Computers & Industrial Engineering 201 (2025) 110878

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Assessment of design approaches for reconfigurable manufacturing systems based on forecasted demand data

Parham Rezaee [a], Shokraneh K. Moghaddam [b,*]

[a] Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran
[b] School of Physics, Engineering, and Computer Science, University of Hertfordshire, Hatfield, United Kingdom

ARTICLE INFO

Keywords:
Reconfigurable manufacturing systems
Reconfigurable machine tools
Optimization
System transformation
Configuration design
Modularity

ABSTRACT

In this paper, the problem of configuration design in Reconfigurable Manufacturing Systems (RMS) is addressed for a scalable production system that can produce different products which belong to the same part family. To satisfy products' demand with minimum cost, RMS primary configuration must be changed according to demand rate of each product during its lifecycle. A new predictive approach is developed to design the system configuration during all production periods based on estimated demand data. A new and practical integer linear programming (ILP) formulation is proposed that highlights the importance of modular reconfigurable machine tools (RMTs) which can be used for adjusting the production capacity of the system by means of module exchange. The ILP model is verified by solving some of the available RMS design problems in the literature. The obtained results are compared with respect to the total system design and reconfiguration costs. Furthermore, to signify the importance of data accuracy, three different scenarios are designed with stochastic demand data and two other approaches namely, reactive, and predictive-reactive, are presented for drawing more useful and comprehensive conclusions. The obtained results from adopting each approach are theoretically analyzed and valuable managerial insights are provided based on total system design costs and unutilized equipment capacity.

1. Introduction

In the 21st century, manufacturing a low-cost, high-quality product as quickly as possible is no longer a dream. In fact, with the help of technological advancements, many companies can fulfill the above successfully. However, lifecycles of many existing products have been significantly shortened as well. This poses a new challenge for many firms since it requires rapid and cost-effective changes throughout the whole system in response to constant changes in the market. In other words, responsiveness is another key factor to survive in today's manufacturing industry.

According to Koren et al. (1999), producing high volumes of products with customized flexibility and certain level of responsiveness can be achieved when we combine the advantages of dedicated manufacturing systems (DMS) i.e., mass production, and those of flexible manufacturing systems (FMS) i.e., producing a wide range of high quality products. Reconfigurable manufacturing systems (RMS) can offer the best of both worlds; these systems are designed at the outset and can be adjusted, converted and scaled in response to unpredictable fluctuations in the market. Six key characteristics of RMS, namely modularity, integrability, customization, scalability, convertibility, and diagnosability are the main facilitators toward achieving the above-mentioned goals (Koren and Kota, 1999).

Reconfigurable machine tools (RMTs) and modular reconfigurable machines (MRMs) are the most important building blocks of RMS and the key enablers of the required system scalability (Landers et al., 2001, Padayachee and Bright, 2012). RMTs have certain basic and auxiliary modules which can be adjusted and/or replaced for achieving the required functionality when needed. Many real-life cases of RMTs have been designed and implemented in production systems (KATZ, R. (2007), Koren and Kota, 1999, Aguilar et al. (2013), Pérez et al., 2014).

In this paper, a new predictive approach is presented to address the problem of RMS configuration design and capacity scalability when a family of parts is being produced. An integer linear programming (ILP) model is proposed with the objective of minimizing total system design costs. These include cost of purchasing and reconfiguring RMTs during multiple periods of production. Simplicity of the model formulation with respect to the number of decision variables and constraints is an advantage of the proposed approach as it increases the chance of solving large scale RMS design problems in a short amount of time. Another

* Corresponding author.
E-mail address: s.khashkhashimoghadam@herts.ac.uk (S.K. Moghaddam).

https://doi.org/10.1016/j.cie.2025.110878
Received 6 May 2024; Received in revised form 18 November 2024; Accepted 8 January 2025
Available online 11 January 2025

Table 1
Summary of the literature regarding RMS layout configuration selection.

Author/Year	IC	PQ	P/T	S	C	TT	LB	R	I	OS	PR	OC	RE	LT
Koren et al. (1998)	✓	✓	✓	✓	✓	✓								
Yang and Hu (2000)			✓											
Zhong et al. (2000)		✓	✓	✓		✓								
Spicer et al. (2002)	✓		✓	✓			✓							
Maier-Speredelozzi and Hu (2002)		✓	✓	✓		✓								
Maier-Speredelozzi et al. (2003)						✓								
Abdi (2005)	✓	✓		✓	✓✓	✓		✓						
Tang et al. (2005)	✓		✓											
Abdi (2009)	✓	✓		✓	✓	✓		✓	✓	✓				
Koren and Shpitalni (2010)	✓		✓	✓			✓							
Mpofu and Tlale (2012)				✓		✓					✓		✓	
Goyal et al. (2013)				✓								✓		
H. Garbie (2014)	✓	✓	✓						✓					
RENNA (2017)			✓										✓	
Abdi et al. (2018)											✓	✓		
Pal Singh et al. (2021)	✓		✓	✓		✓		✓				✓	✓	✓

Legend: ***IC***: Investment Cost; ***PQ***: Product Quality; ***P/T***: Productivity/Throughput; ***S***: Scalability; ***C***: Customization (number of products that can be produced); ***TT***: Transformation Time; ***LB***: Line Balancing; ***R***: Reliability; ***I***: Inventory; ***OS***: Operator's Skills; ***PR***: Process Reconfigurability; ***OC***: Operational Capability; ***RE***: Reconfiguration Effort; ***LT***: Lead Time of Products

major contribution of this paper is investigating the effect of demand data accuracy while choosing an approach for RMS design. Three different approaches namely *predictive*, *reactive*, and *predictive-reactive* are compared with one another considering the demand forecast quality.

The rest of this paper is organized as follows: In section 2, the related literature on RMS layout configuration design and optimization is studied. In section 3, an overview of the predictive method is presented, major assumptions are clarified, and the proposed mathematical formulation is used to solve a simple example. Furthermore, the reactive and predictive-reactive approaches are introduced and verified in this section. In section 4 the above-mentioned three approaches are compared and analyzed, and insightful managerial implications are discussed. Finally, the conclusion and areas for further research are presented in section 5.

2. Related Literature

Emergence of RMS as adjustable systems with the possibility of rapid and cost-effective changes has attracted considerable attention during the past two decades and many studies have been conducted on the concept and its related topics. As a result of these efforts, RMS body of knowledge has been expanded and include diverse research areas such as RMS architecture design, RMS layout design, RMT design and optimization, RMS configuration design, RMS integration and control, production planning and scheduling in RMS, etc. (Renzi et al., 2014, Bortolini et al., 2018, Yelles-Chaouche et al., 2020).

RMS design, specifically in system level has been tackled through many interesting approaches. In this research, based on the presented method toward the problem, the reviewed papers are categorized into two groups; papers in the first category are those focused on layout configuration selection in RMS. The second group of papers are the ones concentrated on optimal RMS configuration design through mathematical and heuristic approaches.

2.1. RMS layout configuration selection

One of the factors that can strongly affect responsiveness of RMS to sudden market changes is the layout configuration of machines in the production system. The main purpose of the studies presented in this section is to analyze the effect of different physical arrangement of machines (series, parallel and hybrid) on system performance, and select a specific layout that outperforms other possible arrangements, with respect to certain criteria. For example, the effect of system structure on six key performance measures including, capacity scalability, product variety, machines and equipment investment costs, quality, throughput, and system reconfiguration costs are studied by Koren et al. (1998).

Spicer et al. (2002) studied the effect of machining layouts on throughput and scalability and conclude that in a single-product flow line (SPFL), when the number of machines does not change, parallel layouts have the best performance. Tang et al. (2005) also proved that in a multi-product flow line (MPFL), parallel layouts can outperform other possible configurations with respect to system investment costs and productivity. The effect of layout configuration on productivity, product's quality and system transformation time is investigated by Yang and Hu (2000), MAIER-SPEREDELOZZI, V. HU, S. J. (2002) and Maier-Speredelozzi et al. (2003).

Multi-criteria decision making techniques such as analytic hierarchy process (AHP) and analytical network process (ANP) are often used to select the best machines' layout; ABDI, M. R. (2005) and ABDI, M. R. (2009) implemented AHP and fuzzy AHP techniques respectively to select the best layout configuration for RMS based on layout reconfigurability, cost, quality, reliability, skill of operators, and inventory. AHP also is used by H. Garbie and I. (2014) for evaluating RMS performance in different layouts based on product's cost and quality, productivity of the system, and inventory. Abdi et al. (2018) implemented ANP to assess system performance based on process reconfigurability, planning horizons and, economical/ operational aspects. A holonic architecture is developed for RMS which is linked to an ANP model. A composite performance metric (CPM) is designed by Pal Singh et al. (2021) for selecting the best flow configuration in RMS. Different criteria which are included in the CPM include configuration cost, reconfiguration time, system availability, system utilization, reliability, product lead time, operational capability, reconfiguration effort, and system throughput. A summary of the above review is presented in Table 1.

2.2. RMS configuration design

One of the most fundamental components of RMS are RMTs. Modularity of RMTs is in fact an essential prerequisite to system scalability and convertibility and enables multiple functionalities for a single machine as well as any smart manufacturing system (Zhu et al., 2022, Huang et al., 2024, Huang et al., 2024). A modular RMT consists of a base and some auxiliary modules. Auxiliary modules can be added to or removed from a certain RMT while base modules are mostly fixed. Through these module switches, RMTs can change into various configurations in a cost-effective manner making the whole manufacturing system more adaptable to demand variations and providing necessary production capacity whenever required (Koren et al., 2018).

In the reviewed papers in this section in addition to the selection of

Table 2
Summary of the literature regarding RMS configuration design.

Author/Year	Objective	Mathematical Model			
		ILP	MILP	MOO	NLP
Son (2000)	Min Cost	✓			
Spicer (2002)	Min Cost	✓			
Youssef and ElMaraghy (2006a)	Max Reconfiguration Smoothness			✓	
Youssef and ElMaraghy (2006b)	Min Cost			✓	
Pattanaik et al. (2007)	Min Alteration of auxiliary modules Min Inter-cellular material movement			✓	
Youssef and ElMaraghy (2007)	Min Cost Max Availability			✓	
Youssef and ElMaraghy (2008)	Min Cost Max Availability			✓	
Dou et al. (2009)	Min Investment costs	✓			
Dou et al. (2010)	Min Investment costs				✓
Dou et al. (2011)	Min Investment costs				✓
Goyal et al. (2012)	Min Total costs Max Throughput Max Machine reconfigurability			✓	
Wang and Koren (2012)	Min Number of added machines Max Throughput				✓
Yu et al. (2012)	Min Maximum machines' workload		✓		
Bensmaine et al. (2013)	Min Total costs Min Total processing time			✓	
Dahane and Benyoucef (2016)	Min Total Costs Max Reconfigurability index		✓		
Koren et al. (2016)	Max Throughput Min Number of added machines			✓	
Ashraf and Hasan (2018)	Min Cost Max Machine reconfigurability Max Operational capability Max Reliability			✓	
Li et al. (2018)	Min Cost Max Production capacity Min Reconfiguration time				✓
Moghaddam et al. (2018)	Min Investment costs Min Reconfiguration costs	✓	✓		
Moghaddam et al. (2020)	Min Investment costs Min Reconfiguration costs	✓	✓		
Bortolini et al. (2021)	Min Reconfiguration time	✓			
Mansour et al., 2023	Min Operation & setup costs Min Reconfiguration costs Min Material handling costs				✓
Yang et al. (2022)	Max Workload balance Min Reconfiguration/ Assembly costs Min Storage costs			✓	
Yelles-Chaouche et al. (2022)	Min Total number of task reassignments		✓		
Zhang et al. (2023)	Min Cost		✓		
This Research	Min Investment costs Min Reconfiguration costs	✓			

machines' layout, other system's design related problems such as equipment selection, task allocation, and taking advantage of RMTs' modularity as a source of capacity scalability are also addressed and analyzed. Various mathematical modeling approaches and optimization algorithms are used in this line of research to maintain *scalability* of a RMS as one of the main characteristics of these systems (Koren and Ulsoy, 2002).

Table 3
Predicted demand and the operation sequence of hypothetical parts in each production period.

Part	Demand rate (parts/hour)			Operation sequence
	Period 1	Period 2	Period 3	
A	20	30	10	2 → 5 → 12 → 17
B	10	30	50	2 → 7 → 12 → 17 → 20
Total	**30**	**60**	**60**	

Table 4
Required production capacity at each stage for satisfying the demand in each production period in the illustrated example.

Stage	Operation#	Required production capacity in each stage (parts/hour)		
		Period 1	**Period 2**	**Period 3**
1	2	**30** (*A*/20; *B*/10)	**60** (*A*/30; *B*/30)	**60** (*A*/10; *B*/50)
2	5	**20** (*A*/20)	**30** (*A*/30)	**10** (*A*/10)
3	7	**10** (*B*/10)	**30** (*B*/30)	**50** (*B*/50)
4	12	**30** (*A*/20; *B*/10)	**60** (*A*/30; *B*/30)	**60** (*A*/10; *B*/50)
5	17	**30** (*A*/20; *B*/10)	**60** (*A*/30; *B*/30)	**60** (*A*/10; *B*/50)
6	20	**10** (*B*/10)	**30** (*B*/30)	**50** (*B*/50)

Many of the previous works formulated the RMS design problem by means of mathematical programming. Integer linear programming (ILP) and mixed integer linear programming (MILP) models were often proposed considering different parameters and constraints. In the presented models, the most common objective function is minimizing investment and/or reconfiguration costs, and constraints such as meeting products' demands, maximum number of production stages, maximum number of RMTs in each production stage, order of operations, and total number of modules that can be replaced or exchanged are often considered (SON, S.-Y. (2000), SPICER, J. P. (2002), Spicer and Carlo, 2007, Dou et al., 2009, Yu et al., 2012, Moghaddam et al., 2018, Moghaddam et al., 2020, Bortolini et al., 2021).

In addition to cost, other objectives including machine reconfigurability, capacity scalability, reliability, throughput, used space, operation capability, and total processing time are also included in the objective function. Since considering more than one of the above criteria in a single formulation require adopting multi-objective optimization (MOO) approaches, many researchers employed different meta-heuristics such as genetic algorithms (GA), non-dominated sorting genetic algorithm (NSGA-II), tabu search (TS), etc. to design a RMS while taking into account all of the considered aspects (Youssef and ElMaraghy, 2006b, Youssef and ElMaraghy, 2006a, Deif and ElMaraghy, 2007, Youssef and ElMaraghy, 2007, Pattanaik et al., 2007, Youssef and ElMaraghy, 2008, Dou et al., 2011, Goyal et al., 2012, Bensmaine et al., 2013, DAHANE, M. BENYOUCEF, L. (2016), Koren et al., 2016, Ashraf and Hasan, 2018).

Non-linear programming (NLP) approaches are also used in cases where products demands are not considered deterministic or when the design problem cannot be addressed simply through a linear approach (Dou et al., 2010, Dou et al., 2011, Wang and Koren, 2012, Li et al., 2018). A summary of the papers reviewed in this section is shown in Table 2.

Based on the reviewed literature, capacity scalability by replacing RMTs' modules has been discussed in a couple of papers. These papers highlight the potential of RMTs to adapt to changing products' demands

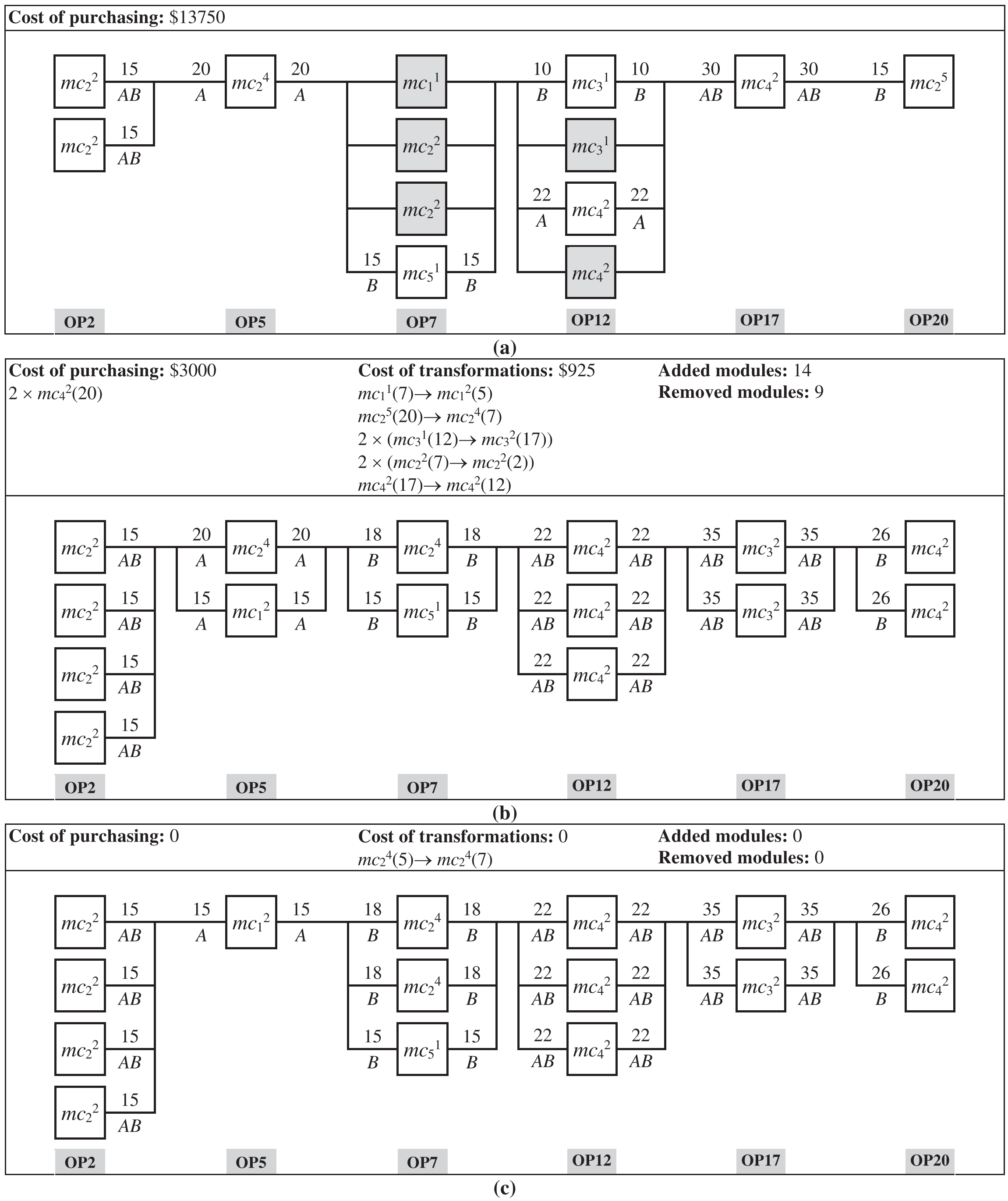

Fig. 1. RMS configuration design in (a) first, (b) second, and (c) third, production periods of the illustrated example, using the proposed predictive approach.

by altering their configuration, allowing for increased or decreased production capacity as needed. The significance of current research cannot be denied but the existing methodologies that underpin available approaches are still open to improvement. Current models, while functional, may not be optimized in terms of efficiency, meaning there is room for enhancements that could deliver better results more quickly. This is particularly important given that the design of RMS is inherently complex. As the number of parameters in the configuration design problem increases, solving the problem becomes significantly more time-consuming. By improving the mathematical models and methodologies, the time required to solve certain problems can be reduced and as a result, performing sensitivity analysis on critical parameters would be considerably facilitated. The proposed ILP model in this research uses fewer decision variables and constraints compared to other similar approaches (Moghaddam et al., 2018, Moghaddam et al., 2020), which allows it to be solved in less amount of time for comparable problems. It can also deliver more efficient outcomes, particularly in terms of reducing total system design costs.

Furthermore, when considering products' demand and products' mix, the existing approaches for designing RMS have not adequately addressed potential inaccuracies in forecasted data. Typically, the available design methodologies can be classified into two categories: predictive and reactive approaches. In a reactive approach, the system is flexible but does not rely on any prior knowledge about future market conditions. Instead, it responds in real time to changes in demand or the introduction of new parts, reconfiguring only when these changes are detected. This approach assumes that no information about future product demand or mix is available, which can lead to operational

Table 5
Comparison of the results obtained from solving sample examples proposed by Moghaddam et al. (2020).

Operation Sequence								**Available Equipment**
A: 2→12→17; *B*: 2→12→11;*C*: 2→1→2→1→1→8								Shown in Table A- 1
Period	**Best solution by:**	**Total Cost ($)**	**Stages of Operation** OP2	OP12	OP17	OP11	OP8	**Demand (parts/ hour)**
1	Moghaddam et al. (2020)	19,390	mc_2^2 (7) mc_3^1 (1)	mc_4^2 (2) mc_3^1 (1)	mc_4^2 (1) mc_3^1 (1)	mc_2^3 (1) mc_5^1 (1)	–	*A*: 20 *B*: 50
	The predictive approach	19,670 **(1 %↑)**	mc_2^2 (3) mc_3^1 (3)	mc_4^2 (4) mc_2^5 (2) mc_2^2 (2)	mc_4^2 (1)	mc_2^3 (2) mc_5^1 (1)	–	
2	Moghaddam et al. (2020)	1475	mc_2^2 (5) mc_2^4 (2)	mc_4^2 (5)	mc_3^2 (2)	mc_2^3 (2) mc_5^1 (1)	mc_3^2 (1)	*A*: 30 *B*: 60 *C*: 20
	The predictive approach	1175 **(20 %↓)**	mc_2^2 (5) mc_2^4 (2)	mc_4^2 (5)	mc_3^2 (1)	mc_2^3 (2) mc_3^2 (1) mc_5^1 (1)	mc_3^2 (1)	
3	Moghaddam et al. (2020)	150	mc_2^2 (4) mc_2^4 (2)	mc_4^2 (5)	mc_2^3 (1)	mc_2^3 (2) mc_5^1 (1) mc_3^2 (1)	mc_3^2 (2)	*A*: 15 *B*: 45 *C*: 40
	The predictive approach	150	mc_2^2 (4) mc_2^4 (2)	mc_4^2 (5)	mc_3^2 (1)	mc_2^3 (3) mc_5^1 (1)	mc_3^2 (2)	
4	Moghaddam et al. (2020)	0	mc_2^2 (4) mc_2^4 (2)	mc_4^2 (5)	–	mc_2^3 (3) mc_5^1 (1)	mc_3^2 (3)	*B*: 30 *C*: 60
	The predictive approach	0	mc_2^2 (4) mc_2^4 (2)	mc_4^2 (5)	–	mc_2^3 (3) mc_5^1 (1)	mc_3^2 (3)	

Legend: mc_i^j (#) = a total number of # RMT of type *i* in its j^{th} configuration exists in the system.
(#%↓) = # percent cost reduction in comparison with the existing solution in the literature.
(#%↑) = # percent cost increase in comparison with the existing solution in the literature.

Table 6
The proposed algorithm for solving examples through a reactive approach.

***Algorithm* (1)**
Input: Model data (all inputs of the mathematical model (1))
Output:A set of RMT configurations for each production period ($M(i, j, t)$)

Begin
$t \leftarrow 1$;// Set *t* to 1
$z(i, j, j', k) \leftarrow 0$;// Set all $z(i, j, j', k)$ variables to 0
Solve Model (2);// Equation (2)–(3) is not considered while solving the model
Reconfigure the system based on the solution obtained by (2)
$M(i, j, t) \leftarrow b(i, j)$;// Save all available RMTs and their configurations in $M(i, j, t)$
For $t = 2$ **to** *T* **do**// *T* is the planning horizon
$a(i,j) \leftarrow M(i, j, t-1)$// Update available RMTs in the system
Solve Model (2);
Reconfigure the system based on the solution obtained by (2)
$M(i, j, t) \leftarrow b(i, j)$;
End
End

inefficiencies if changes are frequent or unexpected. On the other hand, in a predictive approach, forecasts about products' demand and mix are assumed to be fully accurate at the start of the planning period. The system is designed based on these perfect predictions, which guide reconfiguration decisions throughout the planning horizon. However, while predictive approaches are theoretically sound, they rely on the unrealistic assumption that forecasts will be 100 % accurate, with no deviations from the anticipated demand or product mix.

Table 7
Comparison of the results obtained from solving sample examples proposed by Goyal et al. (2012).

First Example

Operation Sequence 17→8→7→1→5 **Best solution by:**	**Total cost ($)**	**Stages of Operation**			**Available Equipment** Shown in Table A- 1		**Demand (parts/hour)**
		OP17	OP8	OP7	OP1	OP5	
Goyal et al. (2012)	17720	mc_3^2 (2)	mc_2^3 (3)	mc_5^1 (4)	mc_5^4 (3)	mc_5^2 (3)	50
The reactive approach	15690 (**11%↓**)	mc_4^2 (1) mc_2^3 (1)	mc_1^1 (3) mc_2^3 (1)	mc_5^1 (4)	mc_5^1 (2) mc_5^4 (1)	mc_5^2 (1) mc_1^2 (2)	
Goyal et al. (2012)	30590	mc_2^3 (5)	mc_2^3 (6)	mc_5^1 (7)	mc_5^4 (5)	mc_5^2 (5)	100
The reactive approach	29256 (**4%↓**)	mc_5^2 (3) mc_2^3 (1)	mc_1^1 (7) mc_2^3 (1)	mc_5^1 (7)	mc_5^1 (5) mc_5^4 (1)	mc_5^2 (5)	
Goyal et al. (2012)	45285	mc_4^2 (5)	mc_2^3 (9)	mc_5^1 (10)	mc_3^2 (5)	mc_5^2 (8)	150
The reactive approach	43375 (**4%↓**)	mc_5^2 (5)mc_4^2 (1)	mc_1^1 (11)mc_2^3 (1)	mc_5^1 (10)	mc_5^1 (7)mc_5^4 (2)	mc_5^2 (6)mc_1^2 (2)	

Second Example

Operation Sequence 15→9→3→11→4 **Best solution by:**	**Total cost ($)**	**Stages of Operation**					**Available Equipment** Shown in Table A- 1 **Demand (parts/hour)**
		OP15	OP9	OP3	OP11	OP4	
Goyal et al. (2012)	15295	mc_3^2 (3)	mc_5^3 (2)	mc_2^3 (2)	mc_2^3 (2)	mc_4^3 (2)	50
The reactive approach	12845 (**16%↓**)	mc_2^2 (1) mc_5^3 (2)	mc_1^2 (1) mc_5^3 (1)	mc_2^3 (2)	mc_2^3 (2)	mc_5^3 (1) mc_1^1 (2)	
Goyal et al. (2012)	26010	mc_2^2 (7)	mc_5^3 (4)	mc_2^3 (4)	mc_2^3 (4)	mc_4^3 (4)	100
The reactive approach	25050 (**4%↓**)	mc_2^2 (7)	mc_1^2 (2) mc_5^3 (2)	mc_2^3 (4)	mc_2^3 (4)	mc_5^3 (3) mc_1^1 (2)	
Goyal et al. (2012)	37330	mc_2^2 (10)	mc_5^3 (5)	mc_2^3 (6)	mc_2^3 (6)	mc_4^3 (6)	150
The reactive approach	36850 (**1%↓**)	mc_2^2 (10)	mc_5^3 (5)	mc_2^3 (6)	mc_2^3 (6)	mc_5^3 (4) mc_1^1 (4)	

Table 8
Comparison of the results obtained from solving sample examples proposed by Ashraf and Hasan (2018).

Operation Sequence								**Available Equipment**
2→5→7→1→5→8→1→								Shown in Table A- 2
Best solution by:	**Total Cost ($)**	**Stages of Operation** OP2	OP5	OP7	OP15	OP8	OP16	**Demand (parts/hour)**
Ashraf and Hasan (2018)	19.49	mc_2^4 (2)	mc_1^2 (3)	mc_1^3 (3)	mc_2^2 (3)	mc_1^1 (4)	mc_1^3 (3)	50
The reactive approach	18.51 (**5 %↓**)	mc_2^4 (2)	mc_5^2 (2)	mc_1^3 (3)	mc_2^2 (3)	mc_1^1 (4)	mc_1^1 (2) mc_1^3 (1)	
Ashraf and Hasan (2018)	37.41	mc_2^2 (5)	mc_5^2 (4)	mc_1^3 (6)	mc_2^2 (5)	mc_4^3 (5)	mc_1^3 (5)	100
The reactive approach	33.92 (**9 %↓**)	mc_2^2 (5)	mc_5^2 (4)	mc_1^3 (6)	mc_2^2 (5)	mc_1^1 (7)	mc_1^1 (1) mc_1^3 (4)	
Ashraf and Hasan (2018)	66.82	mc_2^2 (9)	mc_1^2 (10)	mc_1^3 (12)	mc_2^2 (10)	mc_1^1 (13)	mc_1^3 (10)	200
The reactive approach	65.56 (**2 %↓**)	mc_2^2 (9)	mc_5^2 (8)	mc_1^3 (10) mc_2^4 (1)	mc_2^2 (10)	mc_1^1 (13)	mc_1^1 (2) mc_1^3 (8)	

Legend: mc_i^j (#) = a total number of # RMT of type i in its j^{th} configuration exists in the system.
(#%↓) = # percent cost reduction in comparison with the existing solution in the literature.

In practice, while manufacturing companies often have some degree of foresight based on market trends, customer feedback, and demand projections, it is not realistic to assume that all the data they base decisions on is completely accurate. Market conditions can shift unexpectedly, and deviations from the forecast are almost inevitable. This highlights a gap in the current approaches to RMS design: neither fully accounts for the inherent uncertainty in the system. As a result, there is a need for methodologies that balance predictive insights with the ability to adapt to forecast inaccuracies, ensuring that systems are flexible enough to handle deviations while still leveraging available market data.

Based on the above discussion, The main contributions of this paper are as follows:

- Proposing a novel and practical *predictive* ILP mathematical model for RMS design, that considers modular reconfigurable RMTs for adjusting production capacity of the system across multiple production periods and hence minimizes costs.
- Introducing two additional approaches—*reactive* and *predictive-reactive*—based on the proposed ILP model, to make valuable comparisons between the quality of the results obtained by the suggested approach and those obtained by the available methods in the literature.
- Exploring the impact of demand data accuracy on RMS design decisions by considering all three scenarios—*predictive*, *reactive*, and *predictive-reactive* —with stochastic demand data and comparing system design costs as well as unutilized capacity for insightful managerial implications.

In what follows, a more comprehensive approach is taken towards predictive and reactive RMS design and these methods are compared based on assumptions on accuracy of products' demand forecasts.

3. Overview of the Proposed Methods

As stated before, in most general guidelines and design standards, the modular structure of the system and its components is a fundamental

Table 9
The proposed algorithm for solving examples through a predictive-reactive approach.

***Algorithm* (2)**
Input: Model data (all inputs of the mathematical model (1))
Output:A set of RMT configurations for all production periods ($M(i, j, t)$)

Begin
$t \leftarrow 1$;// Set t to 1
$t' \leftarrow 1$; // Set t' to 1
$z(i, j, j', k, 1) \leftarrow 0$;// Set all $z(i, j, j', k, 1)$ variables to 0
Solve Model (3);
Reconfigure the system during first period based on the solution obtained by (3)
$M(i, j, 1) \leftarrow b(i, j, 1)$; // Save available RMTs during first period in $M(i, j, 1)$
For $t' = 2$ **to** T **do**// T is the planning horizon
$t \leftarrow t'$
$D(k, t) \leftarrow$ actual demand rate for each production stage $\forall\, t = t'$
$D(k, t) \leftarrow$ estimated demand rate for each production stage $\forall\, t > t'$
$a(i, j, t) \leftarrow M(i, j, t'-1)$// Update available RMTs during t^{th} period in the system
Solve Model (3);
Reconfigure the system during period t based on the solution obtained by (3)
$M(i, j, t') \leftarrow b(i, j, t)$;
End
End

Table 10
Demand probability function in each production period for the illustrated example in three different scenarios.

Part	Demand rate (parts/hour)			Operation sequence
	Period 1	Period 2	Period 3	
	First Scenario			
A	20	$N(30,2)$	$N(10,2)$	$2 \rightarrow 5 \rightarrow 12 \rightarrow 17$
B	10	$N(30,2)$	$N(50,2)$	$2 \rightarrow 7 \rightarrow 12 \rightarrow 17 \rightarrow 20$
	Second Scenario			
A	20	$N(30,5)$	$N(10,5)$	$2 \rightarrow 5 \rightarrow 12 \rightarrow 17$
B	10	$N(30,5)$	$N(50,5)$	$2 \rightarrow 7 \rightarrow 12 \rightarrow 17 \rightarrow 20$
	Third Scenario			
A	20	$N(30,10)$	$N(10,10)$	$2 \rightarrow 5 \rightarrow 12 \rightarrow 17$
B	10	$N(30,10)$	$N(50,10)$	$2 \rightarrow 7 \rightarrow 12 \rightarrow 17 \rightarrow 20$

requirement of RMS. Modular RMTs can quickly be reconfigured by adding or removing one or more auxiliary modules. This reconfiguration can hence provide various production capabilities in a system. The main objective of the proposed method in this paper is to satisfy the fluctuated products' demand by emphasizing on RMTs' reconfiguration and making use of the two most important characteristics of RMS: scalability and convertibility. In our proposed methods, RMS is designed around a part family based on the predicted or available market demand information in each period of production. The primary system configuration and its future transformations are determined according to the information about products' demand as well as other available data such as cost and capacity of the production resources, modular capabilities of RMTs, and cost of reconfigurations. Transformations in the RMS take place in one of the following forms:

1. Purchasing new RMTs. (*Type* 1)
2. Adding/removing modules to/from existing RMTs and changing their configurations without changing their production stage. (*Type* 2)
3. Physically relocating existing RMTs in between production stages without exchanging modules. (*Type* 3)
4. Simultaneous module exchange and relocation of RMTs (*Type* 4)

To further elaborate on the proposed approaches, the following assumptions are made about the products and the production system:

3.1. *Assumptions*

- The RMS is designed based on a particular part family and the operation sequence for each part belonging to this family is known in advance. These operations can include and are not limited to milling, boring, tapping, drilling, etc.
- There are no limits on the number of part features.
- The incurred costs to the system include costs of purchasing new equipment (RMTs) and costs of transforming RMTs' configuration by adding or removing modules. (It is assumed that other costs such as those related to setups and module replacement are embedded in transformation costs)
- RMS layout is in the form of a flow shop where in each stage of the production line a certain operation is performed with various RMTs.
- The system is assumed to be empty and idle at the beginning of the planning horizon.
- At the end of each planning period, production is stopped for the purpose of reconfiguration.

3.2. *The predictive approach*

Our first proposed approach is *predictive* in the sense that all information regarding products' type and demand during the planning horizon is known prior to system design. In other words, demand of each part during different production periods is predicted at the beginning of the planning horizon. The proposed model is designed to determine an optimal RMS configuration and its possible reconfigurations (in case of changes in products' type or demand) during different periods of production. The ILP mathematical model presented in (1) is an improved

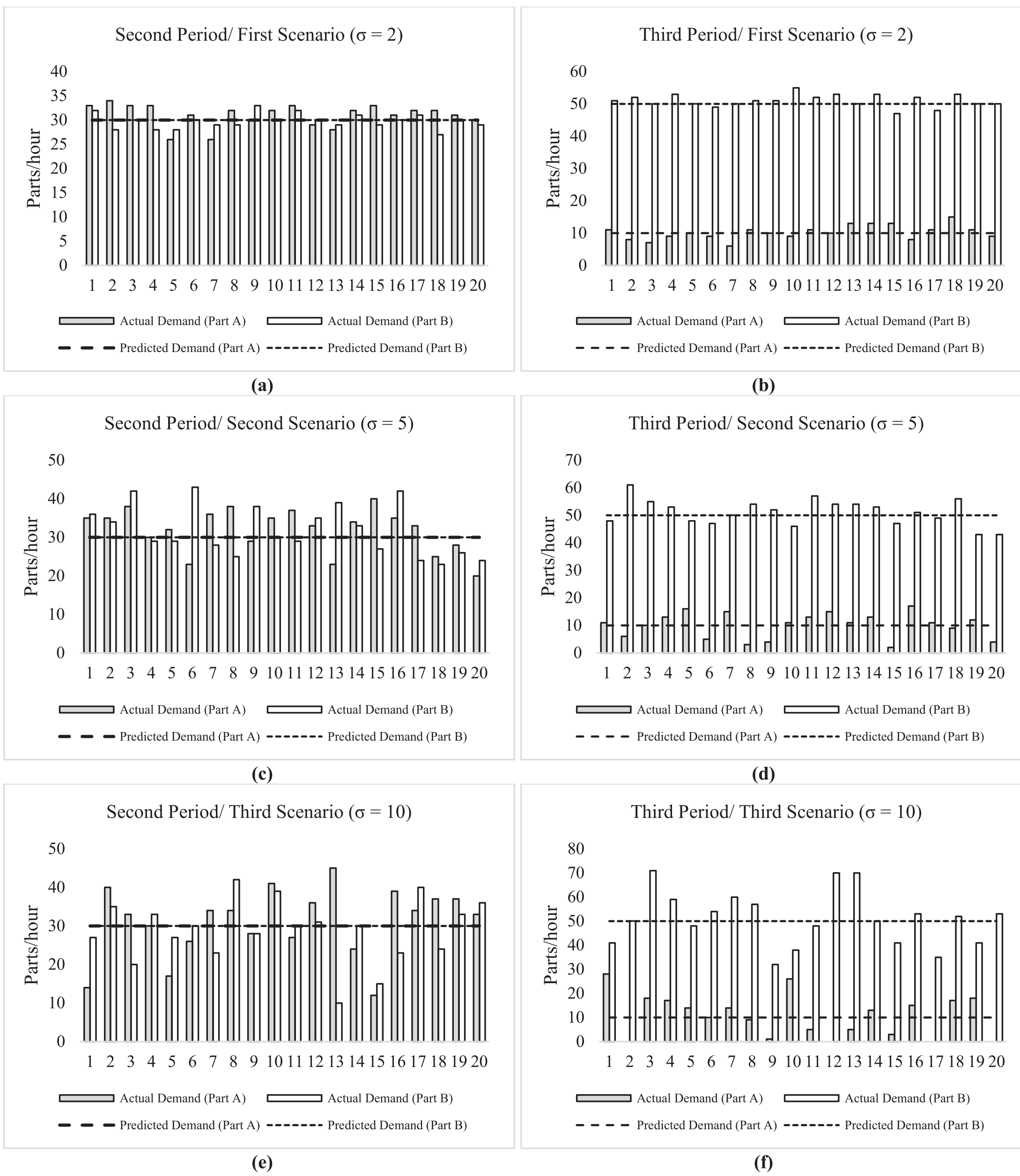

Fig. 2. Randomly generated demand rates for parts A and B during second and third production periods for three different scenarios ($\sigma = 2$, $\sigma = 5$, $\sigma = 10$).

Fig. 3. Total cost of RMS design during different reconfiguration periods using predictive, reactive, and predictive-reactive design approaches for three different scenarios.

formulation of the MILP model proposed by Moghaddam et al. (2020) with fewer number of decision variables and fewer number of constraints. These simplifications can significantly affect computational time specifically in case of larger more complex problems. The input parameters and the decision variables for the model are summarized below:

Parameters:

T	Number of periods.
D_{kt}	Demand rate of the k^{th} operation in period t.
K	Total number of operations.
I	Total number of available RMTs.
J	Number of possible RMT configurations.
C_{ij}	Cost of purchasing the i^{th} RMT in its j^{th} configuration.
P_{ijk}	Production rate of the i^{th} RMT in its j^{th} configuration for performing k^{th} operation.
$n^a_{ijj'}$	Total number of added modules to transform machine type i from its j^{th} configuration to j'^{th} configuration.
$n^r_{ijj'}$	Total number of removed modules to transform machine type i from its j^{th} configuration to j'^{th} configuration.
C_a	Cost of adding a module to an RMT.
C_r	Cost of removing a module from an RMT.

Decision variables:The objective of the optimization model (1–1) is to minimize costs of purchasing new RMTs as well as reconfiguration costs (adding/removing auxiliary modules to/from RMTs) in all production periods. Constraint (1)–(2) ensures that predicted demands are satisfied in all production periods. Products' demand can be met through either purchasing new equipment or RMT reconfigurations. Constraint (1)–(3) guarantees equal number and types of RMTs during reconfiguration periods i.e., the number of RMTs with certain configurations that are purchased, reconfigured, or remained unchanged during one production period must be equal to the number of RMTs at hand in the next period. Finally, domains of variables are defined in constraint (1–4).

$$\min \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} w_{ijkt}C_{ij} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{j'=1}^{J'}\sum_{k=1}^{K}\sum_{t=1}^{T} z_{ijj'kt}\left(n^a_{ijj'}C_a + n^r_{ijj'}C_r\right) \qquad (1-1)$$

$$St:$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} P_{ijk}w_{ijkt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{j'=1}^{J'} P_{ijk}z_{ijj'kt} \geq D_{kt} \qquad \forall k,t \qquad (1-2) \qquad (1)$$

$$\sum_{k=1}^{K} w_{ijk(t-1)} + \sum_{j'=1}^{J'}\sum_{k=1}^{K} z_{ij'jk(t-1)} = \sum_{j'=1}^{J'}\sum_{k=1}^{K} z_{ijj'kt} \qquad \forall i,j,t>1 \qquad (1-3)$$

$$w_{ijkt}, z_{ijj'kt} \in \text{int} \qquad \forall i,j,j',k,t \qquad (1-4)$$

Fig. 4. Total parts/hour RMTs unused capacity in each stage of production during different reconfiguration periods using predictive, reactive, and predictive-reactive design approaches for three different scenarios.

3.2.1. *Solving an illustrated example with predictive approach*

The model proposed in (1) can optimally select and reconfigure RMTs in an RMS that is designed around a *family of products*. Parts that belong to a product family have similar features and hence require similar operations while moving forward stage by stage in a production line. To show how the ILP model handles RMS design for a part family, a simple example is illustrated in this section. The considered part family consists of two different hypothetical parts (*A* and *B*) with similar operation sequences and different demand rates through three production periods (shown in Table 3). In Table 3, operation sequences are arbitrary, and each is based on the information presented in Table A1. As can be seen, operations 2, 12 and 17 are common between the two parts, operation 5 is only performed on part *A* and operations 7 and 20 are only performed on part *B*. Parts *A* and *B* require 4 and 5 operations respectively. In this example and all future analysis, it is assumed that the costs of adding and removing a single module to and from a certain RMT, regardless of the module type, are \$50 and \$25 respectively. However, cost of purchasing a new RMT depends on its basic and auxiliary modules, its capability of performing multiple operations, and its production rate. For this example, these costs are shown in Table A1 as well.

Based on the information provided in Table 3, a total of 6 different operations are performed on both parts. Hence, 6 stages are required for producing all the products. It is noteworthy to mention that for producing a single part of the family, all required operations must be performed based on the demand/hour requirements of that part. For example, in the illustrated example of this section, demand rate of part *B* in the first production period is 10 parts/hour. Therefore, during the first production period, production stages within which operations 2, 7, 12, 17, and 20 are performed, must be capable of simultaneously operating with the rate of at least 10 parts/hour. The required production capacity in each stage of production (in terms of parts per hour) and during each period is shown in Table 4.

Based on the above input information, the model is solved. to solve the problem GAMS v.25.1.2 software was used on a 2.6 GHz Intel® Core (TM) i7-6700HQ CPU system. The RMS design, the required purchased RMTs and the reconfigurations are illustrated in Fig. 1. The solution was obtained in less than a second. In Fig. 1, the primary RMS design and the required transformations during all production periods cost \$17675. As can be seen, almost all required RMTs are purchased in the first period of production (Fig. 1. (a)) and there exists unused production capacity on some of these RMTs (shown by gray squares). The unused equipment is purchased based on the predicted demand and are reconfigured and used during second and third periods of production (as shown in Fig. 1. (b) and Fig. 1. (c)).

Majority of transformations are done in the second production period (Fig. 1. (b)). As mentioned earlier, transformations can take four different forms and in our illustrated example, as depicted in Fig. 1. (b), three out of four possible transformation types can be seen. Some instances of these types are as follows:

- $2 \times mc_4^2(20)$ indicates that two mc_4^2 are purchased to perform operation 20 (*Type* 1)
- $mc_4^2(17) \rightarrow mc_4^2(12)$ indicates that mc_4 in its second configuration performing operation 17 is relocated to another stage to perform operation 12 (*Type* 3)
- $mc_1^1(7) \rightarrow mc_1^2(5)$ indicates that mc_1 in its first configuration performing operation 7 is transformed into its second configuration and is relocated to perform operation 5 (*Type* 4).

All our proposed approaches are verified using available examples in

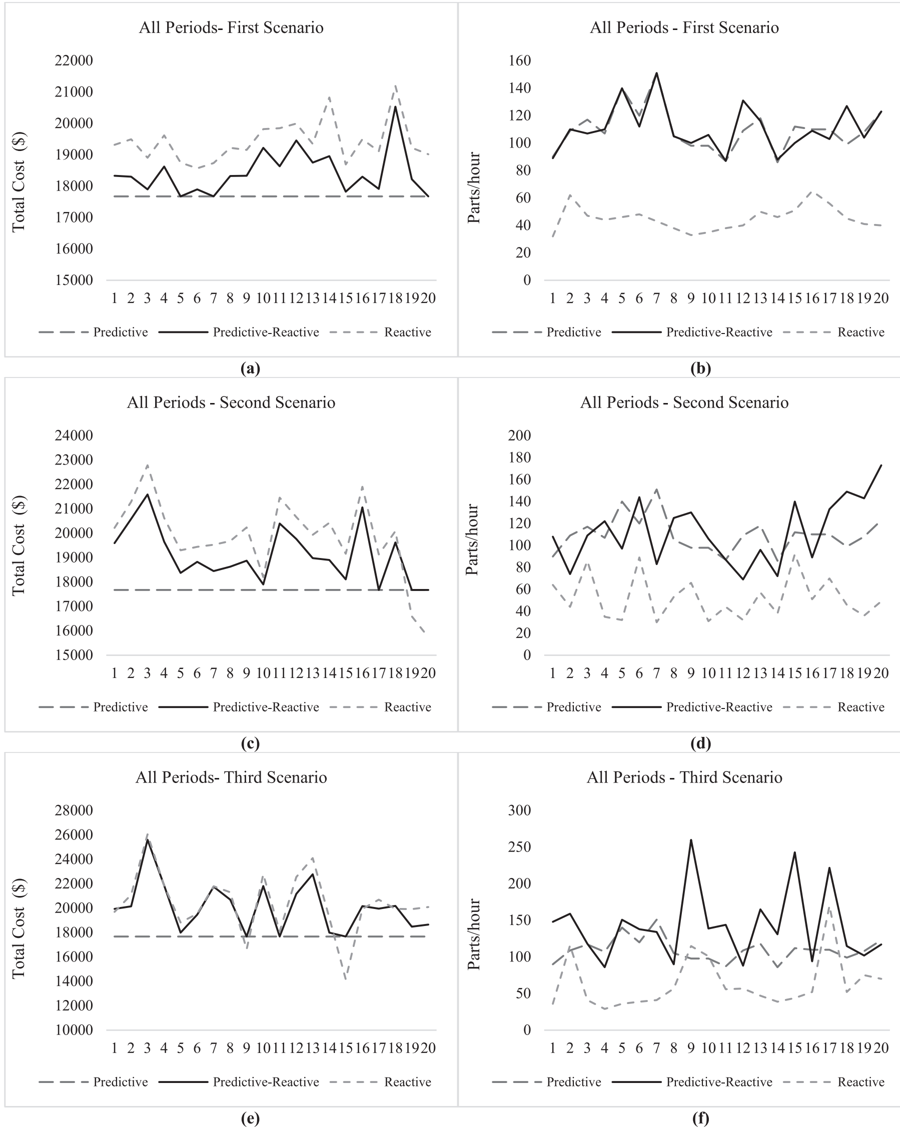

Fig. 5. Total cost of RMS design (a, c, e) and sum of parts/hour RMTs unused capacity in each stage of production (b, d, f), during all production periods using predictive, reactive, and predictive-reactive design approaches for three different scenarios.

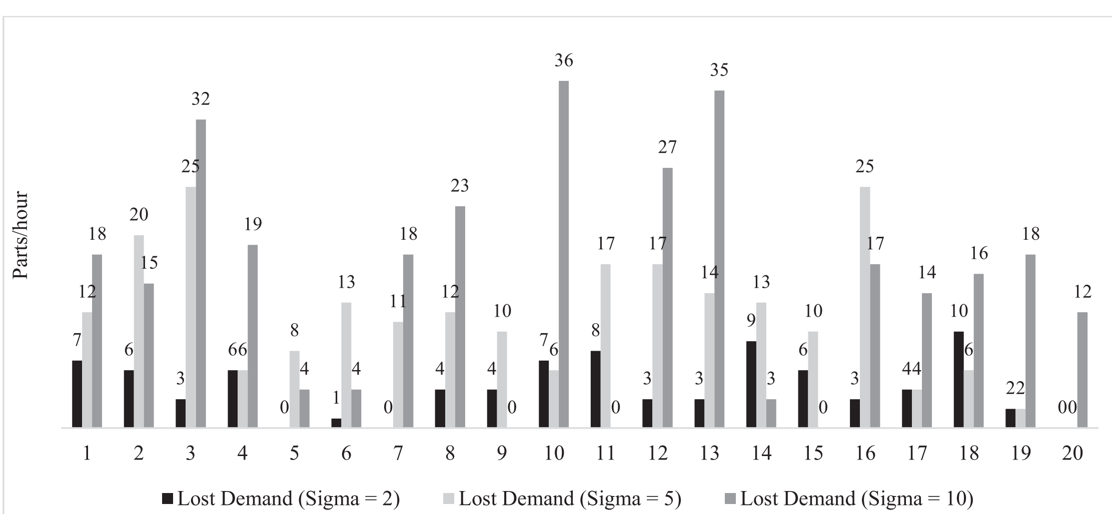

Fig. 6. Lost demand of parts *A* and *B* during all production periods for three different scenarios.

Table 11
Average total RMS design cost for three approaches in different demand scenarios.

	Predictive Approach	Reactive Approach	Predictive-Reactive Approach
$\sigma = 2$	17,675	19,417	18,428
$\sigma = 5$	17,675	19,820	19,118
$\sigma = 10$	17,675	20,083	20,084

Table 12
Average total unutilized capacity for three approaches in different demand scenarios.

	Predictive Approach	Reactive Approach	Predictive-Reactive Approach
$\sigma = 2$	109.85	45	110.9
$\sigma = 5$	109.85	52.25	112.45
$\sigma = 10$	109.85	63.65	142.2

the literature. The selected papers for the verification possess certain degree of similarity to this work and proposed actual or hypothetical examples of RMS design which can be solved by our mathematical model as well. Some important factors that made these studies very good cases for comparison are as follows:

- Possibility of selecting equipment out of a pool of RMTs with basic and/or auxiliary modules.
- Considering the cost of module replacement (as an indicator for reconfiguration smoothness).
- Considering the sequence of processes for each part.
- Including cost as one of the performance criteria in the objective function.
- Considering hypothetical demand for parts in single/multiple production periods.

3.2.2. *Predictive approach verification*

The example selected in this section belongs to Moghaddam et al. (2020) where the problem of selecting the most economic configuration for a hypothetical part family in RMS is studied. The example is designed based on the fact that complete information is at hand about the products' mix and demand at the beginning of the system design (predictive approach). The MILP model proposed in (Moghaddam et al., 2020) is similar to the predictive approach which is taken in this paper and therefore, the final solutions to the example (in terms of total system design cost in each period, the selected RMT configurations, and the reconfigurations in between production periods) are quite comparable as shown in Table 5.

While the system design costs of the first production period are higher in our provided solution, in total, the ILP method outperforms the MILP formulation, and the system design costs are decreased from \$21015 to \$20995 overall. Since both approaches are predictive, it is sensible to compare the total cost of system design during the whole planning horizon. The main reason for the more cost effective solution provided by our predictive ILP method is the larger possible solution space the formulation in (1) has. In the proposed ILP model, it is possible to select and purchase RMTs for production stages in which, those RMTs cannot even be used (in the illustrated example of section 3-2-1, during the first production period, machine configurations mc_2^2 and mc_1^1 cannot be used for operation 7. However, they are purchased so they could later be reconfigured and implemented in other production stages, based on the demand changes of each product).

3.3. *The reactive approach*

In (Moghaddam et al., 2020) it is argued that by assuming 100 %

Table A1
Machine processing information for the example part presented in Goyal et al. (2012).

M_j	mc_i^j	Operation																				Cost	Basic Modules	Auxiliary Modules
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20			
		Production rate in parts/hour for each operation																						
M_1	mc_1^1	–	–	–	14	–	–	–	12	–	–	–	8	–	–	–	18	–	–	–	–	750	{1, 5}	{13, 17, 21, 22}
	mc_1^2	–	–	–	–	15	–	–	–	20	–	–	–	–	–	–	–	–	16	–	–	955		{12, 13, 15, 20, 21}
	mc_1^3	–	–	20	–	–	–	15	–	–	–	–	–	–	–	–	25	–	–	–	–	1025		{11, 17, 18, 20, 21}
	mc_1^4	–	–	–	–	–	–	–	–	–	15	–	–	–	–	–	–	–	–	12	–	840		{15, 17, 18}
M_2	mc_2^1	14	–	–	–	–	15	–	–	–	–	–	12	–	–	–	–	–	–	–	20	1215	{2, 4, 8}	{11, 13, 16, 22, 24}
	mc_2^2	–	15	–	–	–	–	–	–	–	–	–	–	14	–	15	–	–	–	–	–	910		{14, 16, 19}
	mc_2^3	–	–	25	–	–	–	–	18	–	–	25	–	–	–	–	–	20	–	–	–	1140		{13, 19, 24}
	mc_2^4	–	20	–	–	20	–	18	–	–	–	–	–	–	24	–	–	–	–	–	–	1350		{11, 13, 15, 18, 24}
	mc_2^5	–	–	–	18	–	–	–	–	–	–	–	–	20	–	–	–	–	14	–	15	1050		{11, 14, 18}
M_3	mc_3^1	–	12	–	–	–	–	–	–	15	–	–	10	–	–	–	–	10	–	–	–	780	{3, 5, 7}	{11, 12, 14, 16, 18}
	mc_3^2	30	–	–	26	–	–	–	24	–	–	24	–	–	–	20	–	35	–	15	–	1825		{12, 13, 14, 17, 19, 20}
M_4	mc_4^1	–	–	–	–	–	25	–	–	–	30	–	–	–	–	–	–	–	25	–	–	1350	{4, 9}	{18, 23}
	mc_4^2	25	–	–	–	–	–	–	–	–	–	–	22	–	–	–	–	30	–	–	26	1500		{11, 15, 18, 20, 21}
	mc_4^3	–	18	–	25	–	–	–	16	–	–	–	–	22	–	–	28	–	–	20	–	1400		{13, 14, 17, 18}
M_5	mc_5^1	16	–	–	–	–	–	15	–	–	–	15	–	–	18	–	–	–	18	–	–	900	{3, 6, 10}	{20, 22}
	mc_5^2	–	–	24	–	20	–	–	–	–	25	–	–	–	–	–	–	24	–	–	20	1175		{16, 17, 19, 20, 25}
	mc_5^3	–	–	–	24	–	–	–	–	30	–	–	–	–	–	18	–	–	–	–	–	1230		{11, 12. 13, 15, 22}
	mc_5^4	20	–	–	–	–	22	14	–	–	–	–	–	–	20	–	16	–	–	18	–	1175		{20, 22, 24}

Legend: mc_i^j = Machine i in its j^{th} configuration

Table A2
Machine processing information for the example part presented in Ashraf and Hasan (2018).

M_j	mc_i^j	Operation 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Cost (in \$ ($\times 10^5$))	Basic Modules	Auxiliary Modules
		Production rate in parts/hour for each operation																						
M_1	mc_1^1	–	–	–	18	–	–	–	16	–	–	–	10	–	–	–	15	–	–	–	–	0.85	{2, 3}	{12, 17, 20, 22}
	mc_1^2	–	–	–	–	20	–	–	–	12	–	–	–	–	–	–	–	–	20	–	–	1.32		{12, 13, 16, 20, 23}
	mc_1^3	–	–	24	–	–	–	18	–	–	–	–	–	–	–	–	22	–	–	–	–	0.89		{13, 16, 19, 20, 23}
	mc_1^4	–	–	–	–	–	–	–	–	–	18	–	–	–	–	–	–	–	–	23	–	1.45		{12, 16, 17}
M_2	mc_2^1	20	–	–	–	–	16	–	–	–	–	–	22	–	–	–	–	–	–	–	26	1.33	{4, 5, 7}	{10, 11, 14, 22, 24}
	mc_2^2	–	24	–	–	–	–	–	–	–	–	–	–	19	–	20	–	–	–	–	–	1.21		{11, 15, 19}
	mc_2^3	–	–	17	–	–	–	–	28	–	–	21	–	–	–	–	–	30	–	–	–	2.00		{15, 19, 23}
	mc_2^4	–	25	–	–	19	–	20	–	–	–	–	–	–	16	–	–	–	–	–	–	1.58		{10, 14, 15, 18, 23}
	mc_2^5	–	–	–	16	–	–	–	–	–	–	–	–	20	–	–	–	–	14	–	23	1.75		{10, 13, 23}
M_3	mc_3^1	–	15	–	–	–	–	–	–	23	–	–	18	–	–	–	–	20	–	–	–	1.40	{1, 2, 6}	{10, 13, 15, 16, 19}
	mc_3^2	12	–	–	19	–	–	–	29	–	–	22	–	–	–	17	–	24	–	24	–	2.52		{10, 12, 15, 16, 19, 21}
M_4	mc_4^1	–	–	–	–	–	16	–	–	–	18	–	–	–	–	–	–	–	22	–	–	1.92	{7, 9}	{15, 20}
	mc_4^2	22	–	–	–	–	–	–	–	–	–	–	24	–	–	–	–	19	–	–	15	2.02		{10, 15, 16, 20, 24}
	mc_4^3	–	17	–	21	–	–	–	24	–	–	–	–	16	–	–	26	–	–	23	–	1.88		{12, 16, 18, 23}
M_5	mc_5^1	25	–	–	–	–	–	18	–	–	–	16	–	–	10	–	–	–	28	–	–	1.73	{8, 9, 10}	{19, 22}
	mc_5^2	–	–	14	–	25	–	–	–	–	22	–	–	–	–	–	–	24	–	–	30	1.53		{14, 18, 19, 22, 25}
	mc_5^3	–	–	–	17	–	–	–	–	10	–	–	–	–	–	14	–	–	–	–	–	2.16		{10, 14, 16, 19, 22}
	mc_5^4	13	–	–	–	–	27	12	–	–	–	–	–	–	18	–	21	–	–	15	–	1.80		{18, 20, 22}

Legend: mc_i^j = Machine i in its j^{th} configuration accuracy of the available forecasts of products' demand and mix, the predictive approach to RMS design is more cost effective than the reactive approach. In their comparisons however, cost of unused RMT capacity is not considered. Also, the assumption that all available data forecasts are always accurate, is far from reality. To perform a more thorough analysis based on data accuracy, reactive approach must be considered as well. While the ILP formulation in (1) is predictive, it can be solved in a reactive manner using *Algorithm* 1 presented in Table 6.

The mathematical model presented in (2) is a simpler form of the ILP model in (1) where time is not considered in the formulation. a_{ij} are the input parameters which show the number of RMTs of type i that are in their j^{th} configurations at the beginning of each reconfiguration period. b_{ij} are auxiliary variables that calculate the number of RMTs of type i in their j^{th} configurations at the end of each period. Based on *Algorithm* (1), a_{ij} must be updated at the end of each reconfiguration period (i.e., a_{ij} at the beginning of each period are in fact b_{ij} which were set during the previous period by solving the mathematical model (2)).

$$
\begin{aligned}
&\min \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} w_{ijk}C_{ij} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{j'=1}^{J'}\sum_{k=1}^{K} z_{ijj'k}\left(n^{a}_{ijj'}C_a + n^{r}_{ijj'}C_r\right) && (2-1)\\
&St:\\
&\sum_{i=1}^{I}\sum_{j=1}^{J} P_{ijk}w_{ijk} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{j'=1}^{J'} P_{ijk}z_{ijj'k} \geq D_k && \forall k \quad (2-2)\\
&a_{ij} = \sum_{j'=1}^{J'}\sum_{k=1}^{K} z_{ijj'k} && \forall i,j \quad (2-3)\\
&b_{ij} = \sum_{k=1}^{K} w_{ijk} + \sum_{j'=1}^{J'}\sum_{k=1}^{K} z_{ij'jk} && \forall i,j \quad (2-4)\\
&w_{ijk}, z_{ijj'k}, b_{ij} \in \text{int} && \forall i,j,j',k \quad (2-5)
\end{aligned}
\qquad (2)
$$

3.3.1. Reactive approach verification

As mentioned earlier, some existing examples in the literature were solved in a reactive only manner. In what follows, the results obtained from solving these existing examples with the formulation presented in section 3-2 are further discussed and analyzed. Goyal et al. (2012) proposed two examples based on the information provided in Table A1. In these examples, only one part is produced during a single production period. Each example was solved three times for three different demand scenarios. In all these examples the RMS is assumed to be empty and idle at the beginning and the main problem is to select the best set of equipment which can satisfy the required demand during one period of production. The compared results of solving these examples are shown in Table 7.

Since in the above set of examples only one production period is considered, by setting $t = 1$, in our proposed reactive approach, the example is reduced to a simple equipment selection problem where certain demands must be satisfied (reconfigurations and/or module replacements are not required). As can be seen, in both examples, the ILP formulation outperforms the method proposed by Goyal et al. (2012) in terms of total system design cost and cost reductions of up to 16 % are achieved. The main reason for the lower costs is that in our approach, there are no constraints on the type of RMTs which can be selected for performing an operation, if the production capability of that operation stage matches the demand rate in terms of parts/hour. However, in (Goyal et al., 2012) RMT configurations that are selected for performing a certain operation are all of the same type.

Ashraf and Hasan (2018) considered a reconfigurable manufacturing flow line for a single part during a single production period as well. Their designed example was solved for four different demand scenarios while considering four different objective functions namely cost, machine reconfigurability, operation capability and reliability. The required information for solving these examples is in Table A2. Comparison of the solutions provided by Ashraf and Hasan (2018) and our reactive approach is shown in Table 8. As shown in Table 8, for all demand scenarios the exact ILP solution obtained by our reactive approach is more cost-effective and results in cost reductions of up to 9 % in case of 100 parts/hour demand rate.

3.4. The Predictive-Reactive approach

Many of the proposed approaches in RMS design, either predict the products' demand and type in different planning periods (assuming plausible scenarios with certain possibility of occurrence) or react to sudden changes and demand fluctuations. Both approaches have their pros and cons; when forecasts are highly accurate, adopting a predictive approach can result in less costs in the long run and through the whole planning horizon. However, when there are considerable variations between actual and estimated data, using a predictive approach may result in lost demand and/or underutilized resources so a reactive approach might be less costly.

In this section, a *predictive-reactive* approach is also proposed (shown in Table 9) to solve RMS configuration design problem. This third approach is a combination of the above two approaches in the sense that it involves forecasting about future market changes but also provides the possibility of system redesign (reacting) when the predictions happen to be not totally accurate (MOGHADDAM, S.K. and SAITOU, K. (2020) and Moghaddam and Saitou (2022)).

The mathematical model presented in (3) is the exact form of the ILP model in (1). However, to be able to solve problems in a predictive-reactive manner, a_{ijt} are added as input parameters to save the number of RMTs of type i that are in their j^{th} configurations at the beginning of reconfiguration period t. Also, b_{ijt} are auxiliary variables that calculate the number of RMTs of type i in their j^{th} configurations at the end of period t. Based on *Algorithm* (2), model (3) is solved T times. During each reconfiguration period, it is assumed that the actual demand data for that period as well as the forecasted demand data of products during future periods are available. Since this final approach is in fact a combination of the two previous approaches, it has already been verified by the previous examples.

$$\begin{aligned}
&\min \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=t'}^{T} w_{ijkt}C_{ij} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{j'=1}^{J'}\sum_{k=1}^{K}\sum_{t=t'}^{T} z_{ijj'kt}\left(n^{a}_{ijj'}C_a + n^{r}_{ijj'}C_r\right) && (3-1)\\
&St:\\
&\sum_{i=1}^{I}\sum_{j=1}^{J} P_{ijk}w_{ijkt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{j'=1}^{J'} P_{ijk}z_{ijj'kt} \geq D_{kt} \qquad \forall k,t && (3-2)\\
&a_{ijt} = \sum_{j'=1}^{J'}\sum_{k=1}^{K} z_{ijj'kt} \qquad \forall i,j,t && (3-3)\\
&b_{ijt} = \sum_{k=1}^{K} w_{ijkt} + \sum_{j'=1}^{J'}\sum_{k=1}^{K} z_{ij'jkt} \qquad \forall i,j,t && (3-4)\\
&w_{ijkt}, z_{ijj'kt}, b_{ijt} \in \text{int} \qquad \forall i,j,j',k,t && (3-5)
\end{aligned} \tag{3}$$

4. Results analysis and discussion

In this section, an analysis is carried out to compare different approaches to the RMS design problem namely, predictive, reactive, and predictive-reactive with respect to various metrics such as total system design cost, lost demand, and underutilized capacity. To compare the performance of these three approaches, the simple illustrated problem of section 3-2-1 is solved multiple times considering three different scenarios (shown in Table 10). In each scenario, it is assumed that the demand rate for each part during the first production period is estimated with 100 % accuracy. However, the demands for parts A and B during second and third production periods are considered to follow normal distributions with certain means and standard deviations ($N(\mu, \sigma)$). For example, in the first scenario, part A's demand in the second period follows a normal distribution with $\mu = 30$ parts/hour and $\sigma = 2$ parts/hour. The main difference between the three proposed scenarios is the increase of σ parameter (from 2 in the first scenario to 10 in the third scenario).

For each scenario, 20 problems are created. In each problem random numbers are generated for the demand rates of parts A and B during the second and third production periods based on their corresponding distributions. These numbers represent the actual demand rate in each period as opposed to the estimated rates (i.e., the mean value of each distribution). These randomly generated numbers are shown in Fig. 2. As shown in this figure, by increasing σ, the gap between actual demand data from the estimated amount also increases (Fig. 2. (a) and (b) compared with Fig. 2. (e) and (f)). The generated problems are solved by adopting all the explained approaches:

- ***Predictive approach***: for each scenario, the problem is solved in a single stage based on model (1) considering the *expected* value of demand for parts A and B in all periods.
- ***Reactive approach***: for each scenario, the problem is solved in multiple stages based on *Algorithm* (1) considering the *actual* value of demand for parts A and B in each period.
- ***Predictive-Reactive approach***: for each scenario, the problem is solved in multiple stages based on *Algorithm* (2) considering the *actual* and *expected* values of demand for parts A and B.

The final results obtained from solving the problems generated for each scenario, in terms of total system design costs and the sum of unutilized production capacity in each production period are shown in Fig. 3 and Fig. 4 respectively. Also, sum of the abovementioned performance metrics during all periods of production for different scenarios are shown in Fig. 5.

4.1. Theoretical implications

Based on the observed patterns in Fig. 3 and Fig. 5, it is clear that the total system design costs are at their highest when the reactive approach is implemented for solving the RMS configuration design problem. Even though during the first period of production the costs incurred with the reactive approach are lower in comparison with the other two approaches, during the second and third periods, the reactive approach results in higher purchasing and reconfiguration costs (Fig. 3). This applies for almost all generated hypothetical problems and in all scenarios ($\sigma = 2$ to $\sigma = 10$). There are however exceptions in rare occasions; for example, in problem number 15, during the second production period in the third scenario (Fig. 3.(h)), due to the unusually high standard deviation, the sum of actual demand of parts A and B is far less than the predicted amount (27 vs 60 parts/hour). Therefore, the RMS can function properly with the available resources and without significant costs of readjustments. The same reasoning can be applied for problem number 20 during the second production period in the second scenario (Fig. 3.(e)).

The predictive approach results in the least amount of design costs. However, the total amount of lost demand for parts A and B in different periods are considerable as shown in Fig. 6. As σ increases, the number of unmet demands of parts also increases significantly. Average unsatisfied demand of parts during all production periods when $\sigma = 2$, $\sigma = 5$, and $\sigma = 10$ are 4.3, 11.55, and 15.55 parts/hour respectively.

Based on Fig. 3 and Fig. 5, the predictive-reactive approach falls in between the above two approaches in terms of total RMS design costs in all scenarios. It is noteworthy to mention that in this approach, unlike the predictive approach, all the demands are met in all periods of production. It is also understandable that when σ increases, the existing gap between the total RMS design costs in reactive and predictive-reactive approaches becomes smaller (Fig. 5 (e)). This signifies the negative effect of highly inaccurate data on the predictive-reactive approach and shows that when data is not reliably estimated, the performance of both approaches would be similar in terms of total system design and reconfiguration costs. The average total RMS design cost of three approaches for different scenarios are shown in Table 11.

The amount of unused capacity on each RMT in terms of parts/hour could be another useful indicator for system performance while designing and reconfiguring RMS. Based on Fig. 4 and Fig. 5, unlike total system design costs, there are no clear observable patterns in the RMS unused capacity during each production period or in total, in each scenario, when a certain approach is adopted.

However, on average, the total unused capacity is considerably lower when the reactive approach is used (Table 12). Regarding unused capacity, the predictive-reactive approach has the highest amount (on average). As the σ increases, the amount of unutilized capacity also increases in both reactive and predictive-reactive approaches.

4.2. Managerial implications

From a practical point of view the above findings offer the following implications for decision makers in the field of RMS configuration design:

- The predictive approach toward RMS design can offer the lowest total cost of design and reconfiguration when the demand forecasts are 100 % accurate. In case of inaccurate data, if the cost of lost demand is negligible, taking this approach is financially viable (note that in this approach we cannot necessarily meet all products' demands). Otherwise, if the unmet demand could lead to significant losses, taking this approach is no longer cost efficient specially when the variations between actual and forecasted demand data are considerable.
- The reactive approach toward RMS design leads to the lowest unutilized capacity of RMTs and the highest design and reconfiguration costs. In this approach all the demands are met and when the level of demand data uncertainty is high, using the reactive approach toward RMS design may result in the most cost-effective outcome in the long run.
- The predictive-reactive approach is similar to the reactive approach in the sense that by adopting it, all products' demands would be satisfied. However, when the available demand data for multiple production periods is more reliable (lower standard deviation of stochastic data), the predictive-reactive approach outperforms the reactive approach in terms of total RMS design and reconfiguration costs. Furthermore, while the total unutilized equipment capacity is higher when this approach is adopted, in cases where resource sharing with other companies is a possibility, this approach can be considered the most economical.

5. Conclusion and Future Work

In this study, the problem of RMS configuration design and capacity scalability during multiple production periods is addressed for a family of parts through a new predictive approach. This approach minimizes total system design and reconfiguration costs by taking advantage of different production capabilities of available modular RMTs. A simple ILP formulation is proposed which solves the RMS design problem during a planning horizon based on estimated demand data. The final solution is in the form of types of selected RMTs as well as their required reconfigurations in between production periods to satisfy demand fluctuations. The performance of the predictive approach was assessed by solving similar proposed RMS design problems in the literature. Implementing our proposed predictive ILP formulation for solving the available problems improved the obtained solutions in terms of total system design and reconfiguration costs.

Since predictions are seldom accurate, the predictive approach is compared with two other approaches namely reactive and predictive-reactive when demand rates follow a certain probability distribution. Three different scenarios are considered with different standard deviations to test the performance of each approach when the available data for demand becomes less accurate. The approaches are compared with respect to total system design costs, lost demand, and unutilized production capacity. Useful theoretical and managerial insights are provided based on the obtained results.

The predictive ILP model is simple yet functional specially when the size of the problem becomes considerable in terms of stages of production, planning periods, number of part types and possible RMT configurations. Nevertheless, due to the simplicity of the current formulation, the model can be improved in such a way that other objectives and constraints are further included. For instance, in addition to total cost of design and reconfiguration, the total time of module replacement, or the amount of unutilized capacity can also be minimized. Also, constraints can be placed on different parameters such as maximum number of modules allowed to be replaced and/or purchased, or the budget for acquiring new equipment. Adding more objectives and other constraints may increase the time required to solve the RMS design problem hence, developing heuristic or *meta*-heuristic methods can be an area for future research.

While in this paper the RMS is designed in the form of a flow shop manufacturing system, exact flow of parts in between RMTs is not formulated in the model. Considering the exact flow of work in process (WIP) as well as the position of each RMT, when equipment must be relocated or go through certain module exchanges, result in a dynamic layout configuration design problem which is an interesting research topic in the field of RMS layout configuration design.

Finally, another promising area for future studies could be examining the RMS configuration design problem in the context of cloud manufacturing where resources including RMTs and/or base and auxiliary modules can be shared via available platforms. In this regard, problems such as, selling, loaning, and borrowing required equipment can be further investigated. Also, through the cloud, certain operations might possibly be outsourced, and the tradeoff analysis required for such decision makings can be performed by integrating other important aspects of cloud manufacturing (for instance transportation) with RMS configuration design problem.

CRediT authorship contribution statement

Parham Rezaee: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Shokraneh K. Moghaddam:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The significant support provided by the School of Physics, Engineering, and Computer Science at the University of Hertfordshire for this research is greatly acknowledged.

Appendix A: Machine Processing Information of the Example Parts

Table A1
Table A2

Data availability

No data was used for the research described in the article.

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