensional tolerances and surface quality when a large volume of parts is manufactured. For quick, in-process examination of the machined features of a component family of cylinder heads, the RIM was proposed (Koren & Katz, 2003). The RIM was initially created to assess geometric characteristics such as flatness, parallelism, profile related to the cover, and joint faces of an engine cylinder head (Katz et al., 2002; Katz, 2006). The RIM also permits inspection of cylinder head surfaces for porosity and other surface texture flaws in a different configuration by including a machine vision system in the structure. The RIM utilizes high-definition line-scan cameras and commercial laser sensors in conjunction with computer vision as its foundation for non-contact measuring techniques. Since RIM is usually implemented in high-volume manufacturing, this research did not consider RIM in developing the production management framework.

2.2.2 Production Management for RMS

The hierarchy of designing and managing RMS involves the following decision items:

- System configuration: the way the machines are arranged and interconnected.
- Manufacturing equipment: the number and type of machines and the material handling system
- Process planning: assigning operations to each machine in the system (Koren, Wang, et al., 2017).

However, two other items should also be added:

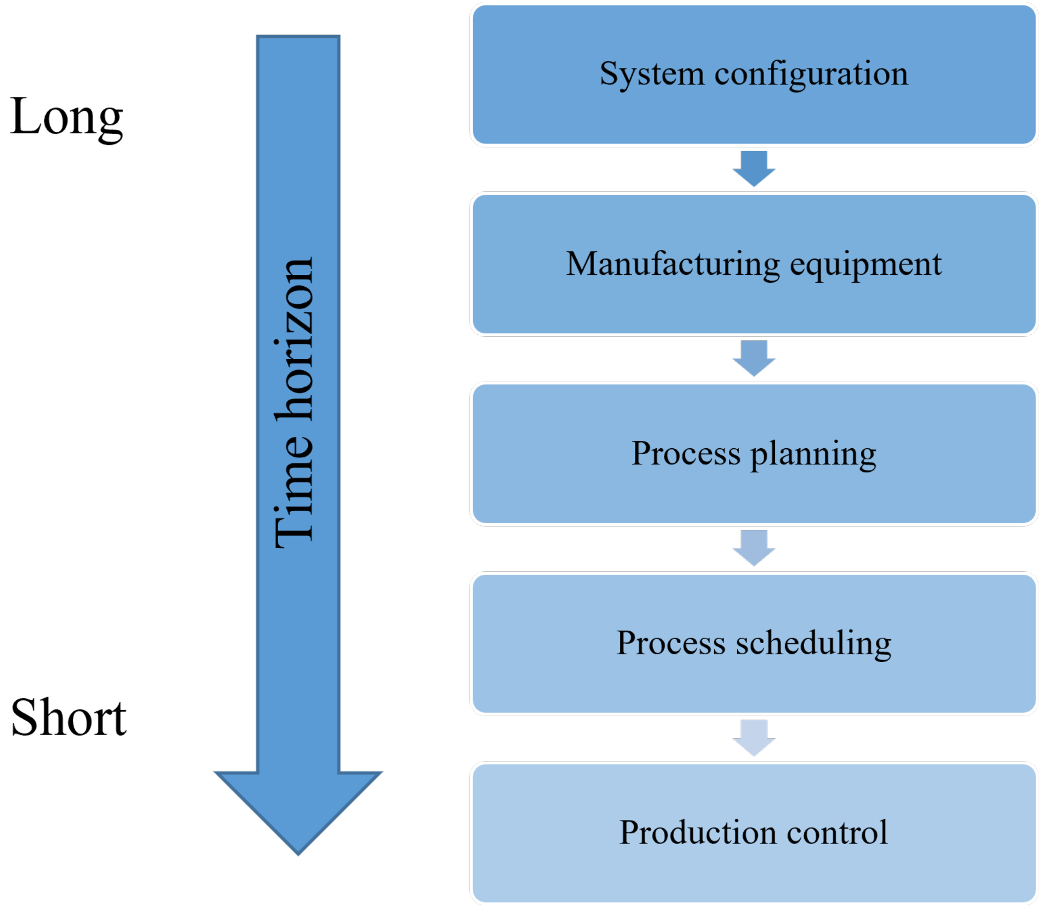
- Process scheduling: determining where and when each process is performed.
- Production control: monitoring and ensuring the proper implementation of the previous steps in real-time (Villa, 1995).

The goals, information, and decisions taken at each level are often very different, and because of that, it is not very easy to integrate them.

Figure 2.2 shows the hierarchy of management problems in RMS based on the time scale at which they are solved. However, drawing a line that separates each level is difficult, especially when dealing with a rapidly changing environment, and the decision must be taken at each management level. It is necessary to use innovative technologies

Figure 2.2

General Overview of Production Management Hierarchy in RMS



and methods that automate and digitalize the decision-making process to efficiently utilize and adopt RMS.

Traditionally these levels of management are solved in a hierarchical approach, which partitions the whole problem into a series of sub-problems that are solved successively, such that the solution at each level imposes constraints on the subsequent lower level. The hierarchical approach's fundamental advantages are reduced complexity and gradual absorption of random events that may appear in successive levels (Nagi & Proth, 1994). On the other hand, it does not guarantee consistency between management decisions, does not consider the interaction between decision variables, and neglects the effect of changeovers and daily inventories (Z. Li & Ierapetritou, 2009). This research focuses on modeling up to levels to address the interaction between decision variables at multiple levels.

2.3 Related Literature

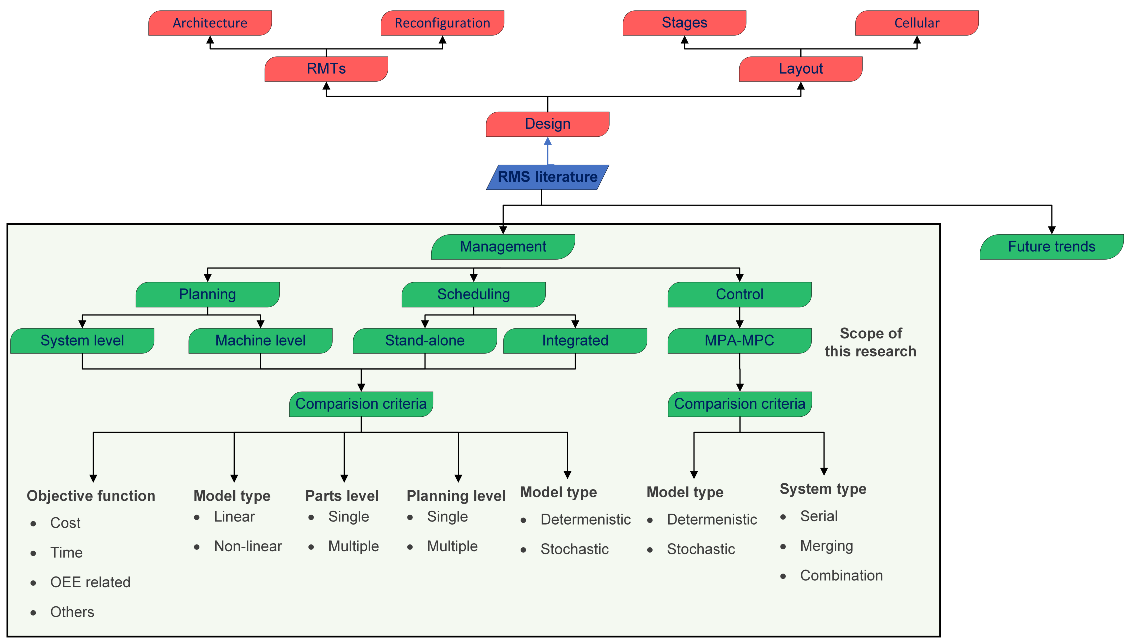
This Section presents a review of RMS literature. Through a non-exhaustive literature review, the reader can classify it under three main streams: management, adoption barriers, future trends, and design. The focus of this research will be on production management. It should be noted that drawing a line separating management and design problems is difficult when we have a rapidly changing system because it is impossible to deal with management while ignoring design issues. The classification presented below is based on the paper's main goal and its planning time scale. Figure 2.3 depicts the structure of RMS literature, the scope of this research, and the comparison criteria. Two types of examinations are carried out on the collected literature; keywords analysis and gap analysis. In keywords analysis, authors-keywords occurrences and overlay visualization are taken into account.

2.3.1 Network Analysis

This analysis aims to identify links between words, detect research trends, and pinpoint research opportunities. Co-occurrence analysis was conducted focusing on authors-keywords. Documents from Scopus database are extracted after conducting a thorough search in the database. The search resulted in 1148 documents. The results were imported into VOSviewer software tool (van Eck & Waltman, 2014). Then duplicate keywords and their variations (plural, singular, British spelling, etc) were removed based on the link strength. The resulting network is shown in 2.4. In the co-occurrence analysis, keywords of interest were reconfigurable manufacturing system(s), optimization,

Figure 2.3

Classification of RMS Literature and the Scope of This Research and Its Relevant Literature



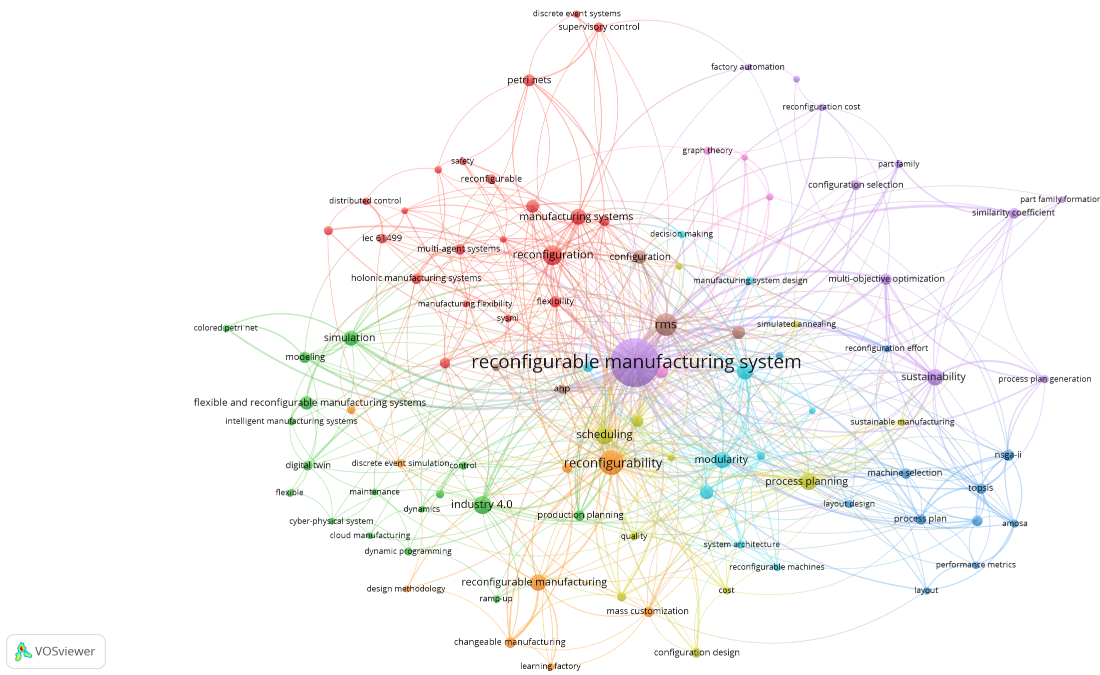
planning, scheduling, control, and industry 4.0. The occurrences and linked keywords to each of the keywords, as mentioned earlier, are recorded in Table 2.4

Then, the overlay visualization tool was used to visualize the network and detect trending keywords in the last couple of years. Figure 2.5 shows that Industry 4.0. digital twin (DT), decision-making, changeable manufacturing, scheduling, and cost are some of the trending keywords in RMS literature. This shows the importance of RMS in Industry 4.0, and future research should focus on the connection between RMS and Industry 4.0. Moreover, Industry 4.0 enabling technologies should be used in the decision-making processes. For instance, there are a different modular RMS-DT framework has been proposed and reviewed in (Hajjem et al., 2021).

The literature shows that optimization has the leading role in addressing these problems and assessing the performance of RMSs. Different KPIs have been analyzed in the literature, such as cost, system flexibility, one or more of overall equipment

Figure 2.4

Generated Network According to Authors-keywords



effectiveness (OEE) factors, etc. In fact, cost is the most widely considered KPIs in RMS optimization. Moghaddam et al. (2018) developed a two-phased method to handle selecting and designing configurations for single-product production. Moghaddam et al., 2019 developed two approaches for selecting and designing the configurations with minimum exploitation and module changing cost. Some papers combined cost with other important performance indicators such as throughput (Musharavati & Hamouda, 2012), system modularity and flexibility (Benderbal et al., 2017b), cycle time minimization (Hsieh, 2017), machines' exploitation time (Touzout & Benyoucef, 2019b), and reconfiguration index (Dahane & Benyoucef, 2016). In these papers, the cost has been considered a sum of capital and operating costs. The capital costs include the purchasing and overhead costs, while operating costs compromise the costs incurred during production.

Table 2.4

Summary of Network Analysis for the Selected Keywords, Their Occurrences, and Most Important Linked Keywords

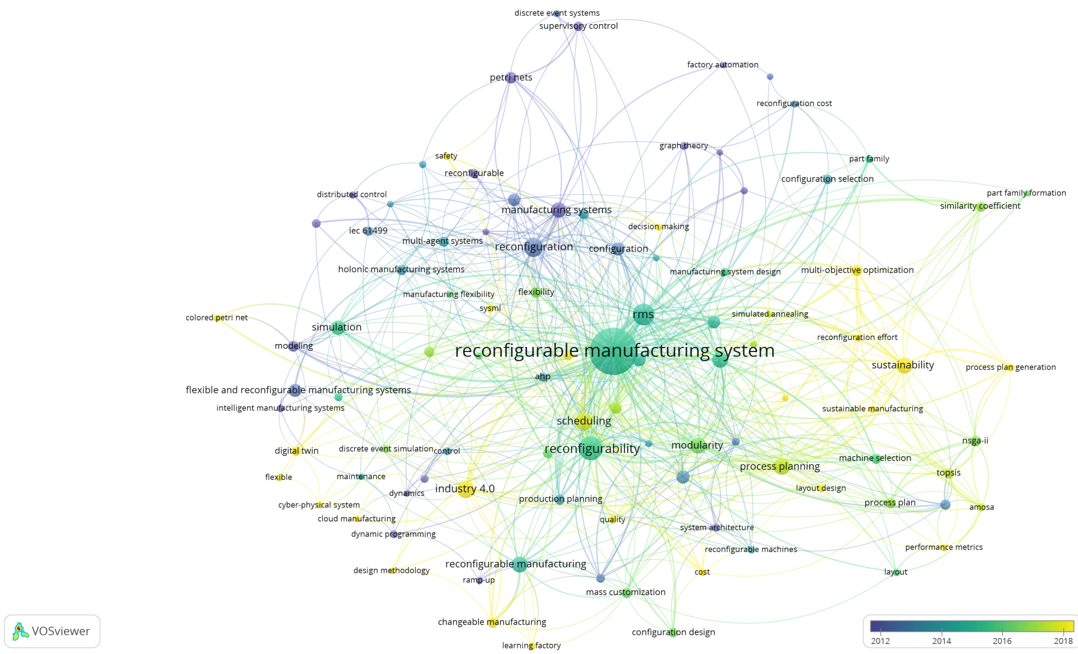
Keyword	Occurrences	Some of the Linked keywords
RMS	255	Optimization; configuration selection; flexibility reconfiguration cost; performance evaluation
Optimization	31	Cost; decision making; configuration selection; productivity; modularity; factory automation; process planning; mass customization
Scheduling	34	Automation; configuration selection; control; optimization; process planning
Process Planning	32	Optimization; cost; quality; mass customization; RMS
Control	8	Dynamic; scheduling; Industry 4.0; RMTs; dynamics; production planning
Indutry 4.0	36	Optimization; cost; quality; mass customization; changeable manufacturing; modularity; diagnosability; cloud manufacturing; reconfigurable manufacturer; RMS
Stochastic models	7	RMS

2.3.2 Process Planning

Process planning focuses on assigning appropriate machines and their corresponding configurations to various manufacturing tasks and determining their sequences on production lines (Yelles-Chaouche et al., 2020). Process planning can be detailed at two levels; system level and machine level. The system level deals with high-level decisions, such as machine configuration selection, machine reconfigurations, processes/machines matching, etc. The machine level deals with detailed machine activities such as tools and modules selection. Most papers addressed process planning detailed machine configurations to perform single-part operations (Sabioni et al., 2021b). Some papers tackled single-part process planning using single-objective optimization such as (Dou et al., 2008; Hsieh, 2017; Maniraj et al., 2014; Shabaka & ElMaraghy, 2008). There are also cases where RMS planning was optimized using multi-objective models.

Figure 2.5

Keywords Network Visualized using Overlay Visualization to Detect Trending Keywords



For example, (Touzout & Benyoucef, 2019a) addressed RMS process planning using multi-objective optimization approaches. Their proposed model focused on minimizing production cost and completion time and maximizing machines' exploitation time. Other papers extended this by adding sustainability aspects to process planning (Khezri et al., 2020; Touzout & Benyoucef, 2019b). Benderbal et al., 2017a developed a multi-objective approach based on completion time and system flexibility to select the best set of machines for process planning. Modularity, completion time, and cost were added to this type of optimization in the work of (Benderbal et al., 2017b). Minimizing total cost and production time (Chaube et al., 2012), number of reconfigurations (Bensmaine et al., 2012), and machine precision and tardiness (Xie et al., 2012) are other objectives that were considered for process planning. Some related literature extended the idea for part family process planning while including system energy or throughput and/or cost in their optimization framework (Dou et al., 2009; Massimi et al., 2020; Musharavati &

Hamouda, 2011; Musharavati & Hamouda, 2012).

In addition, process planning literature ignored the effect of reconfiguration on the consecutive production run in terms of time and cost. For example, (Ashraf & Hasan, 2018; Goyal et al., 2012; Goyal & Jain, 2015) studied process planning considering multiple objectives including cost, reconfigurability, capability, reliability, and utilization as the selection criteria and did not include reconfigurations effect in their model. Other papers interpreted reconfiguration time in terms of cost (Moghaddam et al., 2018; Spicer & Carlo, 2006). Bensmaine et al., 2013 added reconfigurations time and cost in the optimization model for selecting the candidate machines. This work was extended by (Dahane & Benyoucef, 2016) by selecting the machines based on minimizing the total cost and maximizing the reconfigurability levels of the selected machines. In multi-period manufacturing, (Moghaddam et al., 2019) selected machines and their configurations based on the total cost. One of the main factors that influence the effectiveness of RMS systems is calibration which is ignored in most of the previous literature related to their configuration selection decisions (Koren, Wang, et al., 2017). This factor was included in limited articles and only in system-level optimization (Spicer & Carlo, 2006).

The reviewed literature summarized in Table 2.5 reveals that demand has been considered deterministically in most research papers. Integrating stochastic and uncertain aspects are essential in studying RMS as they were designed to cope with uncertain markets. Cui et al., 2020 proposed a multi-period stochastic programming model to optimize the configuration of RMS in each period considering uncertain demand.Abbasi and Houshmand, 2009, 2010 respectively,proposed formulation and a genetic algorithm approach. In both papers, the objective was to maximize RMS efficiency while satisfying market demands. For this, the authors considered that the product arrival order is stochastic, and they tried to find an optimal solution in terms of the length of the considered period, the number of production tasks to be achieved, the sequence of

Table 2.5

Summary of the Reviewed Literature on Planning for RMSs

Author	Focus		Model		Objective function				Product		Planning		Problem	
	P.P	Schd.	Lin.	Non	C	T	OEE	Other	S	M	S	M	Det	Sto
Abbasi and Houshmand, 2009	SL			✓	✓							✓		✓
Abbasi and Houshmand, 2010	SL			✓	✓							✓		✓
Ashraf and Hasan, 2018	ML				✓		✓	✓	✓		✓		✓	
Benderbal et al., 2017a	ML					✓		✓	✓		✓		✓	
Benderbal et al., 2017b	ML		✓		✓	✓		✓	✓		✓		✓	
Bensmaine et al., 2012	ML		✓		✓	✓		✓	✓		✓		✓	
Bensmaine et al., 2013	ML		✓		✓		✓		✓		✓		✓	
Chaube et al., 2012	ML		✓		✓	✓			✓		✓		✓	
Cui et al., 2020	ML		✓		✓						✓			✓
Dahane and Benyoucef, 2016	ML				✓			✓	✓		✓		✓	
Dou et al., 2008	SL		✓		✓				✓		✓		✓	
Dou et al., 2009	SL			✓	✓					✓		✓*	✓	
Goyal and Jain, 2015	SL		✓		✓		✓	✓	✓		✓		✓	
Goyal et al., 2012	ML		✓		✓			✓	✓		✓		✓	
Hsieh, 2017	SL		✓			✓			✓		✓		✓	
Khezri et al., 2020	ML		✓		✓	✓		✓					✓	
Maniraj et al., 2014	ML		✓		✓				✓		✓		✓	
Massimi et al., 2020	ML			✓				✓		✓	✓		✓	
Moghaddam et al., 2019	ML		✓		✓					✓		✓	✓	
Moghaddam et al., 2018	ML		✓		✓				✓		✓		✓	
Musharavati and Hamouda, 2011	ML		✓							✓	✓		✓	
Musharavati and Hamouda, 2012	ML		✓		✓		✓			✓	✓		✓	
Shabaka and ElMaraghy, 2008	ML		✓		✓				✓			✓	✓	
Spicer and Carlo, 2006	SL		✓		✓				✓			✓	✓	
Touzout and Benyoucef, 2019a	ML		✓		✓	✓	✓						✓	

Continued.

Table 2.5– *(Continued)*

Author	Focus		Model		Objective function				Product		Planning		Problem	
	P.P	Schd.	Lin.	Non	C	T	OEE	Other	S	M	S	M	Det	Sto
Touzout and Benyoucef, 2019b	ML		✓		✓	✓		✓	✓			✓	✓	
Xie et al., 2012	SL				✓			✓					✓	
This research	SL	Int.	✓		✓					✓		✓	✓	✓

Table 2.6

Summary of the Reviewed Literature on Scheduling for RMSs

Author	Focus		Model		Objective function				Product		Planning		Problem	
	P.P	Schd.	Lin.	Non	C	T	OEE	Other	S	M	S	M	Det	Sto
Azab and Naderi, 2015		SA	✓			✓				✓		✓*		
Bensmaine et al., 2014	ML	Int.	✓			✓			✓		✓			
Botsalı and Şeker, 2017	SL	Int.	✓			✓				✓	✓			
Dou, Li, et al., 2020	SL	Int.	✓		✓					✓		✓*		
Dou et al., 2016	SL	Int.	✓		✓	✓				✓		✓*		
Dou, Su, et al., 2020	SL	Int.	✓		✓					✓		✓*		
Mahmoodjanloo et al., 2020	SL	Int.	✓			✓				✓	✓			
Mahmoodjanloo et al., 2021	SL	Int.	✓			✓				✓	✓			
Yu et al., 2013		SA	✓			✓				✓	✓			
This research	SL	Int.	✓		✓					✓		✓	✓	✓

Note: *: up to two levels only; ML: machine level; SL: System level; Int.: integrated scheduling (IPPS); P. P.: process planning; Schd: scheduling; Lin.: linear; Non: nonlinear; C:cost; T: Time; OEE: overall equipment effectiveness; S: single; M:multiple; Det: deterministic; Sto: stochastic.

products and their appropriate configurations, and the batch size of each production task. The objective function of both researches was to maximize the earned profit. Other papers developed stochastic models, but they were out of the scope of this research, such as (Azadeh et al., 2010; Kristianto et al., 2013; Xie, 2006).

2.3.3 Process Scheduling

Scheduling as a stand-alone function concerns assigning operations to manufacturing equipment based on defined criteria for due dates and costs (Bensmaine et al., 2014). Or determining the order of releasing the parts/operations into the production system (Khan, 2022). Scheduling and production planning of the reconfigurable systems involves multiple integer and binary variables that increase the computation time to solve them. Therefore, various meta-heuristics such as genetic algorithm and particle swarm optimization (PSO) were utilized to obtain a high-quality solution. In most cases, scheduling was studied in a simplified form (stand-alone function) and only for one or two consecutive production periods as shown in Table 2.6. In one production period, (Yu et al., 2013) incorporated scheduling with sequencing decisions of the parts in a single-period model. They showed that integrating scheduling with planning achieved better product delivery time and utilization for manufacturing systems. Machine configurations selection was not incorporated into their model. In two-period production, (Azab & Naderi, 2015) studied scheduling where the part family was split into different subfamilies defined as jobs. Nevertheless, Some papers addressed integrated process planning and schedulings (IPPSs) within the RMS paradigm. The important assumption in solving the IPPS problem is sequencing and processing flexibility (W. D. Li & McMahon, 2007). One of the first efforts in solving the IPPS problem within the RMS paradigm is (Bensmaine et al., 2014). Their model was limited to single-period manufacturing. Then, (Botsalı & Şeker, 2017) extended their model to multi-part manufacturing. On the other hand, (Mahmoodjanloo et al., 2020) considered this problem by modeling RMS as a flexible job shop with a predefined layout and minimizing the makespan. Then they extended this work for a distributed manufacturing system with several facilities (Mahmoodjanloo et al., 2021). Recent works in the IPPS domain considered one consecutive production period only and ignored reconfiguration effects in terms of cost and time (Dou et al., 2016; Dou, Li, et al., 2020; Dou, Su, et al., 2020).

2.3.4 Production Control

The increasing need to develop efficient and fast optimization methods with predictive capabilities promoted the integration MPA and MPC. The former is an effective tool for modeling the event timing dynamics of a deterministic discrete-event system like a manufacturing line or a job shop manufacturing system (Esmaeil Zadeh Soudjani et al., 2016; Lahaye et al., 2001; M. Singh & Judd, 2012). The latter refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of a plant. At each control interval, an MPC algorithm attempts to optimize future plant behavior by computing a sequence of future manipulated variable adjustments (Qin & Badgwell, 2003; Son et al., 2022). (De Schutter & van den Boom, 2001) was one of the first efforts to integrate MPC with a max-plus-linear system (MPL).The study proved that the MPC problem can be recast as a problem with a convex feasible set. In other words, if an MPL system is controlled using MPC, then this model can be solved using linear programming solvers. (Boom & Schutter, 2004) extended the previous framework to a stochastic MPL systems and modeled a serial line with stochastic processing time. (van den Boom & De Schutter, 2006) developed a switching MPA-MPC model for a parallel system with two stages. However, this approach required modeling all possible cases which increased the modeling and solving efforts. (Mutsaers et al., 2012) used MPA for a parallel production system that merged into one station. However, the model was simplified and developed for calcium silicate stones production. (Nasri et al., 2011a) developed a model based on max-min-plus-scaling (MMPS) functions for a flow shop system and certain jobs may skip certain machines. (Nasri et al., 2011b) developed a model with decision variables for scheduling a job-shop system. A few years later, (Nasri et al., 2012, 2014) incorporated scheduling variables for two different scenarios of periodically and flexible periodic maintenance. (Seleim & ElMaraghy, 2015) developed a method for quick and efficient generation of the max-plus equations for some manufacturing flow lines. (Martínez-Olvera & Mora-Vargas, 2018) developed a model considering a re-entrant manufacturing system (two products – two machines used twice). (Huang et al., 2018) focused on reducing energy waste when machines are in idle states. One of the recent works is the research presented by (Chen et al., 2020) where MPC is incorporated with a max-plus model to control the job release plan of serial production systems. (Rocco et al., 2021) extended the application of MPA to model merging lines with different flow configurations and buffer capacities and provides the approximated probability density functions (PDFs) of selected performance indicators. Other papers, incorporated MPC with mixed logical dynamic model to schedule parallel machines (Cataldo et al., 2015).

2.3.5 Future Trends and Challenges

As we are still at the beginning of a new era of modern manufacturing systems, there are many barriers to their advancement. Therefore, it is necessary to develop a fundamental understanding of the required manufacturing processes, equipment, and technologies and their relation to manufacturers' success. Because the dynamic nature of RMSs makes any manufacturers working with the existing knowledge base skeptical of its adoption (Khan, 2022). For example, (Bruzzone, 2021) defined the required levels of reconfigurability in manufacturing systems. Three levels were defined in this research, low, middle, and high levels, where each level has its features. (Mehrabi, Ulsoy, et al., 2000) identified the key roles of RMSs in future manufacturing and highlighted the proper understanding of the required equipment design and effective communication to ensure the success of future RMSs. Other efforts focused on utilizing Industry 4.0 enabling technologies for managing RMSs. (Hajjem et al., 2021) reviewed RMS-DT. The authors focused on the challenges and requirements to implement RMS-DT modular framework. In addition, they highlighted the importance of information management system (IMS) and human-machine interface (HMI) which are one of the components of the presented research. On the other hand, (Napoleone et al., 2021), focused on RMS diagnosability and reliability problems and its enabling technologies within Industry 4.0 paradigm. The authors analyzed three manufacturers' diagnosability and level of automation and identified the required enabling technologies to achieve their goals.

Although, there are numerous papers with promising results on the success of RMS within Industry 4.0 paradigm, utilizing these enabling technologies is not easy or handy. Therefore, (Maganha et al., 2021) explored the idea of integrating reconfigurability and industry 4.0 technologies and their barriers. The authors classified the barriers in three contexts; technological, organizational, and environmental. The findings showed that technology and organization barriers can be exceeded with the acquisition and use of some novel technologies promoted by Industry 4.0.

2.4 Summary

This Chapter introduces the reader to manufacturing systems and the aim of this research. It discusses the current challenges that manufacturing companies are facing such as globalization, dynamic market, and frequent introduction of products. Moreover, it discusses the deficiencies in the existing manufacturing systems which are DMSs and FMSs in addressing the current challenges. Then, gives a brief introduction to RMSs and their manufacturing equipment. Later, it presents the main elements in the hierarchy of RMSs production management. Lastly, the research methodologies and the proposed framework are presented in the last Section.

This chapter includes the summary of the related literature. The literature reviewed in this chapter mainly include the research that focus on optimizing RMSs. Table 2.7 summarizes the current focus and the research gaps. From planning and scheduling perspective, the existing research provided a good foundation about RMS problems and assessing its performance in terms of different KPI. This research analyzed and discussed a couple of factors that influence the performance of RMS (refer to Section 3.5). In addition, the proposed MILP considered new aspects of the IPPS problem. From production control perspective, RMS optimization literature focused mainly on analytical optimization methods with static parameters rather than data-driven solutions which is the main requirement of the fourth industrial revolution. Few literature found on production control for RMSs. On the other hand, methods such as MPA emphasized on the quantitative system performance and expressed the dynamics of events in terms of a set of algebraic linear equations analogous to conventional state-space linear equations. However, these papers did not fully investigate production planning and scheduling of modular RMSs.

Table 2.7

Summary of Current Focus and Research Gaps

Criteria	Current focus	Research gaps
Level of analysis	Production and machine level analysis	System-level analysis; integration of multiple levels
Production management	Configuration selection; planning; scheduling	Integration of process planning and system layout; controlling methodologies; configuration tracking
Nature of problem	Deterministic problems	Integrating uncertainty in optimization problem
Type of products	Single-product	Multi-product analysis to justify investment and efficiency
Optimization models	Offline with static parameters	Online optimization and stochastic parameters

CHAPTER THREE

Production Management of Job Shops with Reconfigurable Machines

3.1 Introduction

In classical job shop production systems, the production management problem is called job shop scheduling problem (JSSP), which is an NP-hard combinatorial optimization problem concerned with finding the job sequences on the machines (Błażewicz et al., 1996). A job shop typically produces low quantities of specialized and customized products such as aircraft, glasses, and special machinery. The job shop uses general-purpose machines arranged in a process layout to process different parts. Each part requires a different operation sequence and a particular path to be processed. Parts are usually produced in batches and move in a non-uniform fashion. Therefore, a job shop must be designed for maximum flexibility to deal with wide product variations and accommodate a variety of operation sequences for different parts (Groover, 2020). As manufacturing systems evolved, this problem evolved and extended to flexible job shop scheduling problem (FJSSP) (Gao et al., 2019). In the extended version, the operations can be performed on any machine selected from a finite number of a given set of machines, which increases the complexity of the problem (Amjad et al., 2018). When RMTs are introduced, the system type is called RJSs, and the complexity of the problem will exponentially grow since there is a need to select machine configuration and its modules. Therefore, the problem can be considered an extension of FJSSP (Mahmoodjanloo et al., 2020). The problem is more complicated than the FJSSP because three decisions have to be made; these decisions include allocating the operations to the machines, sequencing the jobs, and determining the configuration of the machines to perform the allocated operations. Most of the literature studied RJS while only considering the routing of the parts and RMT configuration selection. This assumption may cause unnecessary reconfigurations to obtain feasible sequencing. Moreover, each RMT needs time to be reconfigured and calibrated, which impacts productivity. This impact was not widely considered in the developed models. Integrating the configuration selection into sequencing and routing problems is more significant (Fan et al., 2022).

In this research, we called the extension of FJSSP, reconfigurable job shop scheduling problem (RJSSP). it is assumed that customers' orders (i.e., production jobs) are assigned to a shop floor, including several RMTs. Each order has a set of operations that can be processed at least on one configuration of one of the existing RMTs. Since parts move in a non-uniform direction, it is necessary to integrate parts routing and operations sequencing in the developed model. A deterministic MILP model was developed to address this problem. The proposed formulation minimizes the total manufacturing cost and includes constraints on machine configuration selections, parts routing, and operations sequencing. A case study adopted from the literature is used to test the applicability of the proposed model. The results were compared with a traditional non-reconfigurable system to test the efficiency of the proposed model and investigate the advantages of RMSs. Then, this model was extended to TSS model to relax some constraints on machine type selection and incorporate stochasticity in demand and machine degradation into the MILP model. The main contributions of this Chapter are summarized as follows:

- Proposing a novel MILP model for a multi-period RMS that integrates machine configuration selection decisions with their production planning and scheduling.
- Investigating the effects of product features, reconfiguration time, calibration rates, length of the production period, and storage capacity on overall performance and productivity metrics (such as systems utilization rate, order fulfillment, and production cost) of these systems.

- Implementing comprehensive experiments based on analysis of variances (ANOVA) to identify the main contributing factors on cost savings of RMSs.
- Proposing a novel TSS model that incorporates machines type selection and stochasticity in demand and machines degradation

The remainder of this Chapter is arranged as follows. In Section 3.2, acRJSSP is described. Then, the proposed mathematical formulations are presented in Sections 3.3 and 3.4. In Section 3.5, numerical results of the deterministic MILP are presented and discussed, then the solution of the TSS model is evaluated in Section 3.6. Finally, the conclusions and future work of this part are presented in Section 3.7

3.2 Problem Description

The RJSSP with machines/ configuration pair selection can be described as follows. There is a set of (M)of RMTs on a shop floor with a predefined layout. Each RMT (m) has a set of (I) configurations. Each configuration can process one or more operations with a known production rate ($\beta_{m,i,o}$). Each product (k) has several (o) operations of the total (O) operations with a known sequence. The RMT needs to be calibrated when it is switched from configuration (i') to (i). The calibration rate ($\gamma_{m,i,o}$) depends on the two consecutive configurations. It is assumed that the calibration rate ($\gamma_{m,i,o}$) affects the production rate ($\beta_{m,i,o}$). Moreover, each RMT can only fit into one configuration at a time, and it can perform more than one operation (o) simultaneously. These operations should be processed to have a finished product. The problem is subdivided into the following two parts: routing and sequencing. In routing, we defined which jobs should be processed on an available set of machines and when to inject them into the systems. While sequencing deals with the order in which the jobs should be processed.

The complexity of this problem is presented by considering continuous changes in manufacturing equipment and products and addressing new aspects simultaneously. For instance, machines and configuration selections, number of products, operations sequence, operations assignments, and reconfigurations continuously change. The MILP formulation should include these changes and optimize their associated decision variables. Otherwise, the workload of the existing RMTs is not balanced, and the system's idle time between reconfigurations is not minimized. The second part provides a new discussion on the reconfigurability feature and encourages the transition to RMSs. Since many reasons hindered the of RMSs in the industry, different analyses that evaluate the effectiveness of RMSs compared with conventional systems from operating perspectives are conducted. These reasons include new design elements (e.g., convertibility), resistance to change, uncertainty about the significant internal and external influencing factors, and high investment costs. The third part is to extend this formulation to a two-stage stochastic formulation to incorporate the uncertainties in volume and mix. In the first stage, the number of RMTs and their configurations are chosen then a cost-optimized plan is generated based on different scenarios. Since this problem is complex and involves solving two subproblems, MILP formulation was chosen to solve this problem. Then, this MILP formulation was extended to a two-stage stochastic model.

3.3 Deterministic Model

A novel MILP formulation for integrated planning and scheduling is presented in this paper. The formulation minimizes the total costs in a manufacturing plant with multi-product orders and identifies the main contributing factors to the success of RMSs. The model is formulated to plan an RMS that produces a part-family of products. The production cost includes machine operating, reconfiguration, raw material, backorders, inventory, and WIP holding costs. The following assumptions are considered in developing the proposed mathematical model:

- Machining features on each part require certain operations such as milling, boring, drilling, tapping, reaming, etc. Since a single-part family is considered, the operations sequences of the different parts do not vary significantly and are known ahead.
- In the beginning, the RMS is empty and idle; WIP units go to each stage, and the selected RMT/configuration pairs perform a specific operation..
- Each configuration is equipped with modules. These modules allow the configuration to perform a certain number of operations. Changing the functionality of the same configuration requires negligible time and effort. In other words, it can perform multiple operations within a single setup (Shabaka & ElMaraghy, 2008). It is the case in RMTs and most multi-axis CNC machines.
- Switching between configurations for the RMT involves a human operator and calibration process (Bortolini et al., 2019), and the production stops during this process. Hence, calibration errors and defects would affect the system (Hariharan et al., 2020).
- The production and schedule are generated over a planning horizon. The planning horizon is divided into multiple production periods. In each production period, one or more parts are manufactured. This period is considered a due date for these parts.
- The demand levels are known before the system design based on data analytics techniques (regression) or future sales orders. Thus, each part is considered as an order with a known demand level.
- In the production plan and schedule, the sequencing of operations is defined based on precedence constraints (the order in which operations are carried out).

- Manufactured units can be held in the inventory until the due date.
- The backorder penalty cost is accrued if the demand cannot be met.

Equations (3.1- 3.27) show the proposed MILP model for production planning and scheduling RMSs. The model is solved using DOcplex (IBM Decision Optimization CPLEX Modelling for Python).

$$\text{Min} \sum_{o=1}^{O}\sum_{k=1}^{K}\sum_{l=1}^{L} CO_m\, t_{o,k,m,l} + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{i'=1}^{I}\sum_{L=1}^{L} \delta\, CT_{m,i,i'}\ z_{m,i',i,l}$$
$$+ \sum_{k=1}^{K}\sum_{l=1}^{L} CP_k w_{k,l} + \sum_{k=1}^{K}\sum_{l=1}^{L} CH_k\ h_{k,l} \quad (3.1)$$
$$+ \sum_{o=1}^{O}\sum_{k=1}^{K}\sum_{l=1}^{L} CB_o\ b_{o,k,l} + \sum_{k=1}^{K}\sum_{l=1}^{L} CU_k u_{k,l}$$

$$\sum_{i=1}^{I} y_{i,m,l} = 1 \qquad \forall m,l \quad (3.2)$$

$$\sum_{k=1}^{K} t_{o,k,m,l} \leq BigM \sum_{i=1}^{I} \beta_{m,i,o} y_{i,m,l} \qquad \forall m,l,o \quad (3.3)$$

$$y_{m,i,l} + y_{m,i\prime,l-1} - 1 \leq z_{m,i',i,l} \qquad \forall m,i',i,l>1 \quad (3.4)$$

$$\sum_{o=1}^{O}\sum_{k=1}^{K} d_{o,k,i,m,l} \leq BigM y_{m,i,l} \qquad \forall m,i,l \quad (3.5)$$

$$\sum_{i=1}^{I} d_{o,k,i,m,l} \leq BigM v_{o,k,m,,l} \qquad \forall o,k,m,l \quad (3.6)$$

$$d_{o,k,i,m,l} \leq \beta_{m,i,o} t_{o,k,m,l} + BigM \sum_{i'=1}^{I} z_{m,i',i,l} \qquad \forall m,i,o,k,l \quad (3.7)$$

$$d_{o,k,i,m,l} \leq \gamma_{m,i,o}\beta_{m,i,o}\ t_{o,k,m,l} + BigM(1 - \sum_{i'=1}^{I} z_{m,i',i,l}) \qquad \forall m,i,o,l \quad (3.8)$$

$$\sum_{o=1}^{O}\sum_{k=1}^{K} t_{o,k,m,l} \leq T_l - \sum_{i'=1}^{I'}\sum_{i=1}^{I} CT_{m,i',i} z_{m,i'.i,l} \qquad \forall m,l \quad (3.9)$$

$$\sum_{o=1}^{O}\sum_{k=1}^{K} v_{o,k,m,l} \leq 1 \qquad \forall m,l \quad (3.10)$$

$$s_{o,k,m,l} + c_{o,k,m,l} \leq BigM\ v_{o,k,m,l} \qquad \forall o,k,m,l \quad (3.11)$$

$$c_{o,k,m,l} \geq s_{o,k,m,l} + \ t_{o,k,m,l} \ - BigM(1 - v_{o,k,m,l}) \qquad \forall o,k,m,l \qquad (3.12)$$

$$c_{o,k,m,l} \leq T_l - \sum_{i'=1}^{I'} \sum_{i=1}^{I} CT_{m,i',i} \, z_{m,i',i,l} \qquad \forall o,k,m,l \qquad (3.13)$$

$$\sum_{m=1}^{M} v_{o,k,m,l} \leq \alpha_{o,k} \qquad \forall o,k,l \qquad (3.14)$$

$$s_{o,k,m,l} \geq c_{o',k',m,l} - BigM \ p_{o,k,o',k',m,l} \qquad \forall o,k,o',k',m,l \qquad (3.15)$$

$$s_{o',k',m,l} \geq c_{o,k,m,l} - BigM \ (1 - p_{o,k,o',k',m,l}) \qquad \forall o,k,o',k',m,l \qquad (3.16)$$

$$\sum_{m=1}^{M} s_{o,k,m,l} \geq \sum_{m=1}^{M} c_{o',k,,m,l} - BigM(g_{o,o',k,l}) \qquad \forall o,o',k,l \qquad (3.17)$$

$$\sum_{m=1}^{M} s_{o',k,m,l} \geq \sum_{m=1}^{M} c_{o,k,,m,l} - BigM \ (1 - g_{o,o',k,l}) \qquad \forall o,o',k,l \qquad (3.18)$$

$$\sum_{m=1}^{M} v_{o,k,m,l} + \sum_{m=1}^{M} v_{o',k,m,l} \leq 2 \ (1 - g_{o,o',k,l}) \qquad \forall o' \to o,k,l \qquad (3.19)$$

$$b_{o,k,l} = \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o,k,i,m,l} - \alpha_{o,k} \, w_{k,l} \qquad \forall o,k,l = 1 \qquad (3.20)$$

$$b_{o,k,l} = \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o,k,i,m,l} - \alpha_{o,k} \, w_{k,l} + b_{o,k,l-1} \qquad \forall o,k,l > 1 \qquad (3.21)$$

$$w_{k,l} \alpha_{o,k} \leq \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o,k,i,m,l} \qquad \forall o,k,l = 1 \qquad (3.22)$$

$$w_{k,l} \alpha_{o,k} \leq \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o,k,i,m,l} + b_{o,k,l-1} \qquad \forall o,k,l > 1 \qquad (3.23)$$

$$\sum_{l'=1}^{l} \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o,k,i,m,l} \leq \sum_{l'=1}^{l} \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o',k,i,m,l} \qquad \forall o' \to o,k,l \qquad (3.24)$$

$$w_{k,l} + u_{k,l} = Q_{k,l} + h_{k,l} \qquad \forall k,l = 1 \qquad (3.25)$$

$$w_{k,l} + u_{k,l} + h_{k,l-1} = Q_{k,l} + h_{k,l} \qquad \forall k,l > 1 \qquad (3.26)$$

$$\begin{aligned} &\sum_{m=1}^{M} \sum_{l=1}^{L} s_{o,k,m,l} + \sum_{m=1}^{M} \sum_{l=1}^{L} c_{o,k,m,l} + \sum_{m=1}^{M} \sum_{l=1}^{L} t_{o,k,m,l} && (3.27) \\ &+ \sum_{m=1}^{M} \sum_{l=1}^{L} \sum_{i=1}^{I} d_{o,k,m,l} + \sum_{m=1}^{M} \sum_{l=1}^{L} v_{o,k,m,l} \leq BigM \alpha_{o,k} \qquad \forall o,k \end{aligned}$$

Equation (3.1) presents the total cost, including machine exploitation, operating, reconfiguration, raw material, production, inventory, WIP holding, and unmet demand penalty costs. Equation (3.2) guarantees that, at most, one configuration is chosen for operating machines. Equation (3.3) ensures that the time spent for each operation is defined only if the selected configuration can be applied for that operation. Equation (3.4) is designed to keep track of configuration changes from one production run to the next run, in cases with more than one configuration ($I>1$). Equation (3.5) assures that no capacity is needed for the configuration when it is not selected. The capacities for operations are defined only if the operation is assigned to that machine Equation (3.6). Equations (3.7-3.8) are set to limit the production rate based on the selected configuration in the production run. The production rate is affected by the change in configuration and calibration rate. The time spent on operations is limited with the available production time minus the time spent for configuration Equation (3.9). Equation (3.10) is designed to prevent any operation assignment to idle machines. Equation (3.11) forces the start and completion time of the operation to zero if the machine is not selected to perform that operation. If the machine is selected for that operation, Equation (3.12) defines the completion time which is the start time plus the time spent for that operation. Equation (3.13) is added to ensure that completion times do not exceed the total available time at each production run. The available time is affected by the time required for reconfiguration. To perform each operation of the order, only one machine can be selected Equation (3.14). No machine is selected if that operation is not required for the order. Equations (3.15-3.16) are valid only in cases with more than one order ($K > 1$) and ensure that two different operations for two different orders cannot be conducted at the same time. Similarly, Equations (3.17-3.18) prevent simultaneous operations of the same order. Equation (3.19) is added to guarantee the predecease relations in each order. Equations (3.20-3.21) are set up to define WIP storage between various production stages of the system. The order delivery in each period is limited based on the required operations of the order Equations (3.22-3.23). Equation (3.24) is defined to prevent starting tasks with precedence relations before completing their requirements. Equations (3.25-3.26) balance the equation for finished products and unfinished products. Extra products are stored as inventory for the next periods. Equation (3.27) sets the value of the variables to zeros for non-existing operations in the orders.

3.4 Two-Stage Stochastic Model

Stochastic formulations are mathematical formulations that involve uncertainty. Stochastic formulations are particularly suited for problems where data evolve, and decisions must be made before observing the entire data stream. For example, uncertainty in demand level and machines' productivity. Under these circumstances, stochastic formulations have yielded more robust solutions than deterministic models and thus have been applied in this research. The most applied and studied stochastic formulations are TSS models. Here the decision maker takes some action in the first stage, after which a random event affects the outcome of the first-stage decision. A recourse decision can then be taken in the second stage, compensating for any bad effects that might have been experienced due to the first-stage decision. For more details on TSS models, interested readers can refer to (Ahmed, 2011).

In this Section, the problem of RJSSP is modeled using TSS model to hedge against uncertainty in demand ($Q_{k,l}$) and machine degradation effect on ($\beta_{m,i,o}$) and to derive a robust process plan and schedule. The probability distributions for these uncertainties are represented with discrete scenarios. We use a subscript (j) to represent the scenarios with a probability (P_j). In a TSS model, defining the first- and second-stage variables is critical. In fact, besides being a simple classification, first- and second-stage variables define when decisions can be taken and their mutual influence. In this research, the first stage decision variables are ($x_{m,l}$), which show which machine types are selected in each production period in the presence of uncertainties. The remaining decision variables introduced in the previous Section are considered the second-stage decision variables. In other words, after solving the TSS model, the types of machines are determined before the realization of uncertainty. Then, after realizing the random events, their configurations are selected, and the process plan and schedule are generated. This model helps decision-makers know which machines to assign for the production and then select the optimum configurations after knowing the uncertain events.

3.4.1 Two Stage Stochastic Model for Demand Uncertainty

The cost function in Equation (3.1) is modified to Equation (3.28), Equation (3.2) is modified to Equation (3.29) to ensure that production is carried on the existing machines - the scenario schedule must be equal to the baseline schedule. The subscript (j) is added to all other Equations to represent a scenario. The model presented in this Section is designed to accommodate flexible decision-making mechanisms that can respond to demand levels as they unfold. The description of these equations is as same as the presented description in Section 3.3.

$$\text{Min} \sum_{j=1}^{J} P_j \Big(\sum_{o=1}^{O} \sum_{k=1}^{K} \sum_{l=1}^{L} CO_m \, t_{o,k,m,l,j} + \sum_{m=1}^{M} \sum_{i=1}^{I} \sum_{i'=1}^{I} \sum_{L=1}^{L} \delta \, CT_{m,i,i'} \, z_{m,i',i,l,j} + \sum_{k=1}^{K} \sum_{l=1}^{L} CP_k w_{k,l,j}$$
$$+ \sum_{k=1}^{K} \sum_{l=1}^{L} CH_k \, h_{k,l,j} + \sum_{o=1}^{O} \sum_{k=1}^{K} \sum_{l=1}^{L} CB_o \, b_{o,k,l,j} + \sum_{k=1}^{K} \sum_{l=1}^{L} CU_k u_{k,l,j} \Big) \tag{3.28}$$

$$\sum_{o=1}^{O} \sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{l=1}^{L} \sum_{j=1}^{J} d_{o,k,i,m,l,j} \le x_{m,l} \qquad \forall m,l \tag{3.29}$$

$$\sum_{k=1}^{K} t_{o,k,m,l,j} \le BigM \sum_{i=1}^{I} \beta_{m,i,o} y_{i,m,l,j} \qquad \forall m,l,o,j \tag{3.30}$$

$$y_{m,i,l,j} + y_{m,i\prime,l-1} - 1 \leq z_{m,i',i,l,j} \qquad \forall m, i', i, l > 1, j \tag{3.31}$$

$$\sum_{o=1}^{O} \sum_{k=1}^{K} d_{o,k,i,m,l,j} \leq BigMy_{m,i,l,j} \qquad \forall m, i, l, j \tag{3.32}$$

$$\sum_{i=1}^{I} d_{o,k,i,m,l,j} \leq BigMv_{o,k,m,,l,j} \qquad \forall o, k, m, l, j \tag{3.33}$$

$$d_{o,k,i,m,l,j} \leq \beta_{m,i,o} t_{o,k,m,l,j} + BigM \sum_{i'=1}^{I} z_{m,i',i,l,j} \qquad \forall m, i, o, k, l, j \tag{3.34}$$

$$d_{o,k,i,m,l,j} \leq \gamma_{m,i,o} \beta_{m,i,o}\, t_{o,k,m,l,j} + BigM(1 - \sum_{i'=1}^{I} z_{m,i',i,l,j}) \qquad \forall m, i, o, l, j \tag{3.35}$$

$$\sum_{o=1}^{O} \sum_{k=1}^{K} t_{o,k,m,l,j} \leq T_l - \sum_{i'=1}^{I'} \sum_{i=1}^{I} CT_{m,i',i} z_{m,i'.i,l,j} \qquad \forall m, l, j \tag{3.36}$$

$$\sum_{o=1}^{O} \sum_{k=1}^{K} v_{o,k,m,l,j} \leq 1 \qquad \forall m, l, j \tag{3.37}$$

$$s_{o,k,m,l,j} + c_{o,k,m,l,j} \leq BigM\; v_{o,k,m,l,j} \qquad \forall o, k, m, l, j \tag{3.38}$$

$$c_{o,k,m,l,j} \geq s_{o,k,m,l,j} + \; t_{o,k,m,l,j} - BigM(1 - v_{o,k,m,l,j}) \qquad \forall o, k, m, l, j \tag{3.39}$$

$$c_{o,k,m,l,j} \leq T_l - \sum_{i'=1}^{I'} \sum_{i=1}^{I} CT_{m,i',i}\; z_{m,i',i,l,j} \qquad \forall o, k, m, l, j \tag{3.40}$$

$$\sum_{m=1}^{M} v_{o,k,m,l,j} \leq \alpha_{o,k} \qquad \forall o, k, l, j \tag{3.41}$$

$$s_{o,k,m,l,j} \geq c_{o',k',m,l,j} - BigM\; p_{o,k,o',k',m,l,j} \qquad \forall o, k, o', k', m, l \tag{3.42}$$

$$s_{o',k',m,l} \geq c_{o,k,m,l,j} - BigM\; (1 - p_{o,k,o',k',m,l,j}) \qquad \forall o, k, o', k', m, l, j \tag{3.43}$$

$$\sum_{m=1}^{M} s_{o,k,m,l} \geq \sum_{m=1}^{M} c_{o',k,,m,l,j} - BigM(g_{o,o',k,l,j}) \qquad \forall o, o', k, l, j \tag{3.44}$$

$$\sum_{m=1}^{M} s_{o',k,m,l,j} \geq \sum_{m=1}^{M} c_{o,k,,m,l,j} - BigM\; (1 - g_{o,o',k,l,j}) \qquad \forall o, o', k, l, j \tag{3.45}$$

$$\sum_{m=1}^{M} v_{o,k,m,l,j} + \sum_{m=1}^{M} v_{o',k,m,l,j} \leq 2\; (1 - g_{o,o',k,l,j}) \qquad \forall o' \to o, k, l, j \tag{3.46}$$

$$b_{o,k,l,j} = \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o,k,i,m,l,j} - \alpha_{o,k}\; w_{k,l,j} \qquad \forall o, k, l = 1, j \tag{3.47}$$

$$b_{o,k,l,j} = \sum_{m=1}^{M} \sum_{i=1}^{I} d_{o,k,i,m,l,j} - \alpha_{o,k}\; w_{k,l,j} + b_{o,k,l-1,j} \qquad \forall o, k, l > 1, j \tag{3.48}$$

$$w_{k,l,j}\alpha_{o,k} \leq \sum_{m=1}^{M}\sum_{i=1}^{I} d_{o,k,i,m,l,j} \qquad \forall o,k,l=1,j \tag{3.49}$$

$$w_{k,l,j}\alpha_{o,k} \leq \sum_{m=1}^{M}\sum_{i=1}^{I} d_{o,k,i,m,l,j} + b_{o,k,l-1,j} \qquad \forall o,k,l>1,j \tag{3.50}$$

$$\sum_{l'=1}^{l}\sum_{m=1}^{M}\sum_{i=1}^{I} d_{o,k,i,m,l,j} \leq \sum_{l'=1}^{l}\sum_{m=1}^{M}\sum_{i=1}^{I} d_{o',k,i,m,l,j} \qquad \forall o' \rightarrow o,k,l,j \tag{3.51}$$

$$w_{k,l,j} + u_{k,l,j} = Q_{k,l,j} + h_{k,l,j} \qquad \forall k,l=1,j \tag{3.52}$$

$$w_{k,l,j} + u_{k,l,j} + h_{k,l-1,j} = Q_{k,l,j} + h_{k,l,j} \qquad \forall k,l>1,j \tag{3.53}$$

$$\sum_{m=1}^{M}\sum_{l=1}^{L} s_{o,k,m,l,j} + \sum_{m=1}^{M}\sum_{l=1}^{L} c_{o,k,m,l,j} + \sum_{m=1}^{M}\sum_{l=1}^{L} t_{o,k,m,l,j} \tag{3.54}$$
$$+ \sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{i=1}^{I} d_{o,k,m,l,j} + \sum_{m=1}^{M}\sum_{l=1}^{L} v_{o,k,m,l,j} \leq BigM\alpha_{o,k} \qquad \forall o,k$$

3.4.2 Two Stage Stochastic Model for Machines Degradation

The impact of machine faults and failures on factory productivity is an important concern for manufacturing industries. Machines degrade due to aging and wear, which decreases performance reliability and increases the potential for faults and failures. In this Section, the machine's degradation is depicted as the percentage of the nominal production rate of the machine. For example, if the machine's nominal production is 100 parts/hour, with degradation of 2%, it may produce 98 parts/hour. In order to study their effects, methods need to be developed to quantitatively evaluate different production scenarios, taking into account the associated cost effects of the resulting production operations, the current and predicted machine degradation levels, system configuration, and production requirements. Furthermore, one needs to devise a methodology to optimize those cost effects by minimizing the adverse effects of degradation and maximizing the benefits of production.

The presented model in the previous Subsection (3.4.1) has been modified to address machines degradation and Equations (3.30, 3.34, 3.35, 3.52, and 3.53) are modified to accommodate the uncertainty in machines production rate ($\beta_{m,i,o}$).

$$\sum_{k=1}^{K} t_{o,k,m,l,j} \leq BigM \sum_{i=1}^{I} \beta_{m,i,o,j}\, y_{i,m,l,j} \qquad \forall m,l,o,j \qquad (3.55)$$

$$d_{o,k,i,m,l,j} \leq \beta_{m,i,o,j}\, t_{o,k,m,l,j} + BigM \sum_{i'=1}^{I} z_{m,i',i,l,j} \qquad \forall m,i,o,k,l,j \qquad (3.56)$$

$$d_{o,k,i,m,l,j} \leq \gamma_{m,i,o}\, \beta_{m,i,o,j}\, t_{o,k,m,l,j} + BigM(1 - \sum_{i'=1}^{I} z_{m,i',i,l,j}) \qquad \forall m,i,o,l,j \qquad (3.57)$$

$$w_{k,l,j} + u_{k,l,j} = Q_{k,l} + h_{k,l,j} \qquad \forall k, l=1, j \qquad (3.58)$$

$$w_{k,l,j} + u_{k,l,j} + h_{k,l-1} = Q_{k,l} + h_{k,l,j} \qquad \forall k, l>1, j \qquad (3.59)$$

3.4.3 Scenarios Generation

According to (Zhang et al., 2011), practitioners often prefer to specify a set of pessimistic, neutral, and optimistic outlooks to account for trends and uncertainties not reflected in the historical data. In this research, the approach was followed. Three discrete scenarios are defined; pessimistic, neutral, and optimistic. The defined scenarios for demand are reported in Table 3.1. The defined scenarios for machine degradation are reported in Table 3.2. It was assumed that demand data follows a normal distribution. Machine degradation follows an exponential distribution as same as (Ye et al., 2021). Then, the demand data and machine production rates are generated based on these parameters to produce two orders in three production periods.

Table 3.1

Defined Demand Scenarios and Their Parameters

Scenario	Mean	Variance
Pessimistic	420	70
Neutral	444	40
Optimistic	480	10

Table 3.2

Defined Machine Degradation Scenarios and Their Parameters

Machine	Scenario	Scale Parameter
m_1	pessimistic	0.3
	neutral	0.15
	optimistic	0.1
m_2	pessimistic	0.1
	neutral	0.075
	optimistic	0.05
m_3	pessimistic	0.15
	neutral	0.125
	optimistic	0.1
m_4	pessimistic	0.2
	neutral	0.1
	optimistic	0.05

3.5 Numerical Results for Deterministic Model

In this section, the models are verified and their applicability is illustrated using a small-scale case study inspired by (Ashraf & Hasan, 2018). A set of experiments were also implemented to gain more insights into the factors that affect the efficiency of an RMS. The sensitivity analyses were conducted to investigate the effects of the following parameters on the total cost:

- Cost settings.
- The reconfiguration parameters.
- The length of the production period.
- The storage capacity.
- Order features.
- Production plant settings.

To compare the efficiency of the proposed technique for planning and scheduling reconfigurable systems, the results are compared with a traditional non-reconfigurable system. In reconfigurable systems, the production plan is optimized using the model presented in the previous section, and the operations are scheduled based on both the number of available configurations per RMT and their configurations operational capability. To derive production plans in nonreconfigurable systems, the reconfigurations variables $(z_{m,i',i,l})$ are set to zero to prevent any reconfiguration. This is because, in traditional systems, the orders are produced based on the number of operations that can be performed in a single setup without any reconfiguration within the planning horizon. At the end of the numerical results, we presented a scalability test to investigate the effects of changing problem dimensions on computation time.

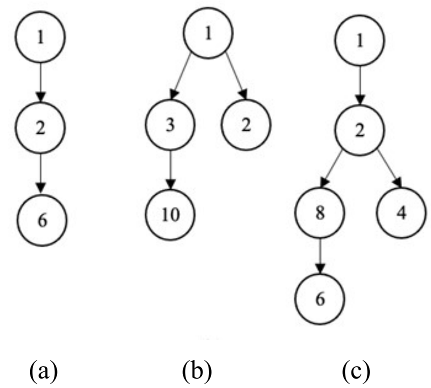
3.5.1 Case Study

The case study applied in this research considers an RMS with four RMTs, each of which has a set of four configurations. Each configuration can perform several operations. Each production period represents five working days, one shift per day, and the orders to be produced with a known demand in each period. Throughout the following sections, the three parts are referred to as orders k_1, k_2, k_3, respectively. Each order k represents a part with a set of required operations. These orders belong to a family of parts whose operations do not vary significantly and have operations in common. k_1 has a demand of 450 units in the first period, k_2 has a demand of 390 units in the third period, and the demand for k_3 is 310 in the second period. The precedence graphs for each order, which present the order in which operations are performed, are shown in Figure 3.1. For example, for the second order, operation 1 must be completed before operations 2 and 3; then, 2 or 3 can be started. After finishing operation 3, operation 10 is performed.

By implementing the proposed model, the production plan and schedule for the

Figure 3.1

Precedence Graph (a) Order k_1 (b) Order k_2 (c) Order k_3



case study are generated, and the results are reported for both the traditional system and RMS. Table 3.3 compares the total cost, demand fulfilment percentage, system utilization for both systems, and the resulted schedule using the RMS is shown in Figure 3.2. System utilization is calculated using Equation (3.60).

$$utilization = \frac{\sum_{o=1}^{O}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{m=1}^{M} t_{o,k,m,l}}{M\sum_{l=1}^{L} T_l} \tag{3.60}$$

The results show that the RMS reconfigurability feature can save up to 29.88% of the total cost. These savings are mainly attributed to the decreased backorders and WIP storage costs. This is achieved by reconfiguring the system between periods that changes its production capabilities and capacity. Reconfiguration alters the production rate of that RMT for performing a certain operation (i.e., RMT's production capability). Through this change, the new configuration could either perform another operation in the system or perform the same operation with a different production capacity. The change in production capacity increases raw material costs and operation costs due to an increase in production level and order fulfilment in RMSs. As a result, the utilisation and demand fulfilment are increased 52.76% and 24.29%, accordingly, compared to a traditional

Table 3.3

Performance Comparison for the Reconfigurable and Traditional Systems in the Case Study

Criteria	Traditional system	RMS	Imporvements(%)
Operation cost ($)	2,481.06	3,595.67	44.92 ↑
Backorder cost ($)	68,200.00	23,320.00	68.81 ↓
Raw material cost ($)	42,000.00	52,200.00	24.92 ↑
WIP cost ($)	390.00	155.00	60.26 ↓
Inventory cost ($)	–	–	–
Reconfiguration cost ($)	–	19.90	–
Total cost ($)	113,071.06	79,290.57	29.88 ↓
Reconfigurations	–	5	–
Total production time (hr.)	82.702	119.86	44.93 ↑
Demand fulfilment (%)	73.04	90.78	24.29 ↑
System utilisation (%)	17	25.97	52.76 ↑

Note. ↓ (resp. ↑) represent a decrease (resp. increase)

(non-reconfigurable) system.

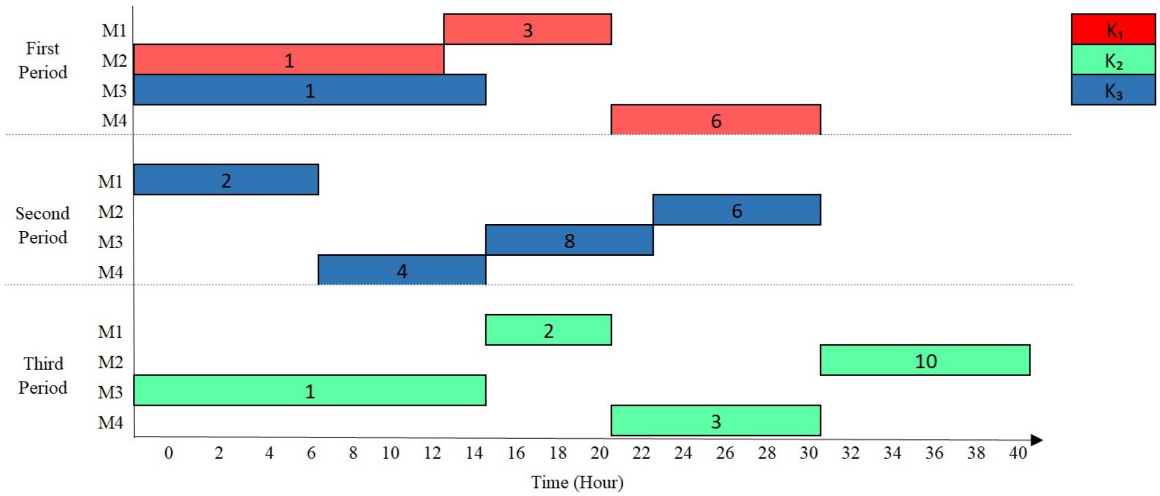
3.5.2 Effects of Cost Parameters

The costs play an important role in production planning decisions. To investigate their effects on total savings in an RMS, sensitivity analyses are conducted for the following cost parameter:

- RMTs operating cost.
- Raw materials cost.
- Backorders penalty cost.
- inventory holding cost.
- WIP units holding cost.

Figure 3.2

Gantt Chart of the Resulted Production Plan and Operations Schedule

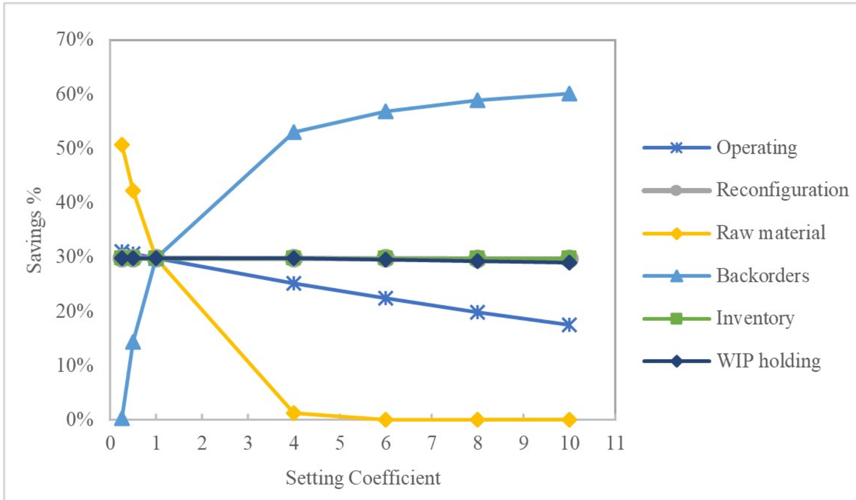


Each cost parameter is multiplied by a set of constant rates (0.25, 0.50, 1.0, 4.0, 6.0, 8.0, 10.0) and after solving the model for both systems, saving percentages for RMS are computed and plotted in Figure 3.3.

The figure shows that increasing the backorder cost pushes the RMS to produce as much as possible to avoid any high backorder cost, thus increasing the savings. Reconfiguration cost (δ), inventory holding cost for WIP (CB_o), and finished units (CH_k) have non-significant effects on the total savings. When the machines/configurations pair are selected based on current and future orders, this saves the cost of holding inventories, reconfigurations, and/or operating new machines. On the other hand, it can be noted that the raw material cost (CP_k) and operating cost ($CO_{o,m}$) have higher effects. This is because these costs are associated with production levels. In other words, when the system produces more units, extra costs are incurred due to production and operating machines. The raw materials cost refers to the cost of components that have been used in the final manufactured units. Operating cost is a variable cost that depends on the work rate of the RMT and occurs only when an RMT is used. This cost includes energy consumption, maintenance, and labour. If the cost of operating an RMT in its specific configuration is

Figure 3.3

Effects Analysis of Cost Parameters on Total Savings



high, it is better to select an alternative machine/configuration to minimise the operating cost. Switching configurations is less costly than maintaining a machine.

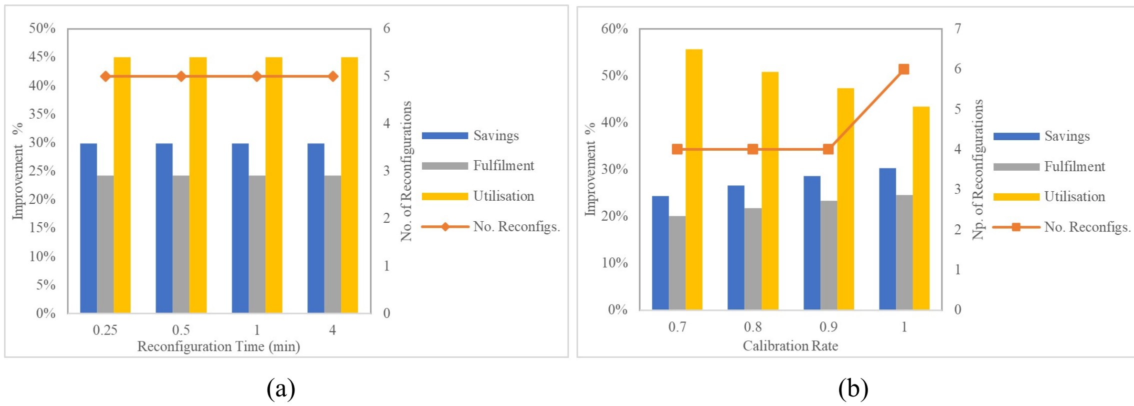
3.5.3 Effects of Reconfiguration Parameters

Sensitivity analysis is also conducted to analyze the effects of reconfiguration time and calibration rate on the total savings of RMSs. The model is solved for both systems and the savings percentages are plotted in Figure 3.4.

The results show that the reconfiguration time has a small effect on the total savings, demand fulfilment and utilisation improvement, and the number of reconfigurations. This is because the reconfiguration can usually be done within seconds to minutes depending on the RMT specifications. Therefore, the effects are negligible when the production period is in hours or days. This confirms that reconfiguration is neither a time-consuming process, nor affects the total production time, and therefore adopting these technologies is both time and cost-effective. On the other hand, reconfigurations require human interaction and calibrations which result in an imperfect production. This includes defective items, idle time, and inaccurate settings for the RMTs.

Figure 3.4

Effects of (a) Reconfiguration Time and (b) Calibration Rate on Total Savings



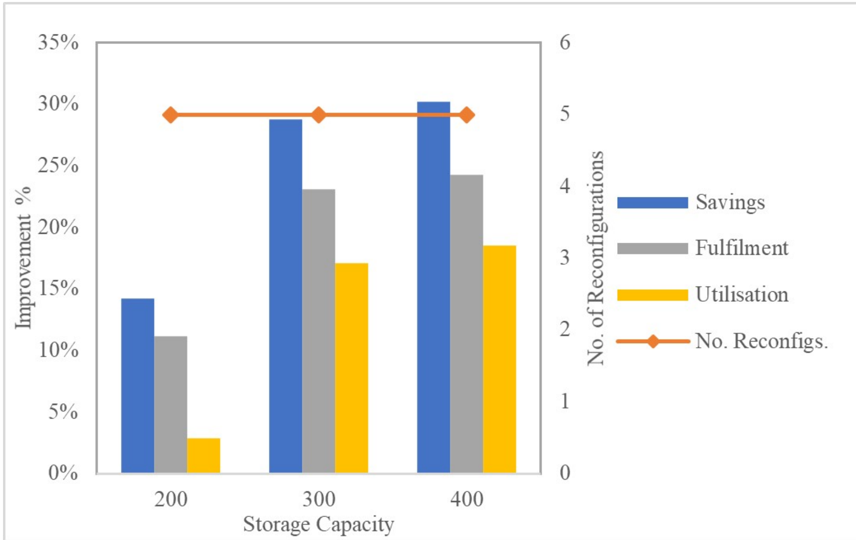
These factors are analyzed to examine their effect on total savings. The calibration rate represents the percentage of the nominal production rate of a machine that can be achieved after reconfiguration in the first period that immediately follows. For instance, if a machine produces 10 good units/hour and after reconfiguration, the machine only produces 9 good units/hours, then it is calibration rate is 90%. As expected, this experiment shows that increasing calibration rate increases total savings and demand fulfilments, and decreases system utilisation, due to the improved system efficiency.

3.5.4 Effects of Storage Capacity

In the real world, there are circumstances where the production level is restricted by the storage capacity. This impacts the overall performance of a manufacturing system. In this paper, the inventory can hold WIP and finished units between any consecutive periods. To study its impact, a limited capacity is defined for holding any WIP and finished units by adding two constraint Equations (3.61 - 3.62) for the two decision variables $b_{o,k,l}$ and $h_{k,l}$. A sensitivity analysis is conducted to study the effects of this limitation on the savings percentage. The studied capacities are 200, 300, and 400. Figure 3.5 shows the effects of each capacity on the total savings.

Figure 3.5

Effects of Storage Capacity on Total Savings



$$\sum_{O=1}^{O}\sum_{k=1}^{K} b_{o,k,l} \leq U \tag{3.61}$$

$$\sum_{k=1}^{K} h_{k,l} \leq U \tag{3.62}$$

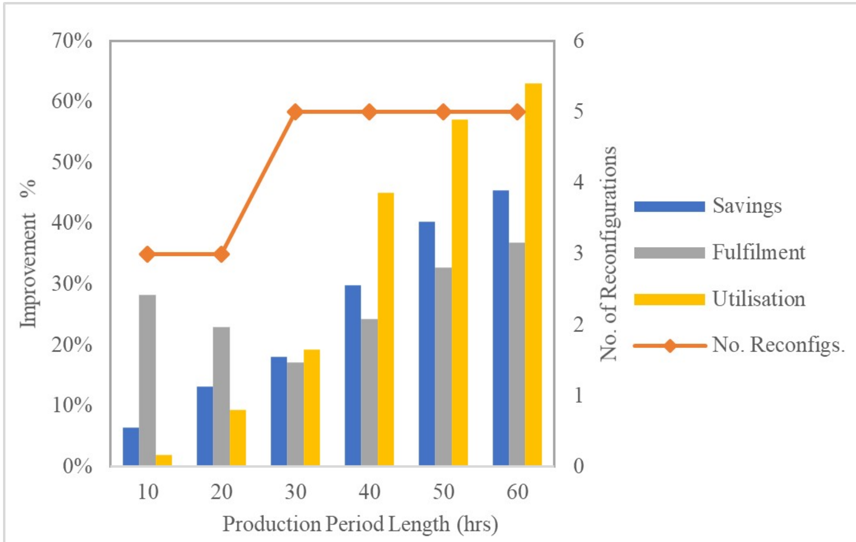
The results show that limited inventory capacity on WIP units impacts the total savings significantly, compared to unlimited or large enough capacity. With limited capacity, the system may not utilise the existing machines to produce some WIP units. For instance, say in period l the existing machines have the needed operational capabilities and time to produce some of period $l+1$ demand or WIP units. However, the allocated inventory capacity in period l is small to hold finished and WIP units. This results that the system is being underutilised and its productivity and cost-effectiveness are decreased.

3.5.5 Effects of Production Length

MS is introduced to cope with a dynamic market where short lead time and high productivity are needed. The production period length here refers to the available

Figure 3.6

Effects of Production Period Length on Total Savings



production time to complete all the production activities and fulfil the demand in that period. Therefore, the length of these periods is changed to study the performance of RMS when a short production time is needed. Figure 3.6 shows that in the circumstances where the demand should be fulfilled in a short time, RMS performs better than a non-reconfigurable system. This represents RMS capabilities to cope with the dynamic market and short lead time.

In the first three levels (10, 20, 30 hours), the available production time is too short to fulfil the demand. Nevertheless, RMS fulfills 18-30% more than the traditional system. This difference in fulfilment decreases since is more time available for the traditional system to produce units without reconfigurations. After that, the difference increases because RMS can satisfy more than 97% of the demand when the length is 50 hours, and 100% when the length is 60 hours. Comparatively, the traditional system could not satisfy more than 73% of the demand even when the available production time is increased by more than 40 hours. The traditional system could not satisfy more than 73% because of no reconfiguration that can be done to increase the capacity of the system. In sum, the results show that the reconfigurability feature increases the production capacity of RMSs which makes them more efficient in fulfilling orders in short and long production periods. This makes them more cost and time-efficient compared to other manufacturing systems.

3.5.6 Effects of Order Features

The characteristics of the received orders may also affect the performance of RMSs. To investigate the effects of order features such as complexity, quantity, and variety, numerous simulation experiments are implemented in this research. These experiments are conducted for 30 different random settings with randomly generated demand levels, required operations, and the number of precedence relationships. Order complexity refers to the number of required operations and precedence relationships between these operations. For example, for simple orders, there is only one precedence relationship, while 3 and 5 relations are set for moderate and complex orders respectively. Increasing the number of relationships means more work is needed to have a finished unit and, consequently, it incurs higher production costs. To investigate the effect of order quantity, the demand levels are generated randomly based on a normal distribution with 4 different settings for distribution mean (50, 100, 200, 500). Order variety implies the number of received orders which are generated randomly in each experiment. The resulted savings percentages are plotted in Figure 3.7.

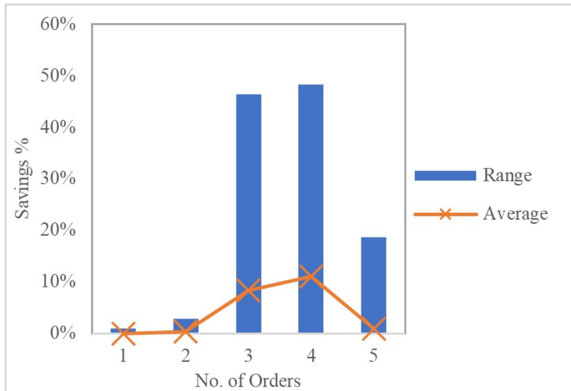
3.5.7 Effects of Production Plant Settings

To identify the influencing factors on total savings of RMS, ANOVA is implemented on different settings of the following factors related to production:

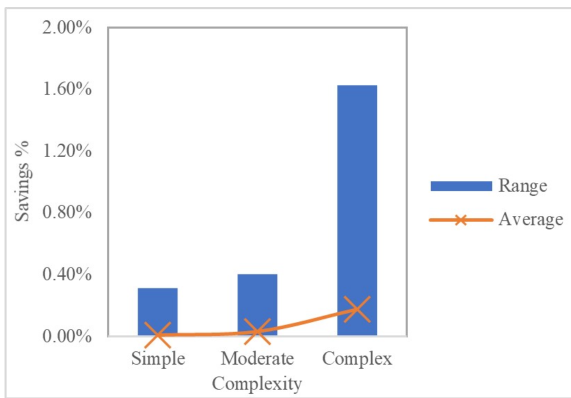
- Number of machines (levels: 2, 3, 4)
- Number of available configurations per machine (levels: 2, 3, 4)

Figure 3.7

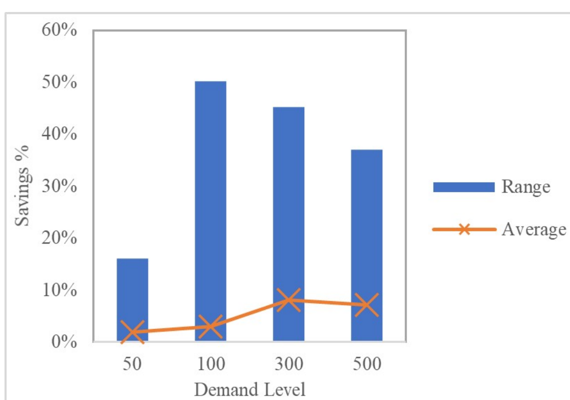
Effect of Order Features (a) Variety (B) Complexity (C) Quantity on Total Savings



(a)



(b)



(c)

Table 3.4

ANOVA Result

Source	DF	Adj SS	Adj MS	F-Values	P-value
Machines	2	0.023653	0.011827	2.59	0.086
Configurations	2	0.036670	0.018335	4.01	0.024
Operations	2	0.000387	0.000193	0.04	0.959
MaxProRate	2	0.001974	0.000987	0.22	0.806
Machines* Configurations	4	0.031468	0.007867	1.72	0.161
Machines* Operations	4	0.006433	0.001608	0.35	0.841
Machines*MaxProRate	4	0.005060	0.001265	0.28	0.891
Configurations* Operations	4	0.040297	0.010074	2.21	0.082
Configurations*MaxProRate	4	0.014158	0.003539	0.77	0.547
Operations*MaxProRate	4	0.019476	0.004869	1.07	0.384
Error	48	0.219257	0.004568		
Total	80	0.398883			

- Number of operations per configuration (levels: 2, 3, 4)

- Maximum production rate (levels: 10, 30, 50)

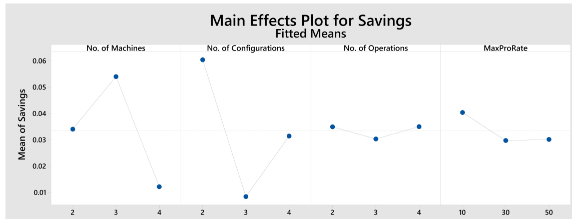
Here, the proposed model is solved for three different randomly generated settings for RMS and a traditional system, and the savings in cost are computed. The results of ANOVA for 95% confidence level are reported in Table 3.4. The main and interaction plots are shown in Figure 3.8.

3.5.8 Scalability Test

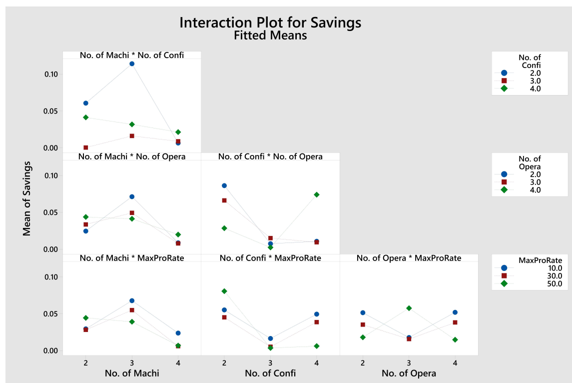
We also investigated the effects of increasing problem dimensions on computation time. The code is ran run on a Ubuntu 20.04 PC equipped with Intel® Core™ i7-8750H and 32GB RAM. The model is solved for a different number of machines and orders and its computation time is recorded in Table 3.5. In each experiment, one parameter is changed while others are kept on their default settings and other related settings to variable parameters are generated randomly The results are recorded in the table below.

Figure 3.8

ANOVA Experiment Results (a) Main Effects Plot and (B) Interaction Plot for Savings



(a)



(b)

The results showed that increasing number of machines exponentially increases codes computation time while increasing number of orders does not have any considerable effect on computation time. Therefore, the model is robust against number of received orders for small and medium manufacturing plants but it may require using metaheuristics for plants with a large number of reconfigurable manufacturing machines.

3.6 Evaluation of the Stochastic Model

To evaluate the performance of the two-stage stochastic programming model and to compare the results from the deterministic and stochastic models, we use the following metrics: expected value problem (EV), wait and see solution (WS), recourse problem (RP), expected results of using the EV problem (EEV), EEV, and expected value of perfect information (EVPI). In wait-and-see situations, the decision-maker makes no

Table 3.5

Scalability Result

Factor	Factor level	Variables	Constraints	Computation time (sec)
Machines	1	4500	2105	0.020
	2	7983	3335	2.020
	4	14949	5795	3.571
	5	18432	7025	42.852
	7	25398	9485	2753.133
	9	32364	11945	16764.832
Orders	1	2751	0.805	843
	2	7650	3.456	1882
	3	14949	422.1168	5795
	4	24648	589.226	8800
	5	36747	2287.673	12405
	6	51246	4223.570	15748

decisions until all random variables in the model are realized. These solutions are called WS solutions in the literature. The stochastic programming solution is the *RP* solution. The EVPI metric is used for determining the worth of collecting additional information. It is the difference between the solutions *RP* and WS where the order of the metrics depends on whether the problem is a maximization or a minimization problem (Hu et al., 2020). The simplest approach to deal with uncertainty is to replace all random variables with their expected values. This modified problem is called the expected value problem or mean value problem. Although the solution of such a simpler problem can be very far from the stochastic optimum, given the solution of EV, it is possible to test its quality in each of the considered scenarios. This quality can be measured through EEV, i.e., the expected value of the performance of the EV solution at the occurrence of each of the scenarios and allowing second-stage decisions to be optimally taken. The EEV can be used to estimate the benefits of modeling and to solve a problem as a stochastic program instead of as an EV problem. Given the value of the objective function in the stochastic programming approach (i.e., *RP*), value of stochastic solution (VSS) represents the worth

Table 3.6

Two-Stage Stochastic (TSS) Model Solution Evaluation for Stochastic Demand Using the Baseline Case Study

Solution					
Deterministic	Problem	Scenario 1	Scenario 2	Scenario 3	EV
	Cost function	\$86,453.35	\$59,928.99	\$129,143.56	\$81,760.17
	Probability	30%	40%	30%	
EEV	Problem	Scenario 1	Scenario 2	Scenario 3	*EEV*
	Cost function	\$110,910.50	\$60,569.80	\$155,686.13	\$104,206.91
TSS evaluation	Problem	WS	EVPI	*RP*	*VSS*
	Cost function	\$88,650.67	\$1,492.53	\$90,143.20	\$14,063.71

of using a stochastic model over a deterministic one and can be found using Equation 3.63 (Alfieri et al., 2011). The steps took to evaluate the TSS model are depicted in Figure 3.9.

$$VSS = EEV - RP \tag{3.63}$$

3.6.1 Demand Stochasticity

In this Section, two sets of experiments are conducted to evaluate the developed TSS model efficiency in addressing the uncertainty in demand. In the first one, a baseline case study is randomly generated for producing two orders in three periods. The results for evaluating the TSS model for demand scenarios are recorded in Table 3.6.

Result show that the TSS model is efficient in addressing uncertainties in demand. Based on VSS value, solving the TSS model saves the manufacturer around \$14,063.71 comparing to solving the deterministic model. In addition, EVPI metric shows the by collecting additional information about the demand, the manufacturer save around \$1,492.53.

In the second experiment, the model is run for four values of the demand mean,

Figure 3.9

Flow Chart Shows the Steps for Evaluating the Two-Stage Stochastic Model Against Its Deterministic Version (DTM)

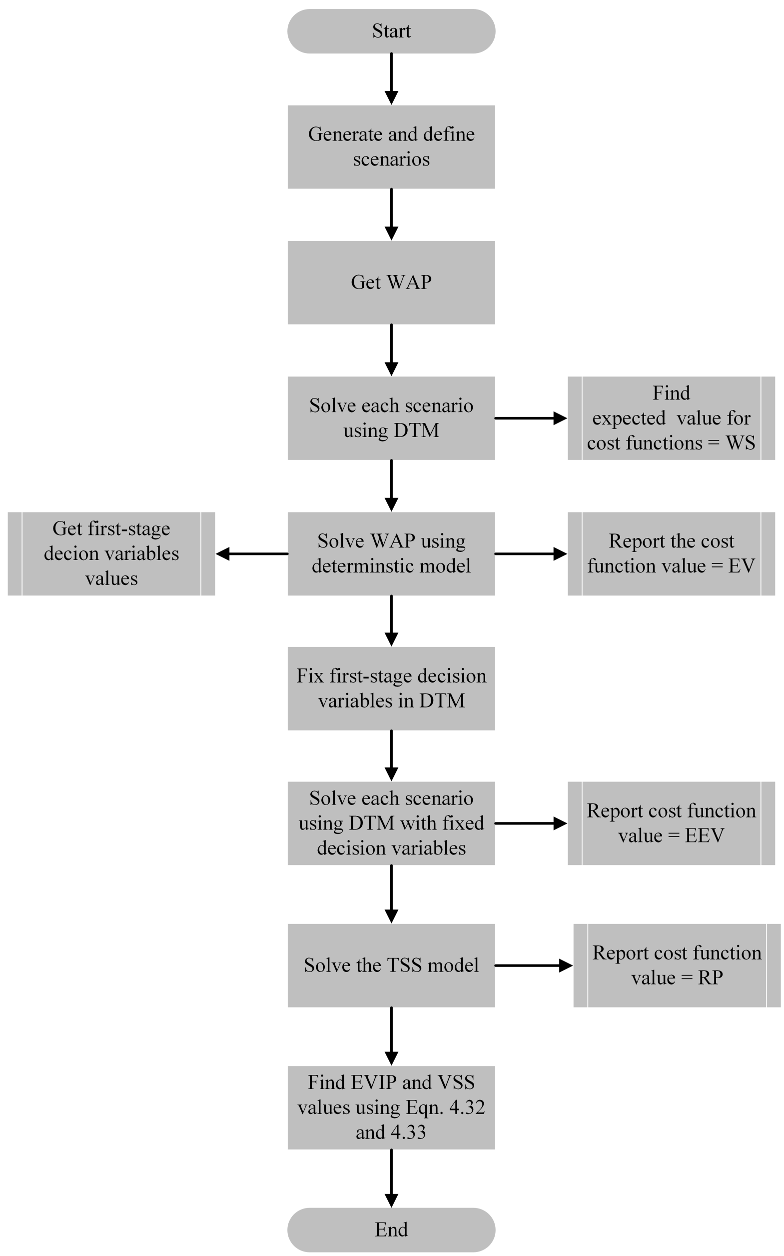


Table 3.7

Two-stage stochastic (TSS) Model Solution Evaluation Using Different Demand Means

% of mean	EV	WS	EEV	EVPI	RP	VSS
80%	\$60,796.18	\$62,080.75	\$67,704.61	\$1,166.81	63,247.56	4,457.05
90%	\$65,339.64	\$65,486.74	\$72,831.64	\$1,695.46	\$67,182.20	\$5,649.44
100%	\$72,812.17	\$76,748.55	\$88,105.49	\$1,385.45	\$78,134.00	\$9,971.49
110%	\$81,760.17	\$88,650.67	\$104,206.91	\$1,492.53	\$90,143.20	\$14,063.71
120%	\$98,138.85	\$105,762.40	\$120,416.77	\$1,550.18	\$107,312.58	\$13,104.18

which are 80%, 90%, 110%, and 120% of the baseline case study. The results for solving and evaluating the TSS for different values of demand mean are reported in Table 3.7. The comparison of the test results are shown in Figure 3.10 and 3.11. The value of RP solution increases as the demand mean increases because of the increase in production levels. As expected, the WS solution are observed to be lower than the RP solutions. From Figure 3.10, EV solutions have the least cost among the four metrics it is compared iwth as its values are obtained by eliminating the eliminating the uncertainties from the models. Also, it can be observed that the EEV solutions are having the highest cost as they are the expected value solutions of EV. The VSS values increases drastically as the demand value increase. As the production capacities and resources increase and as more kits are manufactured, it makes more sense to consider the uncertainties to model the planning and scheduling problem.

3.6.2 Machines Degradation

In this Section, uncertainty in production rate are considered and how machine degradation effect on ($\beta_{m,i,o}$). A case is defined based on the parameters presented in the previous Sections. The results are reported in Table 3.8. The results show that a potential saving of \$1,237.80 when the manufacturer spend more money on improving their knowledge of machines performance.

Figure 3.10

Comparison of Test Results for Four Cases of Demand Mean

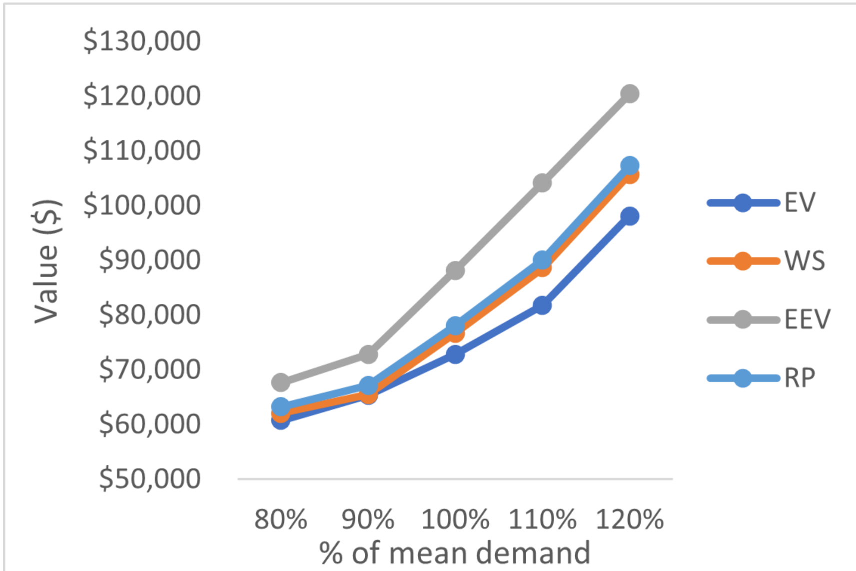


Figure 3.11

Comparison of Value of Stochastic Solution (VSS) And Expected Value Of Perfect Information (EVPI) Test Results for Four Cases of Demand Mean

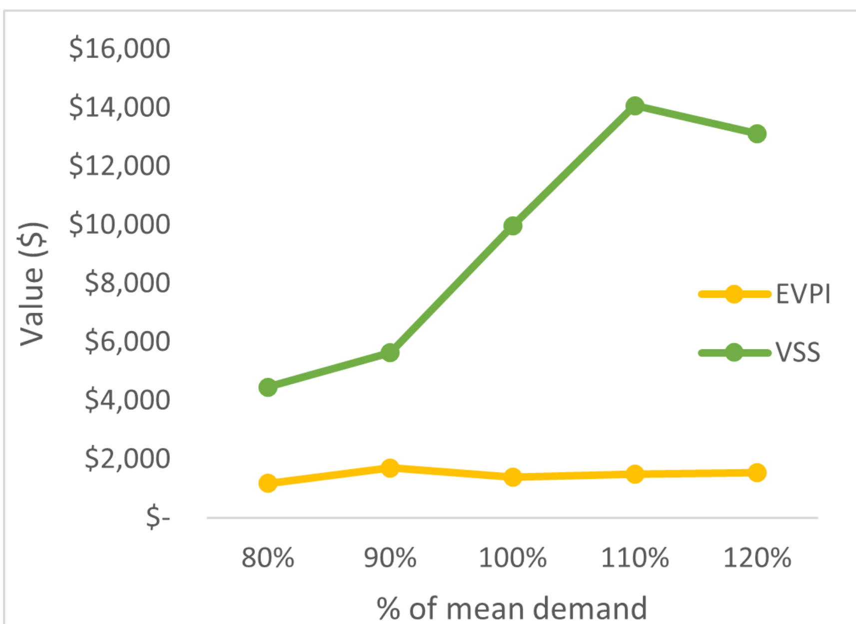


Table 3.8

Two-Stage Stochastic Model Solution Evaluation for Stochastic Production Rate

Solution					
Deterministic	Problem	Scenario 1	Scenario 2	Scenario 3	EV
	Cost function	\$74,188.21	\$73,384.31	\$81,186.99	\$74,454.80
	Probability	30%	40%	30%	
EEV	Problem	Scenario 1	Scenario 2	Scenario 3	*EEV*
	Cost function	\$86,395.50	\$85,405.16	\$84,764.80	\$89,560.13
TSS evaluation	Problem	WS	EVPI	*RP*	*VSS*
	Cost function	\$76,206.28	\$1,237.80	\$77,444.09	\$8,951.42

3.7 Summary

Despite reconfigurable manufacturing system (RMS) strengths, small and medium enterprises (SMEs) lack a clear understanding of RMSs features and advantages, and still widely adopt manual manufacturing processes to support the diversity of their products and small batch sizes. Therefore, this Chapter presents a novel mixed-integer linear programming (MILP) formulation for production planning and scheduling using reconfigurability technologies to present advantages on cost savings and performance improvements.

The problem of RMS planning and scheduling for producing a part family is addressed in this Chapter through two MILP formulation and a case study. These formulation aims at minimizing the total production cost which includes reconfigurable machine tools (RMTs)' operation costs, as well as raw material, backorders, and inventory holding (finished and work-in-process (WIP)) costs. In addition, the cost-effectiveness of reconfigurability is analyzed quantitatively using sensitivity analyses and analysis of variances (ANOVA). The results for investigating the cost-effectiveness of RMS showed that:

- The reconfigurability feature provides extra production capabilities, including lower costs and time-effectiveness.

- Under the same settings, RMS can be 29.88% more cost-effective and 24.9% more productive than a non-reconfigurable system.
- Reconfiguration and inventory holding costs do not have a significant effect on the savings. Raw material, backorders, and operating costs do have significant effects on the total savings since they are associated with the production level.
- The value of the time spent in reconfiguring the RMTs has a negligible effect on the overall performance, regardless of the length and value.
- The available capacity to hold any inventory has a significant effect on RMS overall performance.
- In the circumstances where the demand should be fulfilled in a short time, RMS performs better than a non-reconfigurable system. This represents RMS capabilities to cope with the dynamic market and short lead time.
- Fast reconfigurations and accurate calibration are essential to exploit the reconfigurability feature of RMS.
- Generally, multi-product production is more cost-effective than single-product production because the manufacturing resources are shared among all orders. However, the features of the orders (i.e., variety, quantity, and complexity) may affect that performance.
- The ANOVA results show that number of configurations is the most significant factor. This means reconfigurability is the most significant factor to achieve maximum savings.

- The value of stochastic solution (VSS) values increases drastically as the demand value increase.

- The results of solving the two-stage stochastic (TSS) model show that a potential saving of $\$1,237.80$ when the manufacturer spend more money on improving their knowledge of the customers' demand and machines production rate.

For future research, metaheuristics algorithm can be developed to solve the model and verify it for plants with a large number of RMTs. This research focused on small and medium plants as they still widely adopt manual manufacturing processes. The model can be extended to considered multi part families. The resulted model will be more complex but it brings the problem closer to the practical scenario. More micro-level studies can be implemented by adding operation parameters (e.g., modules, tools, speed, axes) for each specific configuration to study the cost of exploiting each module and their settings on RMS savings.

CHAPTER FOUR

Production Management of Flow Lines with Reconfigurable Machines

4.1 Introduction

As introduced in the previous Chapters, RMSs with multiple RMTs and the part movement is unidirectional and machines are in arranged in sequence in a product layout to maximize efficiency, then, these RMSs can be managed as same as a flow line. In a regular flow line, the production management problem is called flow line scheduling problem (FLSP). This problem consists of the determination of an optimal schedule for the job on the machines. It has been a keen era of research for many years. The elements of FLSP are the set of machines and a collection of jobs to be scheduled. Each job consists of several operations with the same linear precedence structure from the first stage to last stage and one machine performs all the processing for each stage (Ponnambalam & Reddy, 2003). In order to extend the capacity of a single stage, additional parallel machines may be allocated. This extension of a flow line to allow multiple machines in stages transforms the flow line into a flexible flow line (FFL) - also commonly referred to as hybrid flow line, flow line with parallel machines, or multiprocessor flow line. The schdeuling problem is called flexible flow line scheduling problem (FFLSP) (Kurz & Askin, 2003; Quadt & Kuhn, 2007; Wang, 2005). However, one RMTs are used as the manufacturing equipment then this system is called RFL and the scheduling problem is called reconfigurable serial flow line (RSFL) scheduling problem (Ashraf & Hasan, 2018). When parallel machines are used in the processing stages it is called reconfigurable parallel flow line (RPFL) scheduling problem. In this research, these two problems are extended to a real-time reconfigurable flow line scheduling and control problem (RFSCP) for both RSFL and RPFL.

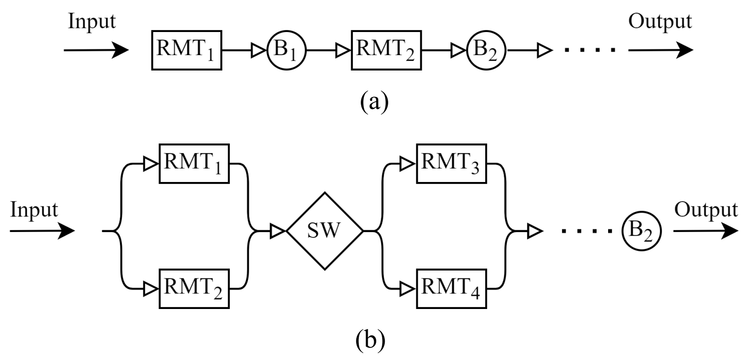
In this Chapter, it is assumed that a customer order (i.e., production jobs) are assigned to a manufacturing plant which includes several RMTs. The order represent a part that has a set of operations which can be performed at least on one configuration of one of the existing RMTs. This problem is more complicated than the FLSP and FFLSP, because three decisions have to be taken; these decisions include allocating of the operations to the machines, determining of the configuration of the machines to perform the allocated operations, reschedule the jobs release plan in a real-time to prevent WIP explosion. Therefore, this Chapter contributes to the base knowledge by proposing a novel real-time model-based controller for scheduling, controlling, and configuration selection for a flow line with RMTs.

4.2 Problem Description

The RFSCP with machines/configuration pair selection, in this research, can be described as follows. There is a set of M of RMTs are available and to be assigned in serial stages. Each RMT m has a set of I configurations. One or more operation can be performed in each configuration with a stochastic production rate $w_{o_p}^{RFL}(k_p)$. Each stage only consists of one type of machine. For a RPFL, machines are placed in parallel in each sage, these machines can be identical or non-identical (Lee & Loong, 2019). It is assumed that the line can operation only one product p in each product run. Each product p has a number of o_p operations of the total O_p operations with a predefined sequence, these operations should be performed to have a finished product. It should be noted that each operation o can be performed in only one stage. In flow lines, time-related objective functions are commonly used, and the most important and treated as the most KPI. Therefore, MPA-MPC methodology was chosen to schedule and control these systems. The objective is to optimize tardiness and WIP levels by controlling the release time of jobs.

Figure 4.1

Considered RMS structures. (a) RSFL (b) RPFL with a Switching Device to Control the Inter-Stage Movements of the Work-In-Process (WIP) Units



To alleviate this issue, our goal is to develop a controlling framework that utilizes systems and machines data to select machines configuration based on the current production requirements. Moreover, the framework can schedule raw material injection and system operations where two performance indicators are optimized, which are WIP level and tardiness. The proposed approach can also react to unexpected events in real-time by rescheduling system operations. This is crucial in the recent smart manufacturing paradigm where the data collected from sensors are used to predict possible equipment failures. The proposed methods are applicable for various types of manufacturing structures such as serial and parallel systems with crossover. In a serial product flow configuration, machines are arranged in a line one after the other separated by finite buffers. A parallel system with crossover allows to cross over between parallel lines (Gupta et al., 2015; P. P. Singh et al., 2021).

4.3 Proposed Framework

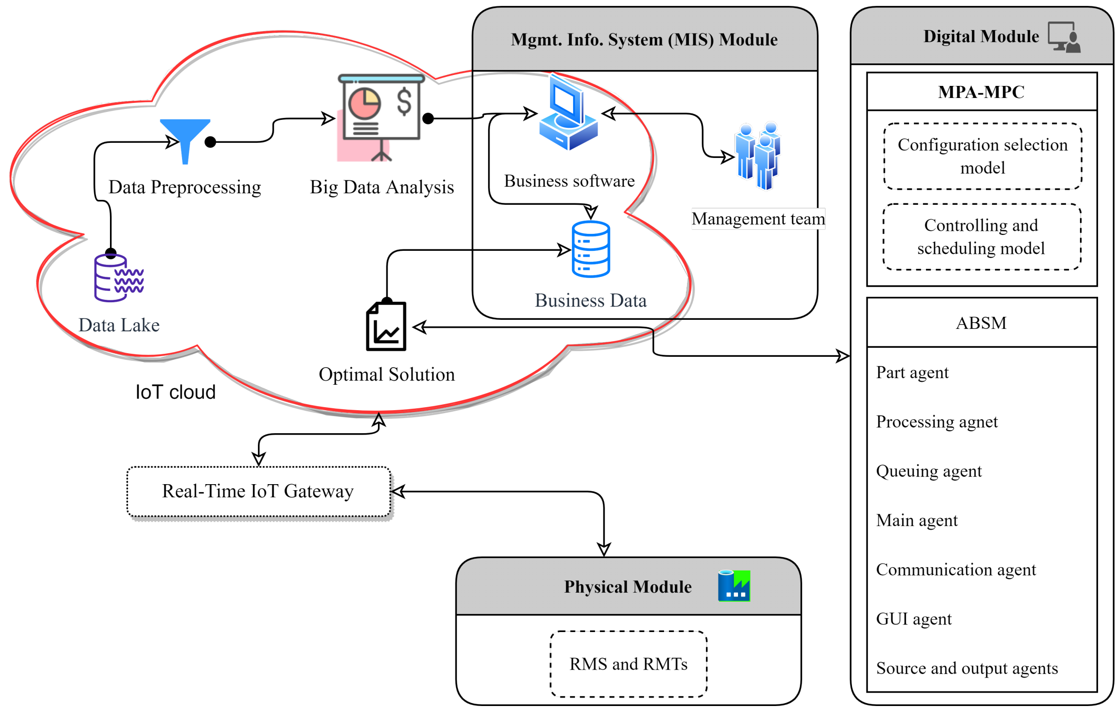
One of the major aims of the framework is to provide a fast, data-driven solution that utilizes the collected data to optimize and monitor RFLs in real-time. The overview of the proposed framework is shown in Figure 4.2. The data collected from the system is fed into the digital module where reconfiguration and production decisions are optimized. In this module, a model-based controller is developed to achieve the goals defined in the previous sections. The controlling algorithm is based on MPA and MPC. MPA is a mathematical technique to model discrete manufacturing systems using only maximization (max) and addition (plus) operations (De Schutter et al., 2020; Heidergott et al., 2014). MPC is an advanced control methodology that is characterized by ease of use and the ability to add constraints on the inputs, states, and outputs. In addition, it optimizes the system performance each time step (Altan & Hacıoğlu, 2020). This study proposes a decision-making algorithm for configurations selection and reconfiguration based on information obtained by the internet of things (IOT) sensors installed in RMTs modules (Han et al., 2020). The proposed system is expected to detect reconfiguration situations quickly to create appropriate reconfiguration planning and achieve fast stabilization after reconfiguration by using IOT information. The proposed framework is expected to be integrated with the existing manufacturing decision-making systems including management software tools such as enterprise resource planning (ERP), production information management (PIM), and customer relationship management (CRM). In addition, the management team and databases should be utilized in implementing the framework. These three components are considered as IMS module which acts as a decision and implementation support system.

4.3.1 Basic Settings and Assumptions

Firstly, the system layout and the required manufacturing operation should be identified to build the model-based controlling model. The optimum system layout is identified by the management team with the aid of management software tools and/or an optimization approach. The MPA-MPC model must be formulated based on the selected

Figure 4.2

The Modules of the Proposed Framework



structure. For both structures, the following assumptions are considered in developing the proposed controlling algorithm:

- There is at least one supplier available to supply the required raw material and one supplier should be selected for each raw material.
- Finished parts are sold as soon as they leave the production system.
- The considered flow lines are single-product RMSs, where one part only is manufactured.
- The sequence of manufacturing is based on the sequence of receiving the order from customers.
- The machines are arranged based on the operations sequence.

- In the crossover parallel RMSs, the stages are connected by an idle station that acts as a switching device for controlling pars movement (Imseitif et al., 2019).
- There is at least one configuration i that can perform the assigned operations to the machine.
- If the configuration cannot perform a required operation, it is excluded from the selection criteria for this operation.
- The processing time of the machines is based on the triangular distribution.

4.3.2 System Modeling and Formulation

At each time step k, a batch of units of product p is fed to the system and passed from the upstream RMTs to the downstream (i.e., one unit in serial system or two units in parallel system). Each RMT operations one operation of the ${k_p}^{th}$ unit(s). The processing time for each operation $w_{o_p}^{RFL}(k_p)$ can be determined based on the selected configuration. As described in (Boom & Schutter, 2004; De Schutter & van den Boom, 2001), system dynamics should be represented in the following form:

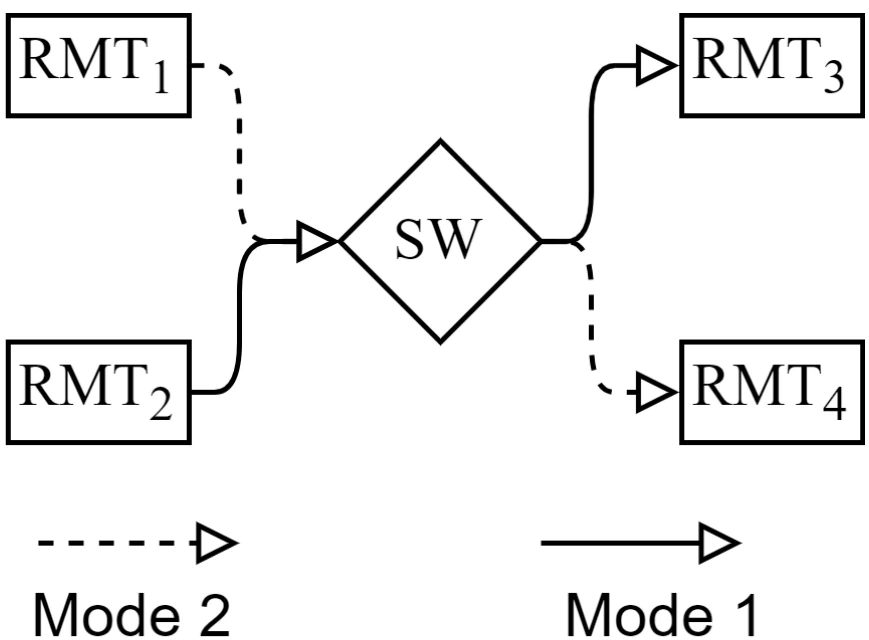
$$x(k) = \boldsymbol{A}(k-1) \otimes x(k-1) \oplus \boldsymbol{b}(k) \otimes u(k) \tag{4.1}$$

$$y(k) \ = \ \boldsymbol{C}(k) \otimes x(k) \tag{4.2}$$

The matrix $\boldsymbol{A}$ is a $M \times M$ matrix that represents the required time for the upstream machines to finish processing a WIP unit. Its elements are constructed based on variable $w_{o_p}^{RFL}(k_p)$. $\boldsymbol{B}$ is a M x 1 matrix represents the required time to ship the WIP unit to downstream machines. $\boldsymbol{C}$ is a 1M matrix representing the production rate for the last machine to finish the last process. A_b is a $M \times M$ matrix that represents the relationship between the buffer and its upstream and downstream machines. For more details on constructing these matrices, readers can refer to (De Schutter et al., 2020). Understanding how these matrices are constructed is essential for controlling the inter-stage movement of WIP units in parallel systems. The approach described above was followed and adjusted to model parallel systems with switching devices installed between stages. In this paper, an algorithm was developed to sort the machines' completion time in each stage at each time step. Based on the sorting results, all system matrices are reconstructed automatically to match machines based on their completion time. A control signal is sent to the switching device to move the first finished part to the fastest downstream machine. In constructing the proposed controlling algorithm for WIP inner-stage movements, two production modes were defined as shown in Figure 4.3.

Figure 4.3

Defined Production Modes in the Parallel Systems



Mode 1 corresponds to "RMT_1 finishes first, RMT_2 finishes later" and mode 2 corresponds to "RMT_2 finishes first, RMT_1 finishes later". Defining these modes is essential for constructing the system matrices and reduce modeling complexity. In De Schutter et al., 2020, these modes were modeled separately and switching between them required defining a decision variable. In addition, the resulted problem was min-max-plus optimization problem and solving this method requires high computation efforts. The complexity of this problem was reduced significantly by the proposed algorithm.

Using the variable $w_{o_p}^{RFL}(k_p) = \sum_{m=1}^{M} \sum_{i=1}^{I} \sigma_{p,m,i,o_p}(k_p) \; z_{p,m,i,o_p}^{RFL}$, the system matrices $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ can be constructed as follows.

$$\boldsymbol{A}(k_p^-) =$$

$$\begin{bmatrix} w_{1_p}^{RFL}(k_p-) & \varepsilon & \cdots & \varepsilon \\ w_{1,o}^{RFL}(k_p) \otimes w_{2_p}^{RFL}(k_p) & w_{2_p}^{RFL}(k_p-) & \cdots & \varepsilon \\ \vdots & \vdots & \ddots & \vdots \\ w_{1,o}^{RFL}(k_p) \otimes_{o_p=2}^{O_p-1} w_{o_p}^{RFL}(k_p) & w_{2,o}(k_p) \otimes_{o_p=3}^{O_p-1} w_{o_p}^{RFL}(k_p) & w_{O_{p-1}^{RFL}}(k_p^-) \otimes w_{O_p}(k_p) & w_{O_p}(k_p) \end{bmatrix}$$

$$\boldsymbol{B}(k_p) = \begin{cases} e & \text{if } \; o_p = 1 \\ \otimes_{o_p=1}^{o_p} w_{o_p}^{RFL}(k_p) & \text{if } \; 2 \leq o_p \leq O_p \end{cases}$$

$$\boldsymbol{C}(k_p) = \begin{cases} e & \text{if } \; o_p \leq O_p \\ w_{o_p}^{RFL}(k_p) & \text{if } \; 2 \leq o_p \leq O_p \end{cases}$$

To model finite buffers; assume a general RMT ($m = 1$) followed by a buffer b with a finite size N_b. For the ${k_p}^{th}$ part to start on station RMT m an additional condition is required to account for the buffer, which is for RMT ($m+1$) to have started processing the part number ${k_p}^{-} - N_b$. Assuming that RMT m mentioned above is part of a general flow line, then matrix $\boldsymbol{A}_{N_b}(k_p^-)$ will be generated. The generation method was adopted from (Seleim & ElMaraghy, 2015).

Then, the MPL-MPC model can be formulated as follows

$$min\ J_p = \sum_{p=1}^{P}\sum_{j=1}^{N_p} \max\left(y_p(k_p+j|k) - r_p(\mathrm{k_p}+j), 0\ \right) + \sum_{q=1}^{Q}\sum_{p=1}^{p}\sum_{s_p=1}^{S_p}\sum_{j=1}^{N_p} \max(\ d_{q,s_p} - u_p^{RFL}(k_p+j-1), 0) \quad (4.3)$$

$$x_{o_p}(k_p) = \boldsymbol{A}(k_p^-) \otimes x_{o_p}(k_p^-) \oplus \boldsymbol{B}(k_p) \otimes u_p^{RFL}(k_p) \oplus \boldsymbol{A}_{N_b}(k_p^-) \otimes x_{o_p}^{RFL}(k_p - N_b - 1) \quad (4.4)$$

$$w_{o_p}^{RFL}(k_p) = \sum_{m=1}^{M}\sum_{i=1}^{I} \sigma_{p,m,i,o_p}(k_p)\ \ z_{p,m,i,o_p}^{RFL} \quad (4.5)$$

$$d_{q,s_p}^{RFL} = T_{q,s_p}^{RFL}\ v_{s_p}^{RFL}, \qquad \forall\ s_p, q \quad (4.6)$$

$$u_p(k_p+j-1) \geq d_{q,s_p}^{RFL} \qquad \forall\ q, p, s,\ j = 1, 2, \ldots, N_p \quad (4.7)$$

$$\Delta u_p^{RFL}(k_p+j-1) \geq \alpha \qquad \forall p, j = 1, 2, \ldots, N_p \quad (4.8)$$

$$\Delta u_p^{RFL}(k_p+j-1) \geq 0 \qquad \forall p, j = 1, 2, \ldots, N_p \quad (4.9)$$

$$y_p^{RFL}(k_p) = x_{o_p}(k_p) \otimes w_{o_p}^{RFL}(k_p) \quad (4.10)$$

Equation (4.3) represents the cost function. It minimizes tracking errors corresponding to due dates and minimizes the time between the arrival of the raw material and the inputs instances. It charges when the inputs time instances are less than the arrival time of the raw materials. Equation (4.4) represents the evolution of the system (i.e. output predictions).Equation (4.5) finds the operating time of the operation based on the selected configuration. Equation (4.6) finds the delivery time of each raw material from each supplier. Equation (4.7) ensures that the input instances are larger than the arrival time of the raw material. Equation (4.8) limits the inputs instances to be larger than a specified parameters ($w_{1_p}(k_p^-)$). Equation (4.9) ensures that input instances are larger than zero. Equation (4.10) finds the time instances at which a unit leaves the system.

4.3.3 Configuration Selection Modeling

The previous decisions are also linked to configuration selection constraints programming using the following equations.

$$\sum_{m=1}^{M}\sum_{i=I}^{I} z_{p,m,i,o_p}^{RFL} = 1 \qquad \forall p, o_p \tag{4.11}$$

$$\sum_{i=1}^{I}\sum_{o_p=I}^{O_p} z_{p,m,i,o_p}^{RFL} \leq 1 \qquad \forall p, m \tag{4.12}$$

Equation (4.11) select one configuration and one machine for each required operation for product p. Equation (4.12) ensures to select one configuration from each machine to perform one operation from the required operations. In addition, it prevents the overlapping of selecting the same configuration for multiple operations. In a parallel line, the same operation is performed but we need another machines to operation the same operation, then the set O_p is duplicated based on it is original elements. For instance, if $O_1 = [1\ 2\ 4]$ then $O_1{}' = \ [1\ 1\ 2\ 2\ 4\ 4]$. Based on that, Equations (4.8 and 4.12) are modified as follows:

$$\Delta u_p(k+j-1) \geq \alpha_p \qquad \forall p, j = 1,2,\ldots,N_p \tag{4.13}$$

$$\sum_{i=1}^{I}\sum_{o_p=I}^{O_p} z_{p,m,i,o_p} \leq 2 \qquad \forall p, m \tag{4.14}$$

Table 4.1

ABSM Agents, Their Attributes, and Description

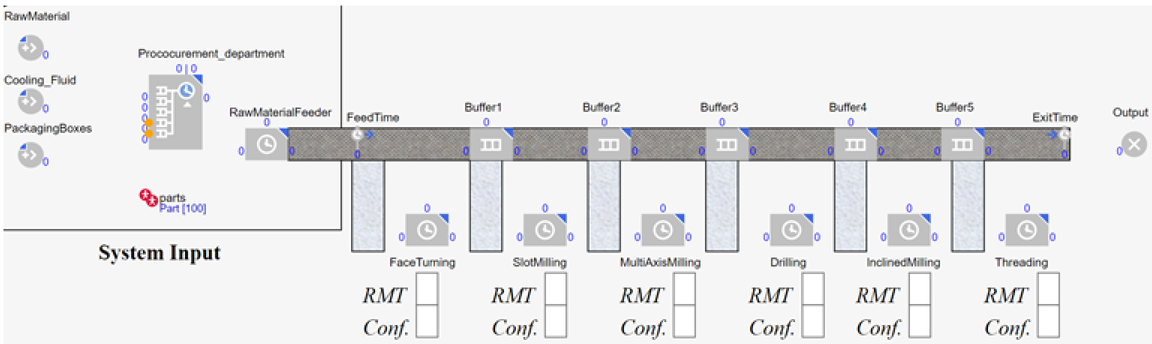
Agent	Attributes	Description
Part	Entry time	WIP unit
processing	Starting time; processing time; MTBF; machine number; configuration number	RMTs
Queuing	Capacity	Buffer
Main	Demand, number of each agent, processing agents layouts, raw material lead time	RMS
Communication	Polling signal	Data gateway
GUI	KPIs of interest	KPIs monitoring
Source	Injection time	Raw material
Output	Exit time; due date	System output

4.3.4 System Simulation

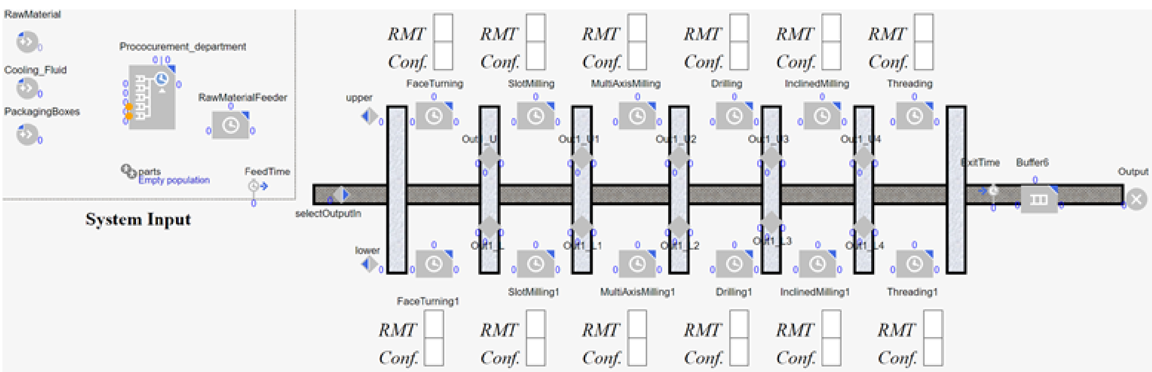
ABS is a relatively new method, especially in operation research where it's often been overlooked in favor of other simulation methods. ABS models consists of self-directed agents which follow a series of predefined logic to achieve their objectives whilst interacting with each other and their environment. This technique has demonstrated its utility in manufacturing system modeling and solving different problems such as (Ruiz et al., 2006). For example, in this paper, AnyLogic has been used to develop the ABS model (ABSM) to send collected system data to the YALMIP MATLAB tool where the MPA-MPC model resides to optimize the line performance (Lofberg, 2004). In addition, ABSM allows us to visualize and simulate the global behavior of each entity, mixing complex and simple behavior at different levels. Figure 4.4 shows the logic flowcharts for the developed ABSMs. Agents details are listed in Table 4.1.

Figure 4.4

RMS ABSMs. (a) RMTs Arranged Serially Separated by Buffers (B) RMTs Arranged in Parallel With a Switching Device to Control the Movement of WIP Units



(a)



(b)

4.4 Numerical Results

In this section, the applicability and efficiency of the proposed framework are analyzed using a case study inspired by (Ashraf & Hasan, 2018). Consider a part with a demand of 40 units that is to be produced using RMTs in a simulated manufacturing environment by performing a set of operations. with the operation sequences: $Faceturning \rightarrow Slotmilling \rightarrow Multi-axis\ milling \rightarrow Drilling \rightarrow Multi-axisinclinedmilling \rightarrow Threading$. With six operations required, six production stages are considered in the system. At each stage, one operation is performed using one

RMT (serial system) or two RMTs (parallel system). The jobs due dates are assumed to be calculated using the following equations $r_p(k_p) = 24.461\ (k_p) + 176$ and $r(k_p) = 27.8(k_p) + 170$ for serial and parallel lines, respectively. These equations estimate the output time for each job. They can be set based on experience. In this research, multiple system runs are conducted to estimate these equations. The simulation results for both systems are presented in this Section. We focused on tardiness, flowtime, the difference between input instances, WIP distribution, and computation time.

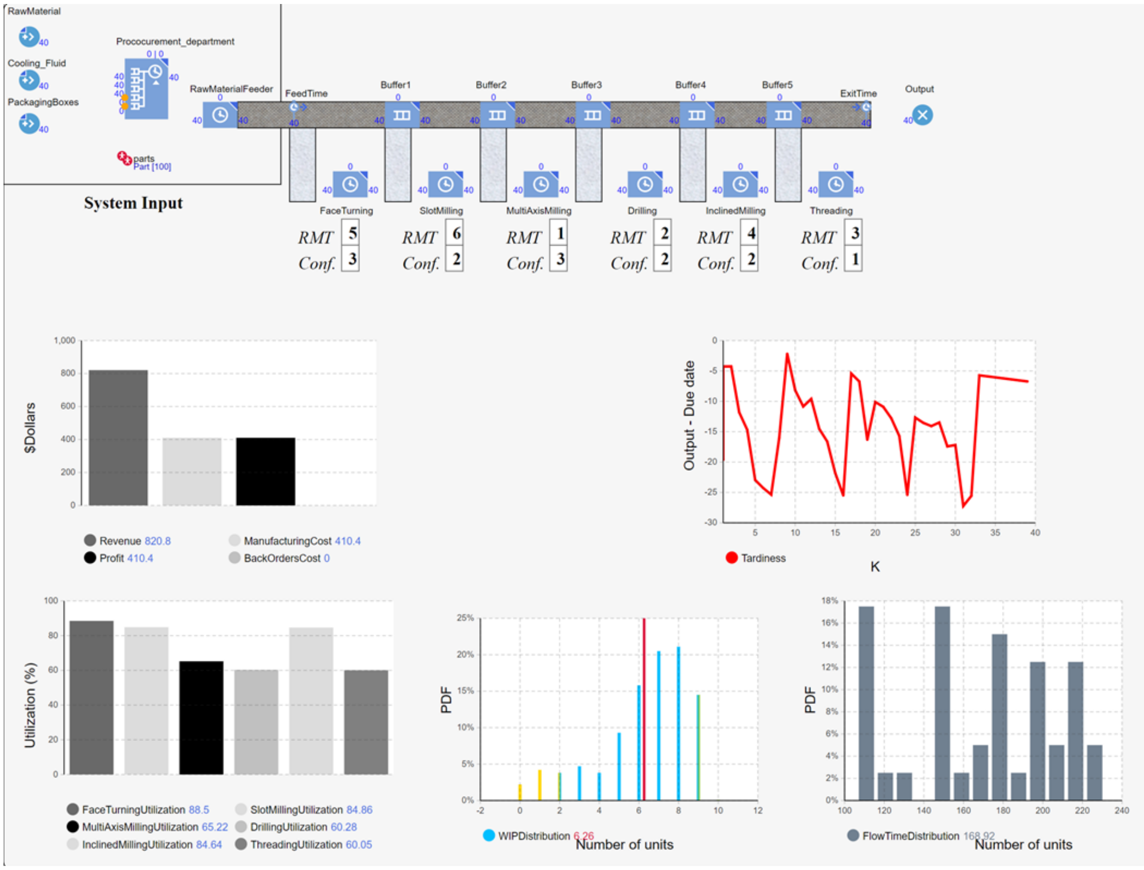
4.4.1 Serial Systems

In serial production systems, where a group of producing units (RMTs) are arranged in consecutive order and WIP units move sequentially from one producing unit to the next, throughput is influenced by varied processing times or unexpected disturbing events. WIP buffers between two adjacent RMTs can be installed to mitigate the effects of these uncertainties. Their level fluctuates drastically with random disturbances in the system. Therefore, it is necessary to keep WIP levels at minimum levels. In the present work, the proposed framework is implemented to control serial RMS which is equipped with six RMTs and five WIP buffers. The simulation results and KPI dashboard are shown in Figure 4.5.

The production started at minute 90 after all raw materials arrived at the plant. Then, the last finished unit left the system at minute 1147.72. A statistical summary of the performance for the 1057.72 minutes of production is presented in Table 4.2. Mean, maximum value and mean absolute deviation (MAD) indicator are considered for the selected KPIs. The developed KPI dashboard shows different performance metrics such as manufacturing cost, output tardiness, machines utilization, WIP level distribution, and flowtime distribution. The total system profit is 410\$. The tardiness chart shows the different between the due date and output instance for each unit. Machines utilization was

Figure 4.5

Simulation Results of Implementing the Proposed Framework on Serial RMS



ranged from 60.28% to 88.5%. WIP distribution chart shows that WIP was 6.26 units with 25%, while flowtime was 168.92 minutes.

As far as tardiness is concerned, the system delivered 40 jobs with an average of 13.52 minutes earlier than their due date which describes the negative values. In the context of RMS, it is necessary to finish jobs on or before the due dates (Grassi et al., 2020). flowtime can be also referred to as the total completion time of a job (Pan & Ruiz, 2013). Low flowtime values reflect optimum WIP levels and stable utilization of resources (Sang et al., 2019). MAD value for flowtime is small compared to the mean and maximum value. This small value indicates stability in the system and parts leave the system within an expected range. Regarding Δu_p, MPC controller feeds raw material to

Table 4.2

Statistical Summary for the Simulated Serial RMS

Criteria	Mean Value	Max. Value	MAD
Tardiness (min)	-13.52	-27.72	5.85
Flowtime (min)	168.92	230.72	32.46
Δu_p (mins)	21.20	29	2.845
B_1 Level (units)	0.44	2	-
B_2 Level (units)	0.17	2	-
B_3 Level (units)	0.11	1	-
B_4 Level (units)	1.36	5	-
B_5 Level (units)	0	1	-
WIP (units)	6.26	10	-

the system on average every 21.20 minutes. If the MAD for Δu_p is high this would indicate high WIP levels in the system and the controller delays inputs to maintain low WIP levels. This is not the case here since the five WIP buffers ($B_1 - B_5$) with 7 units capacity have not reached the maximum capacity during production. In addition, for a system that can hold up to 41 WIP units, 10 WIP units are presented in the system at maximum levels, distributed on RMTs and WIP buffers.

As described above, MPC controller is used to select machine configurations at time step 1 and then is used to schedule system events during the following steps until the demand is met. The computation time for the controller for each time step is plotted in Figure 4.6. It can be noticed that the computation time varies from time step to time step. In the first step, configuration constraints are included in the model, and solving the model requires more time than solving the model for WIP optimization.

4.4.2 Parallel Systems

Parallel systems are classified either as symmetrical or asymmetrical, based on whether an asymmetric axis can be drawn along the system. A structure is then evaluated by its RMTs arrangement and connections (Koren & Shpitalni, 2010). In the present work,

Figure 4.6

MPA-MPC Model Computation Time for Each Time Step for Serial RMS

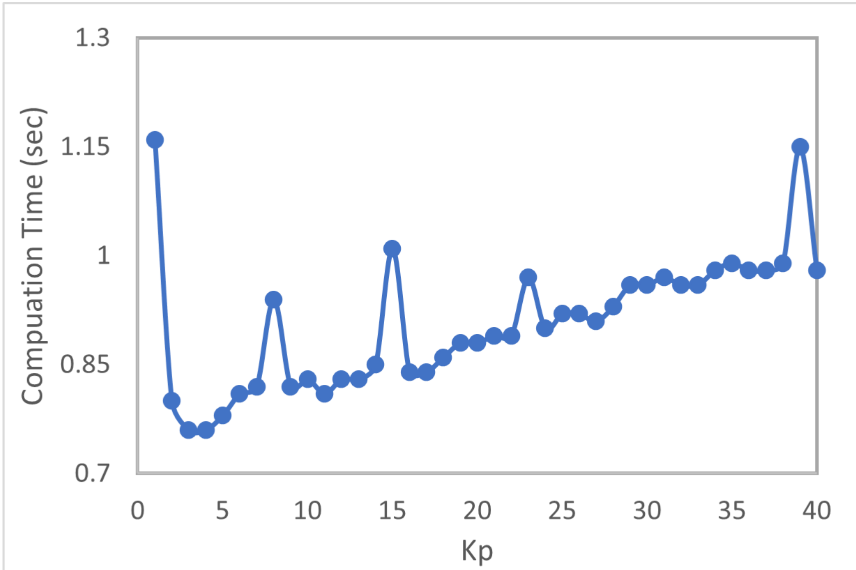


Table 4.3

Statistical Summary for the Simulated Parallel RMS

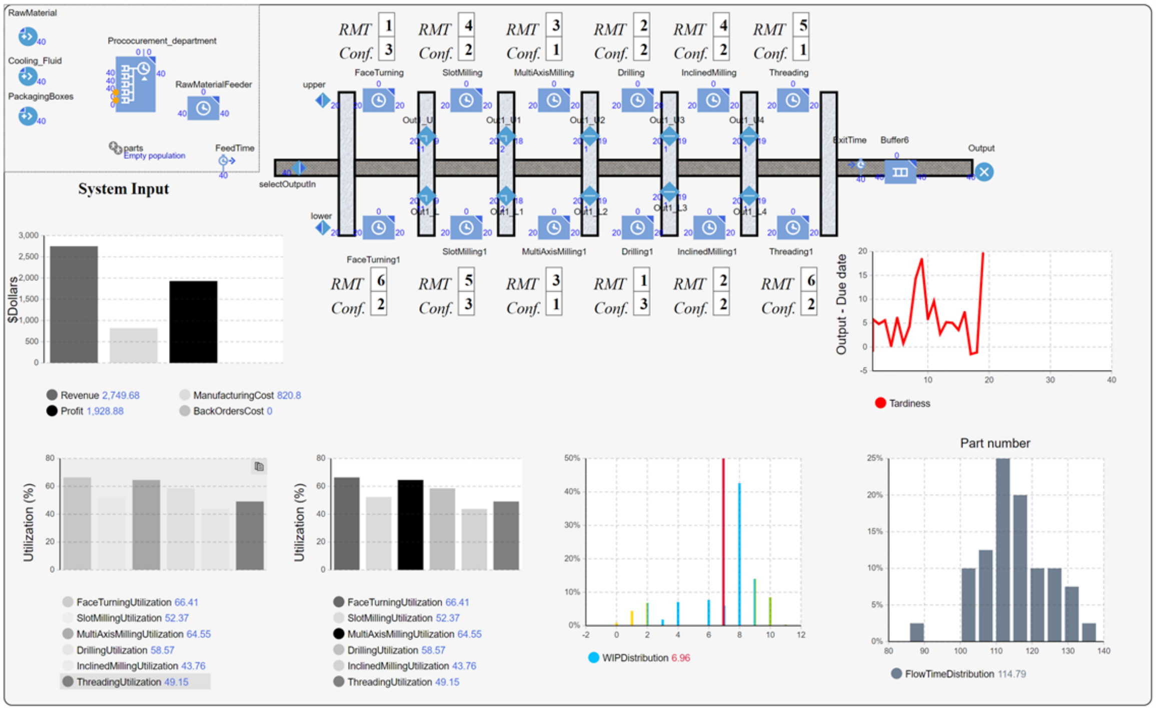
Criteria	Mean Value	Max. Value	MAD
Tardiness (min)	7.25	21.93	4.74
Flowtime (min)	116.35	144.75	6.94
Δu_p (mins)	27.42	35	2.44
WIP (units)	7.08	10	-

the RMTs that are selected to perform the same operations are assigned to the same production stage. These RMTs are connected by switching devices that move WIP units either to the upper RMT or lower RMT at the downstream. The proposed MPA-MPC model equipped with an algorithm for controlling parts movements in ABSM (Figure 4.7) is implemented and the simulation results for the 658.93 minutes of production are recorded in Table 4.3. It can be noticed that the MPC controller performed well in selecting machine configurations, maintaining system stability, and low WIP levels.

The computation time for the controller for each time step is recorded and shown

Figure 4.7

Simulation Results of Implementing the Proposed Framework on Parallel RMS

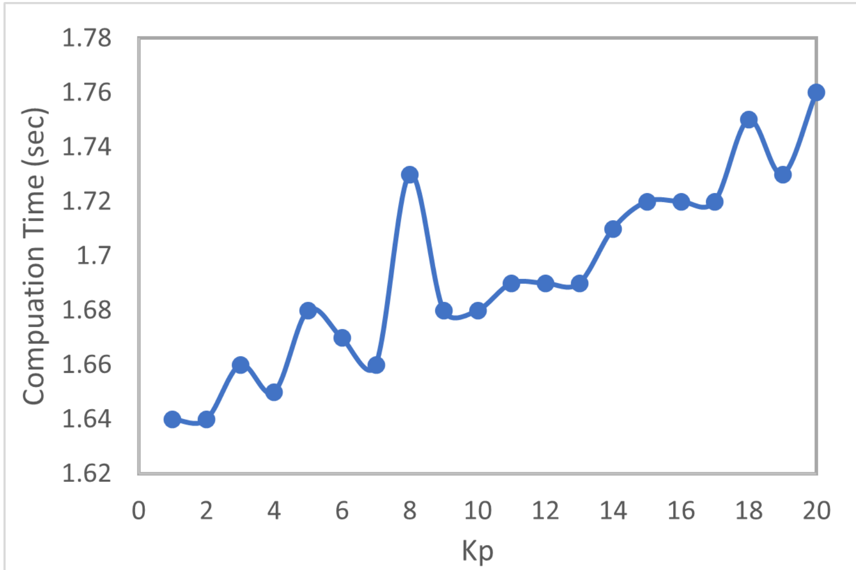


in Figure 4.8. It can be noticed that the computation time increases as the system evolves. However, the computation time is small considered for a system with 16 RMTs.

The proposed algorithm for controlling the WIP inner-stage movement was evaluated against the developed models in (Chang et al., 2013; van den Boom & De Schutter, 2006). These models required modeling each production mode separately and a decision variable was used to find the optimum switching method which can be cumbersome and inefficient in complex systems. The proposed algorithm solves this issue and automating the switching process. For validating the algorithm, the starting times and completion times for the selected RMTs are recorded in Table 4.4. As described in Section 4.2 and show in in Figure 4.7, mode 2 represent that the machines performing ”Face Truning” finishes first and the RMT performing ”Slot Milling 1” is available to receive a part and mode 1 represent that the machines performing ”Face Truning 1”

Figure 4.8

MPA-MPC Model Computation Time for Each Time Step for Parallel RMS



finishes first and the RMT performing ”Slot Milling” is available to receive a part. The switching between production modes is plotted in Figure 4.9.

The results show that sorting the RMTs completion time and reconstructing the system matrices is applicable for controlling WIP inner-stage movement. For example, RMT_1 that is performing the operation ”FaceTurning” finished processing the first part ($K_p = 1$) at minute 107, and RMT_5 was available to receive this part. Based on that, the algorithm sent a signal to the switching device to operate in mode 2. In the next time step, RMT_4 processing time was shorter than RMT_5, and RMT_1 finished process the second part faster than RMT_6. Therefore, the production mode was switched from mode 1 to mode 2.

4.4.3 Model Evaluation

To evaluate the model novelty and applicability, its performance was compared with a deterministic model. Simulation results using deterministic controller are reported in Tables 4.5 and 4.6. Results comparison for serial system show that the stochastic

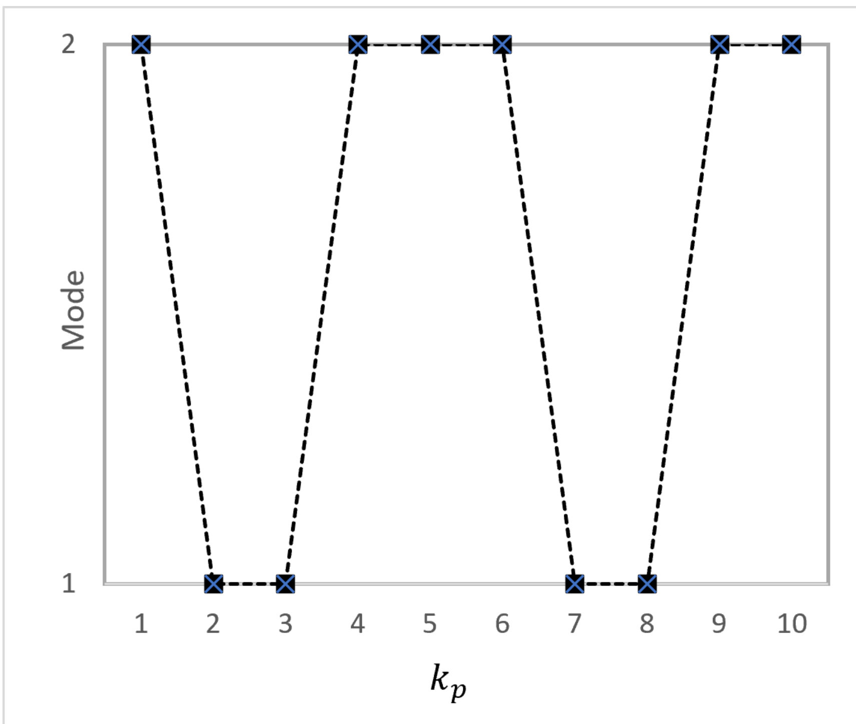
Table 4.4

Face Turning RMT Completion Time and Slot Milling RMT Starting Time for the First Ten Time Steps

	Completion Time									
RMT_1	107	130	160	182	208	231	269	295	319	359
RMT_6	109	139	160	187	213	245	273	299	324	349
	Starting Time									
RMT_4	109	130	160	187	213	245	269	295	324	349
RMT_5	107	139	160	182	208	231	273	299	319	359

Figure 4.9

Switching Device Operating Modes for the Simulated Parallel System



controller achieved lower MAD values for tardiness and flowtime, which means more stable system. The MAD value is higher which means the controller rescheduled raw materials injection time to optimize WIP levels. Therefore, mean and max values for WIP is lower when the stochastic controller was implemented. In parallel system, stochastic

Table 4.5

Statistical Summary for the Simulated Serial RMS Using Deterministic Controller

Criteria	Mean Value	Max. Value	MAD
Tardiness (min)	0	-27.224	0.64
Flowtime (min)	244.8	230.72	61.70
Δu_p (mins)	16.0	16.0	0
B_1 Level (units)	0.35	2.0	-
B_2 Level (units)	1.87	6.0	-
B_3 Level (units)	0.21	1.0	-
B_4 Level (units)	2.23	6.0	-
B_5 Level (units)	0.30	1.0	-
WIP (units)	9.30	16	-

Table 4.6

Statistical Summary for the Simulated Parallel RMS Using Deterministic Controller

Criteria	Mean Value	Max. Value	MAD
Tardiness (min)	9.99	11.82	1.21
Flowtime (min)	106.7	112.0	5.1
Δu_p (mins)	22.0	22.0	0
WIP (units)	8.11	11	-

controller maintained lower WIP levels. Tardiness and flowtime were relatively higher due to machines randomness and the need to reroute the WIP units. However, the values are small and indicates stable system even randomness are present in the system.

The evaluation results for serial systems can be summarized as follows:

- The proposed stochastic controller delivered items earlier on average (-13.52 min). The deterministic controller derived items on time.
- The flowtime for the stochastic model was shorter compared to the deterministic model on average.
- The stochastic controller rescheduled raw material injection time based on the presented randomness in the system.

- The WIP levels were below 24% of the total system capacity while considering randomness. On the the hand, the WIP levels were higher when the deterministic model was implemented.
- The computation time for both controller were around one second.

The evaluation results for parallel systems can be summarized as follows:

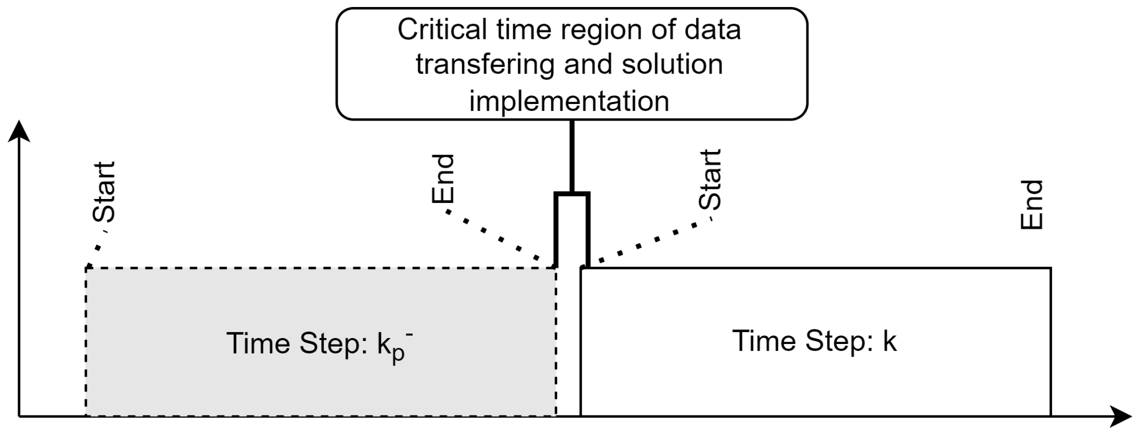
- The proposed stochastic controller delivered items with tardiness of (7.25 min). The deterministic controller derived with tardiness of (10.0 mins).
- The flowtime for the stochastic model was longer compared to the deterministic model on average.
- The stochastic controller rescheduled raw material injection time based on the presented randomness in the system.
- The WIP levels were below 83% of the total system capacity while considering randomness. On the the hand, the WIP levels were higher when the deterministic model was implemented.
- The computation time for the stochastic controller was higher than the deterministic one.

4.5 Discussion

In developing the algorithm and tuning the control the following challenges are encountered. (1) when there is a need to reconfigure the systems to trigger configurations selection model can only be done at the next time step. In other words, machine reconfigurations can only be done after finishing processing the current job and at the start of the next job. (2) data transferring and solution implementation during the critical time

Figure 4.10

Data Transferring and Solution Implementation During the Critical Time Region



region. Solution transferring an implementation should be fast enough and before the time to implement the next time step. For instance, to solve for time step k_p, we need the accurate machine processing time at time step k_p^- which can be obtained at the end of time step k_p. If the required time to send this data, solve the MPA-MPC model, and implement the solution is longer than the optimum time difference between the two-time steps, raw materials will not be injected at the optimum time and the optimum performance will not be achieved. Figure 4.10 depicts the critical time region concept for computations and implementation.

Switching devices for WIP units between two parallel stages are modeled using shifting MPA models in (Chang et al., 2013; van den Boom & De Schutter, 2006). These models require modeling system dynamics for each case, which can be cumbersome and inefficient in complex systems. In this paper, the switching device is based on a simple sort algorithm to reconstruct the system dynamics matrices $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$. First, the upper and lower lines are modeled as serial lines. Then, the RMTs are sorted based on their completion time. The fastest RMT in the upper stream is matched with the fastest RMT in the downstream. Based on that, $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ rows for the downstream RMTs are switched and this result is sent to the ABSM for implementation. In Section 4.4, we noticed that the computation time is small for the proposed algorithm. From analyzing serial and parallel systems performance we can notice the following:

- The parallel system reduced the production time by 42.59%
- The parallel system increased revenue by 70% and profit by 78%
- Serial systems saved 50% in manufacturing costs

4.6 Summary

In the present work, a data-driven controller is proposed to automate planning and scheduling events and optimize system performance in real-time. The proposed controller enabled real-time scheduling of raw material injection time and operations scheduling while minimizing system tardiness and WIP level. The data-driven controlling algorithm is based on max-plus algebra (MPA) and model predictive control (MPC). The former is an effective tool for modeling the event timing dynamics. The latter is a controlling algorithm that utilizes the MPA model to predict future responses and optimizes the cost criterion. In this research, real-time system data collected from an agent-based simulation model (ABSM) is used for prediction and optimization. The efficiency of the MPA-MPC model is analyzed using a case study for part production using serial and parallel system layouts. The results show stable resource utilization, optimum WIP levels, and low flowtime. For future research, other production scenarios can be further addressed. First, extend the production for a part family where multiple-product can be produced simultaneously using RMSs. Second, develop MPA-MPC models for hybrid system structures.

CHAPTER FIVE

Conclusions and Future Work

Reconfigurable manufacturing systems (RMSs) are a recent manufacturing paradigm driven by reconfigurability and high customer focus. The hallmark of RMS is the ability to switch between alternative configurations in a timely and cost-effective manner. This feature overcomes the limitations of the dedicated manufacturing systems (DMSs) and flexible manufacturing systems (FMSs) in coping with globalization and market volatility. In the current market, customers have more power not only to choose exactly the product that meets their needs but also to order and get it in a short time. Because traditional manufacturing systems proved their limitations in coping with these new circumstances, RMSs were introduced in 1999. They consist of multiple reconfigurable machine tools (RMTs), which come in multiple configurations. In addition, reconfigurable inspection machines (RIMs) can be added to the system to inspect the produced parts in real time. In the present work, novel methodologies for planning and scheduling RMS are presented to help manufacturers how to manage RMSs optimally. This research was conducted in two main parts based on RMS types: reconfigurable job shop (RJS) and reconfigurable flow line (RFL).

5.1 Optimizing Reconfigurable Job Shops

In this part, RMSs were studied as RJSs and the problem at hand was called reconfigurable job shop scheduling problems (RJSSPs). This problem is an extension and more complex version of flexible job shop scheduling problems (FJSSPs). This is because three more decisions have to be taken; these decisions include allocating the operations to the machines, sequencing the jobs, and determining the configuration of the machines to perform the allocated operations. Two novel comprehensive mixed-integer linear programming (MILP) models were formulated and evaluated to alleviate this issue. The first model is deterministic and aims to produce a cost-optimized plan and schedule for producing a pat family. Then, sensitivity analyses were conducted to analyze the effects of different internal and external factors such as cost parameters, reconfiguration parameters, length of the production period, storage capacity, order features, and production plant settings. The novelty of this model is that it integrates multiple management levels, planning and scheduling and considers new aspects that are missing from the existing models. In addition, a comprehensive experiment were conducted to investigate RMS performance under different production settings and justify the investment and efficiency. The results in this part showed the effectiveness of RMS compared to other traditional non-reconfigurable systems and a potential saving of 29% of the total manufacturing cost. Then, this model was extended to a two-stage stochastic (TSS) model to quantitatively analyze the uncertainties in demand level and machines' production rate. This result was evaluated against its deterministic version. The results showed that manufacturers could minimize production costs when solving the TSS

5.2 Optimizing Reconfigurable Flow Lines

In this part. RMSs were studied as the same as reconfigurable flow lines (RFLs) and the problem was called real-time reconfigurable flow line scheduling and control problems (RFSCPs) for both reconfigurable serial flow lines (RSFLs) and reconfigurable parallel flow lines (RPFLs). In these systems, the material flow is unidirectional, and machines are arranged sequentially in a product layout to maximize efficiency. The problem is an extension of the classical problem flexible flow line scheduling problem (FFLSP). This problem is more complicated than flexible flow line scheduling problem (FFLSP) because three more decisions must be taken;. These decisions include allocating the operations to the machines, determining the configuration of the machines to perform the allocated operations, and rescheduling the jobs release plan in real-time to prevent work-in-process (WIP) explosion. This research applied a model predictive control (MPC) algorithm that can offer real-time controlling capabilities for RFLs . The main objectives were automating RMTs' configuration selection and optimizing WIP levels and output tardiness. The controller collects real-time sensory data to schedule raw material injection time and control WIP inter-stage movements. A case study was utilized to implement and verify the proposed algorithm in serial and parallel RFLs. Then, the model was evaluated against a deterministic model to measure its applicability. Results showed that the proposed stochastic controller performed better than the deterministic model. In addition, the controlling algorithm for controlling WIP movements was evaluated, and its applicability was proved.

5.3 Future Work

The results presented in the dissertation rely on the latest technological advancements in part-family production, considering reconfigurable systems and modular machines for small to medium production levels. In addition, complementary information and communication tools that support the operation of those systems were an essential part of the developed models—considering either long-term forecasts or processes-level data that mimic real-time processes. This way of utilizing data in production management methods presents essential characteristics of Industry 4.0 applications and cyber-physical production systems (CPPSs). The main future directions of the research can be marked by:

- Developing new ways of utilizing data and data analytic tools to make intelligent decisions with unplanned events. For example, incorporate graph new network methodology for real-time machine reconfiguration decision-making due to its advantages of fast computation and the ability to handle large-scale industrial problems. The proposed framework predicts reconfiguration needs to be based on machine status data and work-in-process buffer levels, especially in reconfigurable flow line (RFL).

- Incorporating the parts grouping methodology with the production management frameworks. As RMS is designed around one part family. In a real shop floor scenario, the manufacturers have to deal with various orders for multiple part families. After producing the orders of a particular family, they need to switch to the orders of a different family. Changing from one part family to another may require the system's reconfiguration, which is a complex process involving both cost and effort. Without optimal planning, this may decrease the effectiveness of RMSs

- In this study, the models were developed for small- to medium-scale production. Developing heuristic or meta-heuristic methods may be required to solve the model for large-scale production.

- The developed max-plus-algebra-model-predictive-control (MPA-MPC) did not consider asymmetrical parallel RFL, where the number of machines in each stage is different. In asymmetrical systems, the product route throughout the system is not fixed, and one machine needs to process more than one part. This requires adding new equations to handle these constraints and increases the complexity of the problem.

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