IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 31 May 2022, accepted 22 June 2022, date of publication 1 July 2022, date of current version 8 July 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3187812

RESEARCH ARTICLE

Problem-Specific Heuristics for Diagnosability and Inventory Analysis in a Reconfigurable Manufacturing System

ABDUL SALAM KHAN

Department of Operations and Supply Chain, NUST Business School (NBS), National University of Sciences and Technology (NUST), Islamabad 44100, Pakistan

e-mail: abdul.salam@nbs.nust.edu.pk

ABSTRACT Reconfigurable manufacturing systems are complex systems that are prone to malfunctions and performance decay. Thus, such systems need to be safeguarded against quality issues and decline in production efficiency to ensure the optimal health of machines. The product quality and health of a reconfigurable manufacturing system can be analyzed by using the diagnosability characteristic. This study examines the diagnosability characteristic in a multi-stage reconfigurable manufacturing system. The aim is to understand the impact of time-based diagnostics on the functionality performance of a reconfigurable manufacturing system and the level of inventory used during production. The diagnosability is analyzed regarding product variation and system diagnosability. A mathematical model is proposed, and it is subsequently applied in deterministic and stochastic settings. The deterministic setting is examined through a set of two problem-specific heuristics. The stochastic setting, subject to the gamma process, is examined by using a simulation-based optimization approach. The results suggest that the use of line replacement units can restore a reconfigurable system to optimal functionality, reduce the level of inventory, and complete production in a minimum time at the expense of additional cost. These findings apply to the context of healthcare emergency response systems, reconfigurable supply chains, reconfigurable integrated manufacturing systems, etc. Finally, a conclusion and future research avenues are provided.

INDEX TERMS Reconfigurable manufacturing system, quality, cost, diagnosability, inventory, optimization, multi-objective, heuristic.

I. INTRODUCTION

Reconfigurable Manufacturing System (RMS), as an advanced manufacturing system, has addressed many challenges facing modern practices. It offers a novel Reconfigurable Manufacturing Tool (RMT) which enhances its functionality and changeability attributes. Besides this, RMS possesses a set of characteristics i.e., modularity, scalability, integrability, diagnosability, etc. which distinguishes it from other manufacturing systems [1]. It has become the focus of researchers as well as practitioners in the context of Industry 4.0 (I4.0) and as part of the Next Generation Manufacturing Systems (NGMSs) [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Mostafa M. Fouda.

The RMS is built on the core characteristics of scalability, customization, integrability, modularity, and diagnosability [3]. These characteristics play an important role in making the production system responsive and reconfigurable. A close relationship exists between the design of a reconfigurable manufacturing system and its performance metrics. Few authors have considered the economic aspects of configuration design while ignoring other beneficial aspects such as the diagnostics of configuration design. There is a need to consider several other factors to assess the performance of a reconfigurable manufacturing system [4]. The RMS is still an emerging manufacturing paradigm; hence, it offers enough opportunities for exploration, improvement, and investigation.

Quality is an important attribute to gauge the performance of any manufacturing system. An ill-quality-based manufacturing system impacts profitability and can cause distress for the customer. RMS is a complex manufacturing system as it offers several machine configurations, modules, and tools to perform the same operation. Thus, several production routes can be formed depending on several possible combinations of machine configurations, modules, and tools [5]. A product may pass through any of these routes, enhancing the difficulty in tracking and examining the product quality in each route. In addition, RMS contains information at multiple levels i.e., at the level of machine configuration, modules, tools, and axes of motion. This aspect further elevates the difficulty of analyzing the quality and pinpointing a specific level that causes the deterioration in quality. A poor-quality production can have manifold consequences. For example, it will decrease the number of optimal quality products and hence a reduced level of products will be delivered to customers. As a result, either back-ordering will be exercised, or inventory will be used to meet the demanded quantity.

The quality-related diagnostic of a reconfigurable manufacturing system can be performed by using the diagnosability characteristic. In this sense, a trade-off analysis between diagnostic and inventory decisions in a reconfigurable manufacturing system can be made, i.e., diagnostic can impact the level of inventory needed to fulfill the customer's demand. A well-diagnosed reconfigurable system will enhance production efficiency and will warrant higher customer satisfaction. Thus, from a cost viewpoint, a well-diagnosed RMS will result in fewer defects, will require fewer inventory items, and will be more cost-efficient from the production point of view. However, the diagnostic itself is a costlier process and managers may want to assess the cost of diagnostics as opposed to the savings attained by implementing a well-diagnosed manufacturing system.

The functionality or production profile of any manufacturing system cannot indefinitely remain in an ideal condition due to decay, wear and tear, and malfunctions. This means that the manufacturing system will produce optimal quality products in the beginning and this quality will start deteriorating with time. This deterioration will increase the chances of failure and the production of failed products [6]. Consequently, the total cost of manufacturing will increase [7]. The existing literature on RMS considers machines with a constant/optimal manufacturing functionality which is an assumption and against the real manufacturing practices. It is more appropriate to investigate the functionality of a reconfigurable manufacturing system during different phases of its operation. Each phase will have its quality attributes and fitness for use. The sum of functionalities of all phases of reconfigurable machines will help in selecting such configurations which result in maximum utility. The utility of a manufacturing system can be defined in terms of its production of conforming products, production of failed products, cost, or total manufacturing functionality throughout the production. If more configurations are selected with compromised functionality, this will imply that more failed products are produced and hence inventory items may be used to replace the failed quantity of products. More deterioration of machines and less functionality will ultimately result in the use of a higher inventory of products. The functionality degradation can be viewed as a deterministic as well as stochastic phenomenon. The stochastic/random degradation can be modeled by using the gamma process which is more suitable for modeling the deterioration of manufacturing systems [8], [9].

To summarize, this study addresses the research questions concerning the quality of manufacturing, functionality decay, line replacement units, and the use of inventory. More specifically, this study addresses the following research questions:

— Is it cost-effective to replace the defective units and restore the functionality of a reconfigurable manufacturing system?
— What is the behaviour of reconfigurable machines in different phases of functionalities?
— What is the trade-off between the use of inventory, line replacement units, and the total cost of manufacturing?
— Does the considered problem behave similarly under deterministic as well as stochastic working conditions?

To address these research questions, this study proposes a reconfigurable manufacturing system framework by modelling the diagnosability characteristic. The diagnosability characteristic is analyzed from the viewpoint of the product as well as the manufacturing system. The latter is further divided into the detectability, predictability, and distinguishability of a manufacturing system. The functionality of RMS is assessed in each phase of its working condition, i.e., detectability, predictability, and distinguishability. An emphasis is given to understanding the role of inventory decisions in the diagnostic of a reconfigurable manufacturing system. The analysis is performed by using deterministic and stochastic working conditions. The deterministic setting is examined by using a set of two problem-specific heuristics whereas the stochastic setting subject to the gamma process is examined by using a Simulation-Based Optimization (SBO) framework. An extensive analysis of the proposed approaches, compared to the published approaches, is presented by using different criteria.

The remaining study is organized as follows. Section II offers a literature review on the RMS design, diagnosability analysis in RMS, solution approaches used in RMS problems, and deterioration in manufacturing processes. Section III provides the assumptions related to the mathematical model. Section IV discusses the problem formulation and mathematical model. Section V discusses the solution approaches for deterministic and stochastic settings. Section VI implements the model to demonstrate the findings. Section VII discusses the implications for managers. Section VIII concludes the study and offers future research directions.

II. LITERATURE REVIEW

A. RMS DESIGN

The RMS is custom-designed to offer exact functionality and production capacity by using the reconfiguration aspects [10].

The design problems are integrated at the outset of a reconfigurable system design i.e. before the RMS is implemented for production purposes. Detailed reviews on the RMS design problems can be found in [11] and [12]. The RMS is designed to be responsive to market and product changes and to cost-effectively react to production system failure. Though the RMS literature addresses the market and product-based concerns, there is a dearth of literature focusing on the reactivity of RMS subject to failure and functionality decay. The RMS design problems can be broadly classified into architecture design [13], decisions taken at the reconfiguration level [14], layout and spatial analysis [15], [16], process planning problems [17], and other problems.

An overwhelming number of articles on RMS design problems have focused on the process planning aspects. Process planning is the assignment of machine configurations to various operations while optimizing the Key Performance Indices (KPIs) or objective functions. The literature has considered the KPIs of cost, time, and responsiveness in the design of RMS process planning. In a recent effort, Khan *et al.* [5] considered the aspect of quality in the process planning problem. The RMS was subject to deterioration and quality decay; however, the diagnostic aspect and phase-wise analysis of production system performance were not conducted. To the best of our knowledge, none of the studies focused on RMS design problems has studied the functionality performance of RMS in different phases of production. The sub-section below presents an overview of the diagnostic analysis in a reconfigurable manufacturing system.

B. DIAGNOSTIC OF RMS

The ultimate job of a production manager is to deliver the products at an optimal quality level. However, it will become difficult to produce optimal quality products if there are reliability and quality issues. In such events, diagnosability enables the RMS to quickly identify the sources which cause reliability and quality issues [18]. Diagnosability can be used at multiple levels i.e., system, machine, and product-level to ensure its effectiveness. Once the system is reconfigured, diagnosability helps in the rapid detection of products that compromise quality [19]. Thus, these problematic products and production system units can be removed to ensure the optimal performance of a manufacturing system.

In [4], the authors proposed nine industrially relevant factors to assess the product flow in RMS. A metric was defined, based on these factors, in the form of a composite performance metric. The user can assign subjective as well as objective weights to each performance metric. Koren and Shpitalni [10] examined the relationship between configuration design and reliability, productivity, quality, scalability, and cost analysis. In another study [20], the availability, reliability, and maintenance analysis of a reconfigurable manufacturing system were performed. However, the diagnostics-based analysis of RMS was not performed in different phases of production. The integrated design and scheduling in a reconfigurable manufacturing system both at the stages of initial design and reconfiguration were studied in [21].

A mixed-integer programming model was proposed in [22] for a reconfigurable flow line. The equipment cost was optimized for RMS containing turrets, spindles, and modules. Bortolini *et al.* [23] provided a linear programming model to study the alternative part routing in a cellular reconfigurable manufacturing system. The objective function of time was optimized for alternative part routing. Prasad and Jayswal [24] proposed an approach based on the Shannon entropy and evaluation technique for optimizing effort, profit, and due date in a reconfigurable manufacturing system. Kumar *et al.* [25] considered a tri-objective model to analyse the optimal sequence of product family in RMS. Khan [26] examined the impact of modularity and scalability characteristics on the efficiency of a vehicle routing problem and RMS. A multi-objective model was proposed and implemented by using a set of heuristic approaches.

Gumasta *et al.* [27] proposed a reconfigurability index to assess the performance of a reconfigurable manufacturing system. This index was based on RMS characteristics such as diagnosability, scalability, modularity, and convertibility. The diagnosability characteristic was modeled keeping in view the system indication and checking the line replacement units of a system. A system can be readily assessed by using the proposed index. A multi-attribute utility theory was used to calculate the overall index of reconfigurability.

Khezri *et al.* [28] studied the diagnosis of energy and preventive maintenance in a reconfigurable manufacturing system. A mixed-integer non-linear model was proposed to analyze the energy loss due to the use and energy consumed due to maintenance. A bi-level decomposition approach was used to examine the behavior of the model. Napoleone and Andersen [29] considered the role of digitization as an enabler to increase diagnosability and the role of a human operator in the shop floor diagnostic. As a result of the literature review, a theoretical 3-e model (error reduction, easiness, and ergonomics) was proposed.

Though product/component failure is central in examining the ramp-up, there is a lack of a systematic mechanism to carry out diagnosability in a reconfigurable manufacturing system [1]. The authors believed more focus needs to be given to identifying the root causes of failure/variation. Artificial intelligence techniques can be used to diagnose faults and select modules in RMS.

C. SOLUTION APPROACHES USED IN RMS PROBLEMS

Several solution approaches have been used to solve the RMS problems. These approaches can be divided along different dimensions, among which the noteworthy dimension is scalarization vs. posteriori approaches [30] whereas scalarization approaches are exact and posteriori approaches are non-exact/evolutionary, resulting in Pareto-optimal solutions [31]. The prominent exact solution approaches adapted to RMS problems are weighted goal programming, ε-constraint, and CPLEX solver-based solutions.

The RMS problems are complex and non-polynomial hard in nature and thus evolutionary approaches are more often applied to solve such problems.

Among the evolutionary approaches, the family of non-sorting genetic algorithms (GA, NAGA, NSGA-II, and NSGA-III) has predominantly been adapted to RMS problems. Other noteworthy approaches applied to solve the RMS problems are Archived Multi-Objective Simulated Annealing (AMOSA), Multi-Objective Particle Swarm Optimization (MOPSO), Tabu Search (TS), Strength Pareto Evolutionary Algorithm (SPEA-II), etc. These approaches have proved to be adequate in solving complex RMS problems in adequate computation time. However, these are not tailor-made/designed for RMS problems and are modified to some extent before applying them to the considered problems. There has been a trend of using problem-specific/tailored solution approaches/meta-heuristic in RMS literature. A brief review of the problem-specific approaches is provided in the following paragraph.

Saliba *et al.* [32] presented a heuristic to identify the modules at the beginning of RMS design. A heuristic method, based on the design structure matrix (DSM), was used for module synthesis in a reconfigurable manufacturing environment. Azab *et al.* [33] studied the semi-generative process planning problem in a reconfigurable manufacturing system. The authors tailored a random-based heuristic with simulated annealing to solve the problem. In another study, Bensmaine *et al.* [34] considered integrated process planning and scheduling in a reconfigurable manufacturing system. A heuristic approach was proposed which considered the multi-configuration-based aspects of different machines while integrating the process planning with scheduling. The heuristic started by calculating the availability time of each machine, and then it computed the selection index of each operation. Following this, an operation with the highest selection index was scheduled on a machine with minimum availability time. There are other applications where exhaustive search-based heuristics [35], and hybrid heuristics [36] have been used to solve the RMS problems concerning machine layout and machine availability, respectively.

The problem-specific approaches may not be generalized to other problems; however, they can provide excellent solutions to the problem for which they are designed [37]. Motivated by the precedence in the RMS literature, this study designs two problem-specific heuristics for the deterministic problem setting and one problem-specific heuristic in the form of simulation-based optimization for the stochastic problem setting. Each heuristic is designed according to the mathematical model and the definition of diagnosability reconfigurable manufacturing system characteristic. A detailed description of these approaches is provided in Section V.

D. DETERIORATION IN MANUFACTURING PROCESSES

The manufacturing processes have traditionally been stable with constant processing times and non-deteriorating functionality; however, the real-manufacturing environment is based on deteriorating functionality due to decay, wear and tear, spoilage, etc. [38]. The performance degradation of manufacturing systems is a well-established stream of research where the production system partly performs in an in-control state and partly in an out-of-control state due to deterioration [39]. The deterioration of a manufacturing system has been examined in several contexts i.e., Economic Production Quantity (EPQ) [40], [41], Condition-Based Maintenance (CBM) [42], Preventive Maintenance (PM) [43], etc. Though there has been enough emphasis on the deterioration of several manufacturing systems, the reconfigurable manufacturing system is yet to be examined in the presence of deterioration. As the deterioration reaches a specific threshold (called failure threshold), condition-based maintenance (CBM) is performed to restore the functionality of a manufacturing system. In some cases, the maintenance/restoration can be performed based on the available degradation data before the system reaches the state of failure (out-of-control) [44]. In the current study, the Line Replacement Units (LRUs), i.e., replacement of modules/fixtures/tools can be considered as maintenance tasks where the functionality of RMS is restored to an optimal performance level.

This study examines the diagnosability RMS characteristic due to deterioration, both in deterministic and stochastic settings. [45]–[48] are some of the examples where deterioration has been considered a stochastic phenomenon. The degradation of a manufacturing system is generally modeled as a stochastic, time-dependent phenomenon such as random deterioration rate, Wiener, Inverse Gaussian, gamma processes, or Markov processes, each method is known for its modeling properties and interpretations [49]. This study assumes that the deterioration is random in time, and it follows the gamma process. The advantage of using the gamma processes is that its mathematical formulation is easy [8].

The literature summary of the existing focus on diagnosability in RMS is provided in Table 1. We identified 13 studies in the existing literature that discusses the diagnosability RMS characteristic. These studies were analyzed w.r.t different features, i.e., whether diagnosability is mathematically modeled, the use of objective function, single/multi-period analysis, the analysis of inventory and cost in the diagnostics of RMS, examination of variable functionality of RMS in different phases of its production, the use of LRUs to restore the functionality of a manufacturing system, and the use of problem-specific heuristic to examine the problem concerning diagnosability.

It can be observed that though diagnosability is defined in a few studies and is mathematically modeled as well, a dedicated objective function for diagnosability is lacking in the existing literature. Moreover, an ill-diagnosed manufacturing system will need additional inventory and will bear the excessive cost. Diagnosability will necessitate variable functionality in different phases of manufacturing, up until the Line Replacement Units (LRUs) are used to restore the manufacturing system to an optimal functionality level. The

TABLE 1. The literature summary of diagnosability analysis in RMS.

Author	Modelling diagnosability	Definition of diagnosability	Mathematical model	Objective function	Periods		Inventory analysis	Cost assessment of diagnosability	Variable functionality of production	Use of LRUs	Problem-specific heuristic
					S	M					
Khezri et al. [28]	✓	Diagnostic of energy: Energy loss due to aging of components and during maintenance	✓	Energy loss	✓						
Youssef and ElMaraghy [50]		Identification of reliability problems									
Gumasta et al. [27]	✓	Checking the status of line replacing unit	✓	Reconfigurability index	✓						
Khanna and Kumar [51]		Detecting the reasons behind failed quality production									
Mehrabi et al. [1]		The identification of sources of reliability issues and quality variation									
Napoleone and Andersen [29]		A key aspect of reconfiguration in shop floor digitization									
Xie et al. [52]	✓										
Liu et al. [53]	✓	Rapid diagnostics									
ElMaraghy [18]		A theoretical definition: Identification of quality issues									
Koren and Shpitalni [10]		Design for easy diagnostics									
Wang et al. [54]	✓	Rapid diagnostics	✓	Quantitative models for RMS characteristics	✓						
Liu et al. [55]	✓	optimal Design for Diagnosability (DFD)	✓	Rate of Diagnosability (RD)							
Rosio et al. [56]		Assessing the characteristics of reconfigurability		Machine and product diagnosability	✓						
Current research	✓		Yes	Diagnosability	✓		✓	✓	✓	✓	✓

S=Single period, M= Multiple periods

LRUs are part of the inventory, and their use will increase the overall cost of production. All these aspects are lacking in the existing literature on reconfigurable manufacturing systems. The last row of Table 1 provides the novelty of current research in filling the literature gaps. The novelty of the current research is summarized below:

- Through this study, a comparative analysis between product as well as system diagnostic and inventory analysis in a multi-stage reconfigurable manufacturing system is presented.
- A mathematical model is proposed to analyse the diagnosability reconfigurable manufacturing system characteristic in a multi-stage manufacturing system.
- The performance of RMS is assessed by considering different manufacturing functionalities in different phases of its working condition, i.e., during detectability, predictability, and distinguishability.
- The analysis is performed in the presence and absence of the distinguishability phase i.e., when the line replacing units (LRUs) are not added to restore the functionality versus when the LRUs are added to the manufacturing system. The replacement of LRUs can be considered a maintenance policy.
- The analysis is performed for deterministic as well as stochastic manufacturing systems. The deterministic problem setting is examined by using two-problem specific heuristics whereas the stochastic problem setting is examined by using a simulation-based optimization (SBO) approach.
- The performance of the proposed approaches is compared with the exact and evolutionary approaches, for small as well as large problem sizes, by using three performance assessment metrics.

III. MODEL ASSUMPTIONS

The assumptions related to the problem and mathematical model are provided below:

— Only modules/tools/turrets are considered as the Line Replacement Units (LRUs) which are the main components of the RMS.
— Each reconfigurable machine is subject to performance decay and degradation. The time at which the decay starts may change from machine to machine.
— The RMS is designed to work in different phases. Each manufacturing phase has its functionality and fitness for use.
— The considered RMS is designed to produce a single product; however, it can be extended to produce a variety of products.
— A Just-In-Time (JIT) based inventory approach is adopted, hence there is no delay in replacing the malfunctioned units.
— The system performs as well as a new system upon changing the units and there is no loss of functionality.
— The processing time in different stages/functionality profiles is known as apriori.
— Each reconfigurable machine works for a specific time and cannot be indefinitely used for production.

IV. PROBLEM STATEMENT AND MATHEMATICAL MODEL

Diagnosability is the ability of a reconfigurable manufacturing system to automatically read the current state of

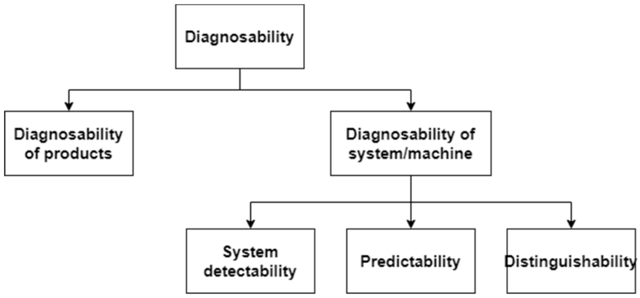

FIGURE 1. Classification of diagnosability rms characteristic into component and system diagnosability.

a system and diagnose the root causes of system failure. Gumasta *et al.* [27] classified the diagnosability characteristic into the diagnosability of components/products and the diagnosability of the system, as shown in Figure 1. The first part is related to the diagnosis of products whereas detectability, predictability, and distinguishability are the three phases related to the diagnosis of a production system. These aspects are discussed below:

Diagnosability of component/product

It is related to monitoring and diagnosing the quality of products and their associated variation.

Detectability

Detectability is related to the perfect quality-based condition of a manufacturing system. It measures the elapsed time before the initiation/recognition of a failure/defect. In this phase, a manufacturing system is capable to process such product units which do not have any quality issues.

Predictability

In this phase of diagnosability, an error/failure originates after some time, resulting in optimal quality products and failed products. Thus, there is some loss of functionality due to the production of failed products. However, the production system continues to perform with a continuous decay in functionality. Predictability measures the time that elapses before a critical failure occurs. During this phase, managers can identify the root cause of error/failure. RMS can operate the same product through the combination of different machine configurations called routes. Through predictability, such production route can be identified which contains less/more quality variation and defects.

Distinguishability: In this phase, a Line Replacing Unit (LRU) is identified within a production route which is responsible for the loss of functionality. The LRU can be any part of a reconfigurable machine that needs adjustment to restore the functionality of a system. For example, LRU can be configurations, basic/auxiliary modules, and/or tools. LRU can be a complex mechanical component that can be quickly replaced to restore the performance of a manufacturing system. Distinguishability measures the time required to identify the system's LRU which causes the loss of functionality. Subsequently, such LRUs are replaced by using inventoried machine tools/components.

Figure 2 describes the functionality decay profile of a system/machine in the absence of distinguishability (Figure 2(a)) and in the presence of distinguishability Figure 2(b)). From Figure 2, it can be observed that a system works with constant functionality in the detectability phase. As time elapses, the system functionality profile shows a continuous decay which eventually results in a complete system failure, unless the LRUs are replaced in the distinguishability phase (Figure 2(b)).

Figure 3 shows the quantity of production in different phases of system diagnosability. In Figure 3(a), which is based on only detectability and predictability, it can be observed that the Optimal Quality Production Curve (OPC) decreases in the predictability phase whereas the Failed Production Curve (FPC) increases. As distinguishability and the use of LRUs are not considered here, thus, there is a considerable proportion of failed products in this case. Consequently, an inventory of optimal quality products will be

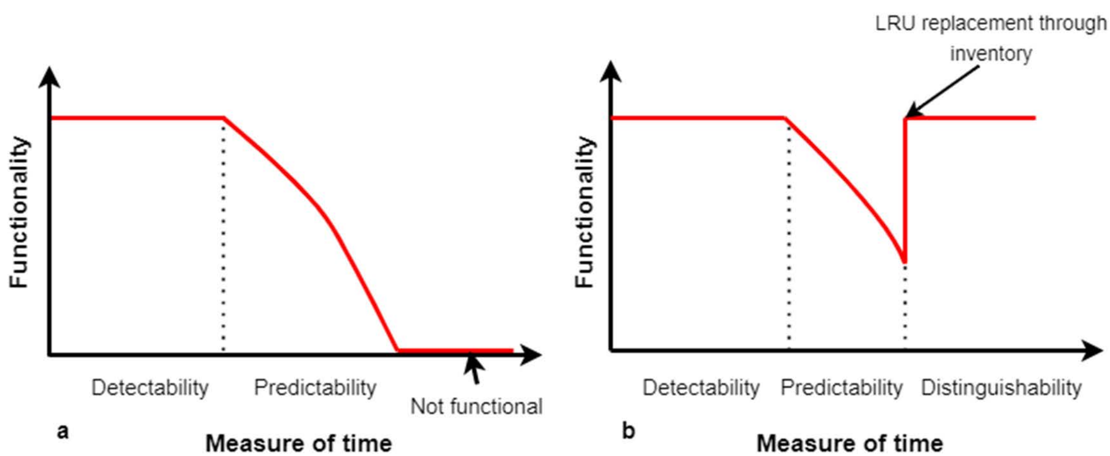

FIGURE 2. Diagnosability of machine (a) in the absence of distinguishability, (b) in the presence of distinguishability.

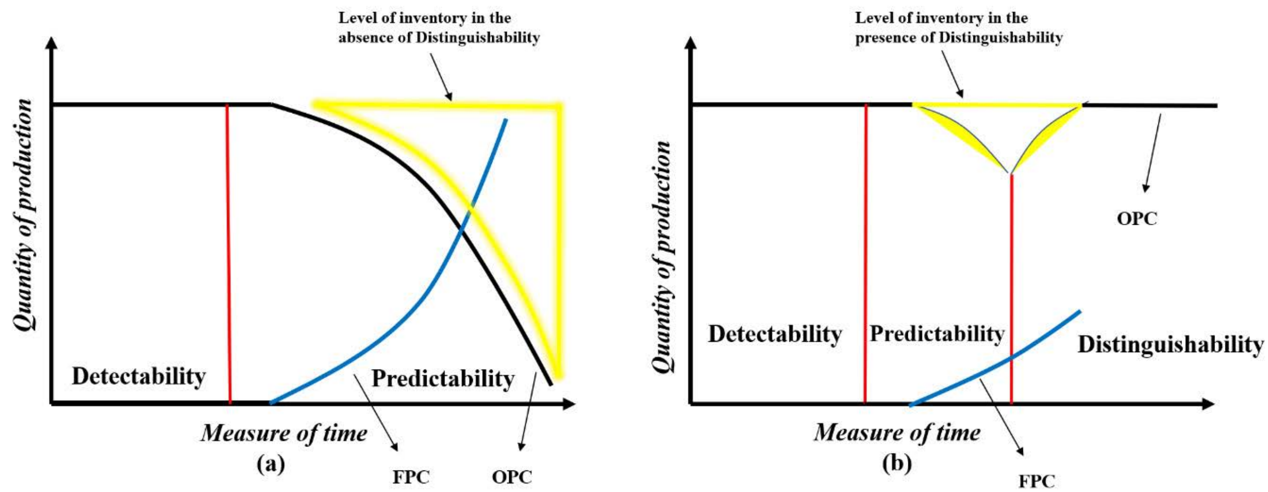

FIGURE 3. Diagnosability of component/product (a) in the absence of distinguishability, (b) in the presence of distinguishability.

used to ensure the delivery of the required level of demand. This level of inventory is determined by the multiplication of production rate and time, as represented by the yellow shape in Figure 3(a).

This inventory will serve as a replacement for failed production in the predictability phase. On the other hand, Figure 3(b) shows the quantity of production in the presence of the distinguishability phase. As shown, there is a loss of production in the predictability and distinguishability phases i.e., once the loss of functionality in the system/machine configuration starts and when the system is restored to an optimal functionality level by using the LRUs. However, the quantity of failed products and the use of inventory is minimal, as compared to the case discussed in Figure 3(a). To summarize, a higher level of inventory is posited to be used in the absence of distinguishability; however, the use of LRUs will incur additional cost and effort to restore a system to an optimal functionality level. To this end, a mathematical model is proposed in this study to examine the diagnosability characteristic of RMS in different phases of a system.

The problem statement is summarized with the help of Figure 4. Several reconfigurable machines are designated to multiple production stages. The product passes through a combination of different machines to get the final shape. As can be observed on the left side of Figure 4, the quantity of conforming products reduces from one stage to another, up until the Line Replacement Units (LRUs) are used to restore the system as well as to increase the quantity of conforming/optimal quality products. The aim is to understand the impact of restoration (use of LRUs) on the total cost and functionality of RMS in different phases.

The model notations and objective functions are given below. Each phase of the reconfigurable manufacturing system (i.e., detectability, predictability, and distinguishability), as well as the product performance, is assessed through its respective functionality. The presented model is used for deterministic settings and the model for stochastic settings is provided in Section VB.

A. INDICES

i *set of configurations* $i \in (1, 2, ..I)$

o *set of operations* $o \in (1, 2, ..O)$

B. PARAMETERS

	Description	Units
$\aleph$	*units entering the RMS*	*No units*
ρ_{di}	$probability\ of\ performance\ decay\ of\ conf.i$	*No units*
t_o	$processing\ time\ of\ operation\ o$	*Minutes*
TRT_i	$total\ run - time\ of\ conf.i$	*Minutes*
$T_{det.i}$	$Time\ in\ detectability\ for\ conf.i$	*Minutes*
$T_{dist.i}$	$Time\ in\ the\ distinguishability\ phase\ for\ i$	*Minutes*
C_P	$penalty\ cost\ per\ unit\ failed\ product$	*USD/unit*
C_I	$per\ unit\ cost\ of\ using\ inventory\ iterm/LRU$	*USD/unit*
∂	$number\ of\ ops\ performed\ by\ the\ LRU$	*No units*

C. DECISION VARIABLES

	Description	Units
x_{io}	$1, if\ \ i\ is\ used\ for\ \ o, othersie\ 0$	*No units*
F_{det}	$Functionality\ during\ detectability$	*No units (time/time)*
F_{pred}	$Functionality\ during\ predictability\ in\ the\ absence\ of\ distinguishability$	*No units (time/time)*
$F_{Pred_{dist}}$	$Functionality\ during\ predictability\ in\ the\ presence\ of\ distinguishability$	*No units (time/time)*
OP	$Optimal\ quality\ products$	*No units*
FP	$Failed\ products$	*No units*
I	$Inventory\ used$	*No units*

D. DETECTABILITY

The relationship of functionality during the detectability phase is provided in Eq. (1). It is the ratio of the time spent by configuration i in the detectability phase and the sum of the processing time of all operations assigned to configuration i.

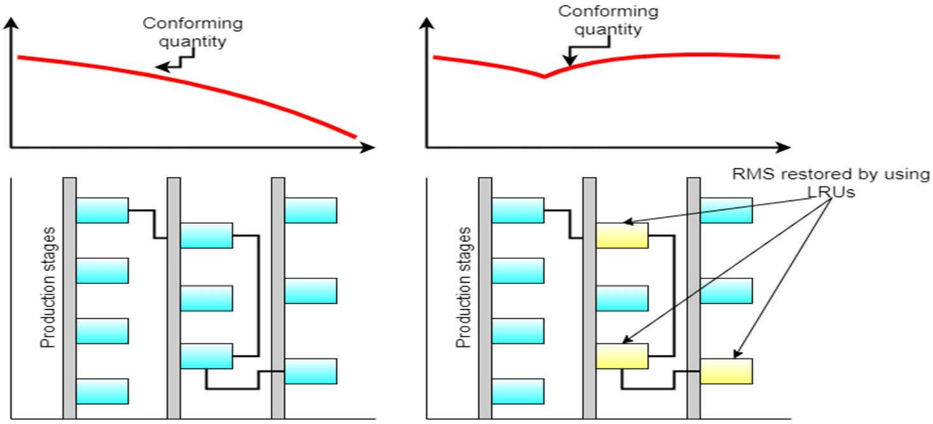

FIGURE 4. **Summary of problem statement.**

The value of F_{det} can be maximized by assigning operations to configurations with a higher profile of the time spent in detectability before the deterioration starts occurring.

$$F_{det} = \sum_{o\in O}\sum_{i\in I} x_{io} \times \frac{T_{det.i}}{t_o} \tag{1}$$

E. PREDICTABILITY

Predictability is modeled in the absence as well as in the presence of distinguishability. In the former, the system is not restored to the optimal working conditions, i.e., the problematic LRU's are not replaced. The LRUs can be tools, basic, and/or auxiliary modules in the case of RMS. The functionality during predictability (in the absence of distinguishability) is described in Eq. (2). It is the product of the probability of functionality/performance decay and the ratio of the total run time minus the effective time of production in the detectability phase and the processing time of all operations.

$$F_{pred} = \sum_{o\in O}\sum_{i\in I} x_{io} \times \rho_{di} \times \left(\frac{\mathrm{TRT}_i - T_{det.i}}{t_o}\right) \tag{2}$$

The functionality during predictability (in the presence of distinguishability) is mapped through Eq. (3). Here, the effective time of a configuration in the running state is prolonged by the time a system works in the distinguishability phase. Nonetheless, there is still some loss of functionality defined by $(TRT_i - T_{det.i} - T_{dist.i})$ as any manufacturing system cannot indefinitely work in an ideal working state.

$$F_{Pred_{dist}} = \sum_{o\in O}\sum_{i\in I} x_{io} \times \rho_{di} \times \left(\frac{\mathrm{TRT}_i - T_{det.i} - T_{dist.i}}{t_o}\right) \tag{3}$$

F. DIAGNOSABILITY OF PRODUCTS

The loss of functionality of RMS will impact the quality of products. A perfect quality RMS will only produce optimal quality products and this quality will start deteriorating as the manufacturing system starts losing its functionality.

Eq. (4) computes the optimal quality products in the absence of distinguishability. Eq. (5) calculates the failed product units which are equal to the difference in quantity entering the RMS and the optimal quality production. Eq. (6) calculates the inventory needed to replace the failed products.

$$\mathrm{OP}_{det} = F_{det} = \sum_{o\in O}\sum_{i\in I} x_{io} \times \frac{T_{det.i}}{t_o} \tag{4}$$

$$\mathrm{FP}_{det} = \aleph - \mathrm{OP}_{det} \tag{5}$$

$$I_{det} = \mathrm{FP}_{det} \tag{6}$$

The optimal quality production (in the presence of distinguishability) is provided by Eq. (7). Due to distinguishability, the effective life of configuration is extended, and more optimal quality products can be produced in this case.

$$\mathrm{OP}_{det+dist} = F_{det} + F_{dist} = \sum_{o\in O}\sum_{i\in I} x_{io} \times \frac{T_{det.i}}{t_o} + \sum_{o\in O}\sum_{i\in I} x_{io} \times \frac{T_{dist.i}}{t_o} \tag{7}$$

The failed quantity of products, in the case of distinguishability, is provided in Eq. (8). Eq. (9) presents the inventory used in the presence of distinguishability. LRUs are replaced in the distinguishability phase to restore the manufacturing system's performance. These LRUs are also part of the inventoried items. Eq. (10) provides the number of LRUs needed in the distinguishability phase. Each LRU can process ∂ number of operations and thus the ratio in Eq. (10) provides the number of LRUs to complete all operations.

$$\mathrm{FP}_{det+dist} = \aleph - \mathrm{OP}_{det+dist} \tag{8}$$

$$I_{det+dist} = \mathrm{FP}_{det+dist} + \mathrm{LRU}_{dist} \tag{9}$$

$$\mathrm{LRU}_{dist} = \sum_{o\in O} \frac{O_{LRU}}{\partial} \tag{10}$$

The mathematical model presents two important research questions, i.e., Should the RMS be restored by using inventoried LRUs so that the optimal quality products and customer satisfaction level can be enhanced? and will the reconfigurable system be more cost-effective if its life is not prolonged through distinguishability by adding/replacing the LRUs? The cost-effectiveness of RMS can be evaluated by using the simple functions given in Eq. (11) and Eq. (12) in the absence and presence of distinguishability, respectively.

$$C_p \times \mathrm{FP}_{det} + C_I \times I_{det} \tag{11}$$

$$C_p \times \mathrm{FP}_{det+dist} + C_I \times I_{det+dist} \tag{12}$$

V. SOLUTION APPROACHES

Reconfigurable manufacturing system problems are non-polynomial hard [31]. Exact solution approaches may not provide accurate results, especially with large problem sizes. Meta-heuristic approaches have predominately been used to address the RMS problems (e.g., refer to [21], [57], [58]). There has been a trend of using problem-specific heuristics in the RMS literature (e.g., refer to [32], [35], [36]). In this study, two problem-specific heuristics are used for the deterministic problem. In addition, a Simulation-Based Optimization (SBO) approach is adopted to solve the stochastic problem setting. These approaches are discussed below:

A. HEURISTICS FOR DETERMINISTIC PROBLEM

Two problem-specific heuristics are designed for deterministic problem settings. The first heuristic is used to examine the functionality of RMS in the absence of distinguishability. The second heuristic examines the functionality of RMS in the presence of distinguishability. In the first heuristic (called HAD hereafter, a heuristic that works in the absence of diagnosability), the input information regarding operations processing time, and profiles of configurations (i.e., detectability, predictability, and diagnosability of products) is fed to the heuristic. A time counter is generated that tracks the working time of each machine configuration. The framework and pseudocode of the HAD are provided in Figure 5 and Algorithm 1, respectively. The detailed steps in executing the HAD heuristic are provided below:

Step 1: Execute the heuristic for g number of iterations. Input the problem data comprising the order of operations, processing times, and the diagnosability profiles of configurations.

Step 2: Initiate a time counter T that tracks the working time of each configuration.

Step 3: Select a configuration at random and check its feasibility to process operation o.

Step 4: Continue processing the set of operation o, until the counter time T_i equals T_{deti}. At this point, compute the functionality during detectability (F_{det}).

Step 5: Archive the completed operations O_D. These are the optimal quality units of operations as they are processed during the detectability phase of configuration i. Eq. (5) calculates the failed units of operations in the absence of the distinguishability phase.

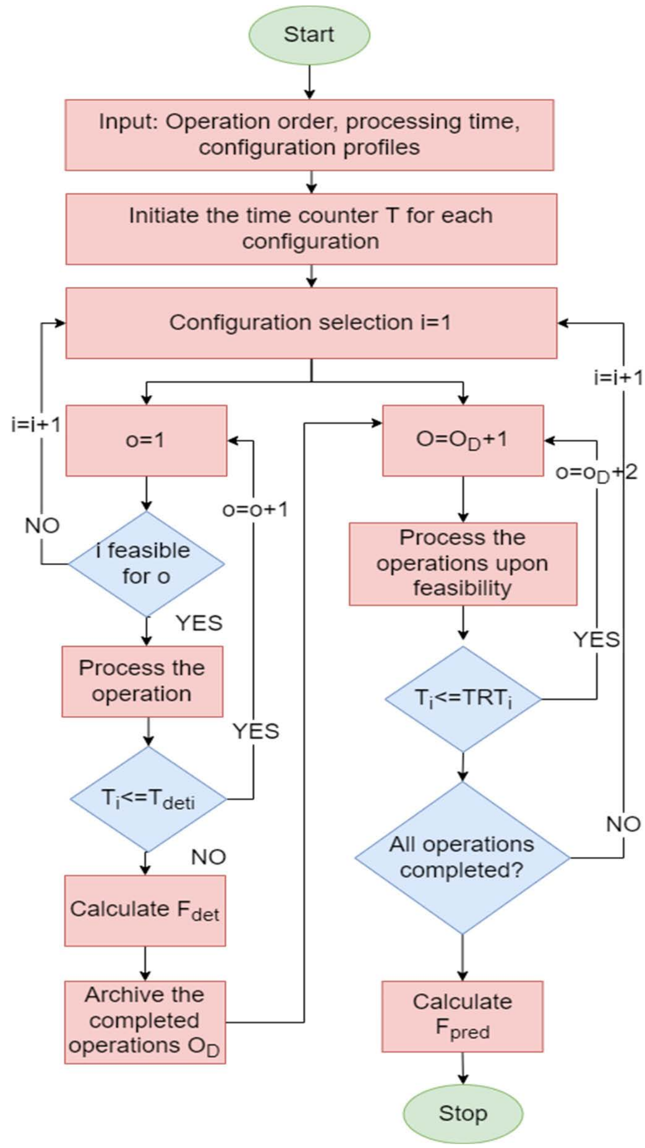

FIGURE 5. Flow-diagram for HAD heuristic.

Step 6: For all remaining operations (i.e., $\aleph$-O_D), assign configurations to operations starting from O_D+1 upon fulfilling the feasibility constraint.

Step 7: Process the operations on the selected configuration up until time counter T_i equals the total processing time of a configuration (TRT_i).

Step 8: As the processing time of a configuration saturates, increment the configuration to $i+1$ until all operations are completed.

Step 9: Compute the functionality during the predictability phase (F_{pred}). Stop the heuristic after exhausting the generations g.

The second heuristic (called HPD henceforth, a heuristic that works in the presence of diagnosability) uses the LRUs to restore the RMS to working conditions. It is used to assess the diagnosability in the presence of distinguishability. The framework and algorithm of HPD are provided in

Algorithm 1 Algorithm 1 for Had

For g=1 to g_{max} do
Input information of configuration profiles
Input information of operations
For $o \in O_D$
$i = 1$
Initiate counter $T_i = 0$
While $T_i \leq T_{deti}$do ##($\acute{T}_i$)
Compute F_{det}
o=o+1
End While
$i = i+1$
End For
Archive O_D
For $O_{D+1} \rightarrow O$
$i = 1$
While $\acute{T}_i \leq TRT_i$**do**
Compute F_{pred}
$O_{D+2} = O_{D+1}+1$
End While
$i = i+1$
End For

Algorithm 2 Algorithm 2 for HPD

For g=1 to g_{max} **do**
Input information of configuration profiles
Input information of operations
For $o \in O_D$
$i = 1$
Initiate counter $T_i = 0$
While $T_i \leq T_{deti}$**do** ##($\acute{T}_i$)
Compute F_{det}
o=o+1
End While
$i = i+1$
End For
Archive O_D
For $O_{D+1} \rightarrow O'$
$i = 1$
While $\acute{T}_i \leq TRT_i$- T_{ddi}- T_{disti}do ##(T_i'')
Compute F_{pred}
$O_{D+2} = O_{D+1}+1$
End While
$i = i+1$
End For
Archive $O_{PD} = O'$
For $O_{PD+1} \rightarrow O$ (O_{LRU})
$i = 1$
While $T_i'' \leq TRT_i$**do**
Compute F_{det}
$O_{PD+2} = O_{PD+1}+1$
End While
$i = i+1$
End For
Archive O_{LRU}

Figure 6 and Algorithm 2, respectively. Herein, an additional loop is created to restore the machine configurations to the optimal functionality level (i.e., to the level of predictability). Steps 1 to 5 are common in Figures 5 and 6. The remaining steps in implementing the HPD heuristic are provided below:

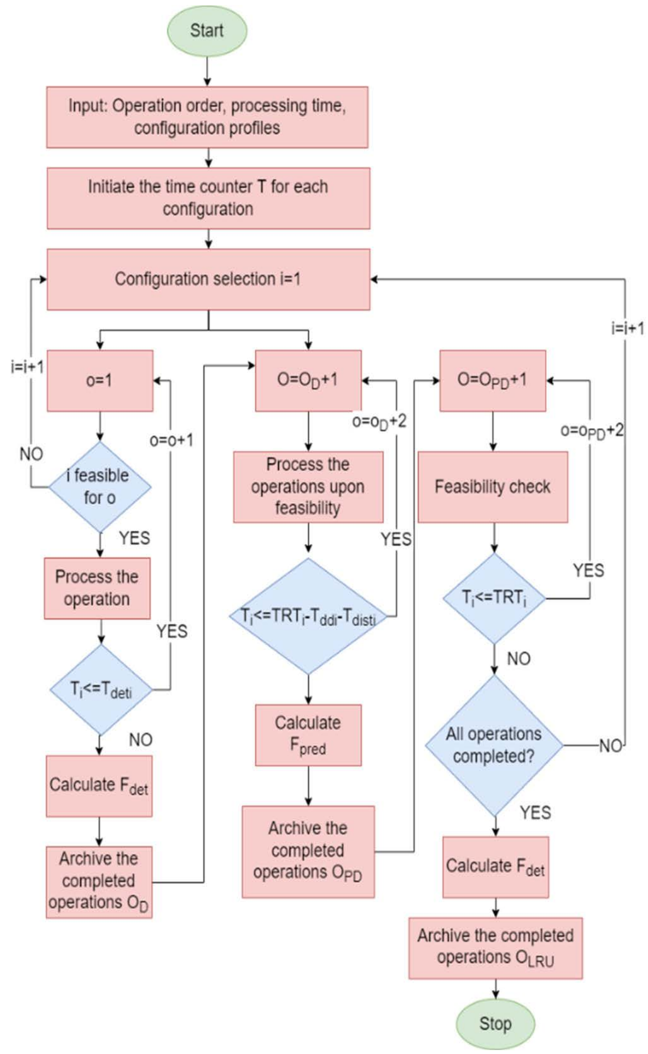

FIGURE 6. Flow-diagram for HPD heuristic.

Step 6: For operations starting from O_D+1, assign configurations to each operation upon fulfilling the feasibility constraint.

Step 7: Process the operations on the selected configuration up until the time counter T_i equals the time when distinguishability restores the system.

Step 8: Calculate the value of functionality during predictability and archive all operations completed in this phase. These operations will comprise the failed units of operations.

Step 9: For remaining operations (i.e., ℵ-O_{PD}+1), assign a configuration to each operation upon fulfilling the feasibility constraint.

Step 10: Increment the configuration number up until all operations are processed, as the total processing time of the selected configuration saturates.

Step 11: Compute the functionality during this last phase. In the distinguishability phases, the system works as well as it was working in the diagnosability phase (Figure 2(b)).

Step 12: Archive the completed operations processed during the distinguishability phase. The total number of optimal quality operations units is equated by summing O_D and O_{LRU}.

Step 13: Stop the heuristic after exhausting the generations g.

B. SIMULATION-BASED OPTIMIZATION (SBO) FOR STOCHASTIC SETTINGS

The deterministic model considered the decline in production functionality subject to the static failure of a manufacturing system. The real-life processes involving failure and deterioration are stochastic in nature. A stochastic process is a time-bound function where the random rate of deterioration per unit of time is considered. For this study, the deterioration rate is assumed to be random in time and it follows the gamma process. The advantage of using the gamma processes is that its mathematical formulation is easy [8]. The notations and mathematical formulations of gamma processes in different phases of reconfigurable machines are provided below:

NOTATIONS

u, v	*parameters of beta distribution*
$\propto$	*shape parameter of gamma process*
γ	*scale parameter of gamma process*
$X(t)$	*stochastic gamma process to demonstrate the funcitonality degradation of RMS with time t*
b	*ratio of geomatric process*
$X(\mathrm{TRT}_i - T_{deti})$	*functionality degradation level in the absence of distinguishability*
$X(T_{disti} - T_{predi})$	*funcitonality change in the presence of distinguishability phase*
$\propto(\mathrm{TRT}_i - T_{deti})$	*shape parameter in the absence of distinguishability*
$\propto(T_{disti} - T_{predi})$	*shape parameter in the presence of distinguishabilityphase*
$Y(.)$	*gamma function*
L_{AD}	*failure threshold in the absence of distinghuishability*
L_D	*failure threshold in the presence of distinghuishability*

Each machine configuration i is subject to functionality degradation which follows the gamma distribution function. The gamma distribution functions for the manufacturing system in the absence and presence of distinguishability phases are provided in eq. (13) and (14), respectively.

$$f_{\propto(TRT_i - T_{deti}),\,\gamma}{}^{(x)} = \frac{\gamma^{\propto(TRT_i - T_{deti})}.x^{\propto(TRT_i - T_{deti})-1}}{Y[\propto(TRT_i - T_{deti})]} e^{-\gamma x}, x \geq 0 \quad (13)$$

$$f_{\propto(T_{disti} - T_{predi}),\,\gamma}{}^{(x)} = \frac{\gamma^{\propto(T_{disti} - T_{predi})}.x^{\propto(T_{disti} - T_{predi})-1}}{Y[\propto(T_{disti} - T_{predi})]} e^{-\gamma x}, x \geq 0 \quad (14)$$

$$Y(b) = \int_0^\infty u^{b-1}.e^{-u}du, b > 0 \quad (15)$$

The time to failure is anticipated once the failure threshold is crossed. The failure threshold is denoted by L and the failure time in the absence of distinguishability (once L_{AD} is crossed) and in the presence of distinguishability (once $L_D$is crossed) phase are provided in eq. (16) and eq. (17), respectively.

$$T_F = \inf\{t\,|X(t) \geq L_{AD}\} \quad (16)$$

$$T_F^D = \inf\{t\,|X(t) \geq L_D\} \quad (17)$$

The distribution function for the failure time in the absence and presence of the distinguishability phase is provided in eq. (18) and eq. (19), respectively.

$$F_{T_F}(t) = P(T_F < T_{det}) = P(X(t) > L_{AD}) = \frac{Y(\propto t, L_{AD}\gamma)}{Y(\propto t)}, t > 0 \quad (18)$$

$$F_{T_F^D}(t) = P\left(T_F^D < T_{dist} - T_{pred}\right) = P(X(t) > L_D) = \frac{Y(\propto t, L_D\gamma)}{Y(\propto t)}, t > 0 \quad (19)$$

The proportion of failed product units in the absence and presence of the distinguishability phase are provided in eq. (20) and eq. (21), respectively. As per the relationships given in eq. (18-21), the functionality of reconfigurable machines starts producing failed units once the threshold is crossed. Accordingly, in the absence of the distinguishability phase, this threshold is crossed once the detectability phase is elapsed. On the other hand, in the presence of the distinguishability phase, this threshold lasts between the start of the predictability phase and the time when RMS functionality is restored by replacing the LRUs. The number of LRUs used to complete the level of demand in the presence of the distinguishability phase is provided in eq. (22).

$$pX(t) = \sum_{i\in I}\sum_{o\in O} X\frac{(TRT_i - T_{deti})}{t_o}\aleph \quad (20)$$

$$pX(t) = \sum_{i\in I}\sum_{o\in O} X\frac{(T_{disti} - T_{predi})}{t_o}\aleph \quad (21)$$

$$LRU_{dist} = \frac{pX(t)}{\partial} \quad (22)$$

The framework of the simulation-based optimization approach for detectability and predictability phases is provided in Figure 7. The main difference between the SBO and deterministic approaches is that the former considers a stochastic decay/deterioration in functionality profiles, a phenomenon very well-aligned with modern-day practices.

The performance of different heuristics was assessed by using the metrics of Hyper Volume (HV), Number of Pareto-optimal Solutions (NPS), and Inverse Generational Distance (IGD). The HV and NPS are described below while the metric of IGD is discussed later.

HYPER VOLUME (HV)

It calculates the volume of objective space; a higher volume refers to the closeness as well as the spread of solutions [60].

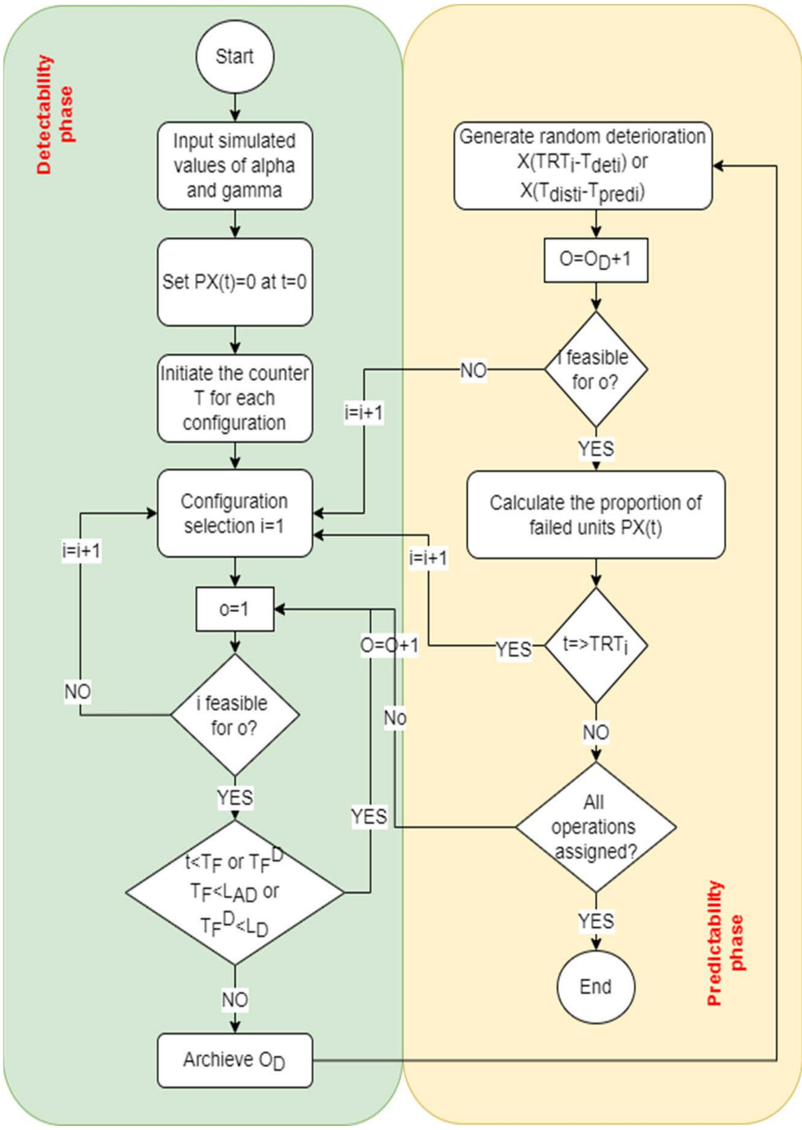

FIGURE 7. Simulation-based optimization framework for detectability and predictability phases.

A higher value of HV refers to a good quality solution. Its representation is provided in eq. (23).

$$\mathrm{HV} = \bigcup_{i=1}^{N} a(x_i) \forall x_i \in P \tag{23}$$

$a(x_i)$ = the rectangular area covered by a reference point

P= Pareto set

NUMBER OF PARETO-OPTIMAL SOLUTIONS (NPS)

The NPS metric represents the number of Pareto-optimal solutions offered by a heuristic. In general, a high-performing heuristic will have a higher score of NPS.

VI. RESULTS

A. PERFORMANCE ASSESSMENT

Initially, the performance of HAD was compared with the exact ε- constraint approach. The ε- constraint method has frequently been adapted to manufacturing system problems. The ε- constraint approach was applied in CPLEX while the heuristics were coded in MATLAB 2016a. The computation time and optimality gap between ε- constraint and the HAD heuristic is provided in Table 2 for 10 problem sizes. The problem size is defined by the number of operations of a product and the number of RMS configurations. The optimality gap is provided as a percentage and $\uparrow$ means that the ε- constraint method is more effective whereas $\downarrow$ means that the HAD has improved performance. The ε- constraint returns the results in less computation time for the first three problems. However, as the problem size increases, the HAD heuristic proves to be more effective. The ε- constraint approach takes indefinitely large computation time for problem 7 and onwards, hence it is not a suggested approach for the problem set 7-10. For such problems, the optimality gap is at least 100%, meaning that the HAD heuristic is more robust and suitable.

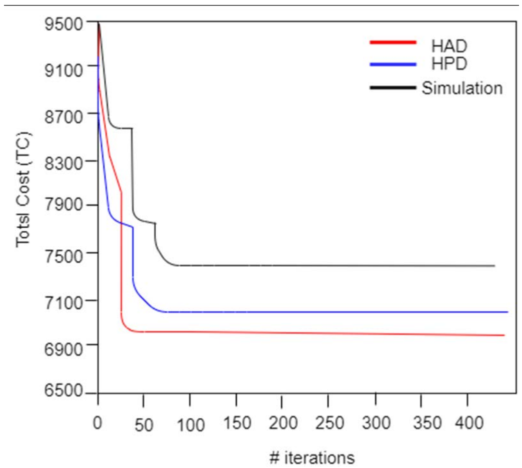

FIGURE 8. Convergence efficiency of different approaches.

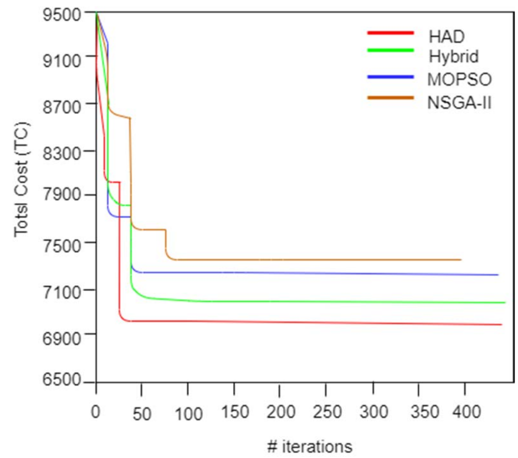

FIGURE 9. Convergence of evolutionary approaches to optimal value of cost.

TABLE 2. Comparison of solution efficiency between exact approach and HAD for small problem instances.

Problem instance	Computation time (sec)		Optimality gap
	ε- constraint	HAD	
1	28	32	↑ 12.5%
2	41	55	↑ 25.5%
3	48	63	↑ 23.8%
4	780	135	↓ 82.7%
5	1350	177	↓ 86.9%
6	1958	282	↓ 85.6%
7	----	322	↓ 100%
8	----	341	↓ 100%
9	----	365	↓ 100%
10	----	389	↓ 100%

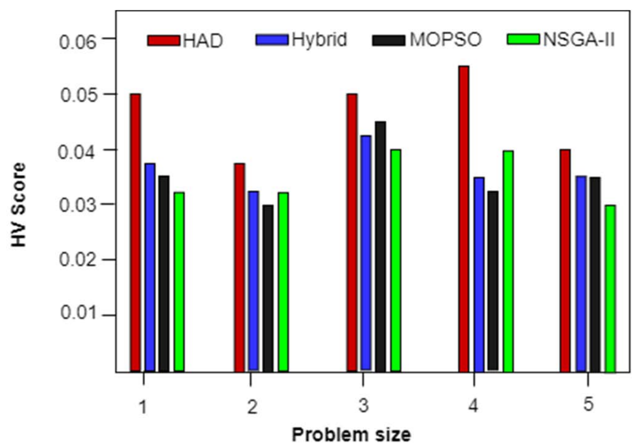

FIGURE 10. HV values for small problem sizes.

The convergence of HAD and HPD heuristics and the simulation framework to the optimal value of cost are provided in Figure 8. It can be observed that the HAD heuristic takes minimum iterations (47) in converging to the optimal value of the objective function. Thus, out of the proposed approaches, the HAD heuristic is more efficient in fast convergence of the solution.

The performance of the HAD heuristic was compared to other published algorithms/heuristics in the established literature. In this regard, the hybrid framework of non-sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization (MOPSO) (called hybrid NSGA-II-MOPSO) was selected from [5]. In addition, NSGA-II [57] and MOPSO [59] heuristics were also selected. The results of the convergence efficiency of the HAD heuristic, hybrid NSGA-II-MOPSO, NSGA-II, and MOPSO are provided in Figure 9. The HAD heuristic outperforms other heuristics and it converges much faster to the optimal solution. This is primarily because of its simple structure and problem adaptiveness which results in quick attainment of feasible as well as optimal solutions.

The HV values of HAD, hybrid heuristic, MOPSO, and NSGA-II for small as well as large problem sizes are provided in Figure 10 and Figure 11, respectively. The small problem sizes ranged between 4-11 operations and 6-8 configurations. On the other hand, the large problem sizes ranged between 12-28 operations and 10-14 configurations. It can be observed from both figures that the HAD heuristic had better HV values for all problem instances. The hybrid heuristic HV values were better than the corresponding HV values of MOPSO and NSGA-II.

The performance of the second metric (NPS) can be assessed from the non-dominated solutions of all heuristics for small and large problem sizes in Figure 12 and Figure 13, respectively. The objective functions of functionality (F) and the total cost (TC) were used as conflicting objectives. The functionality function was based on the summation of functionalities in all manufacturing phases (i.e., detectability, predictability, etc.). The objective function of the total cost was based on the summation of inventory cost and penalty cost. A solution with the maximum value of functionality (F) and

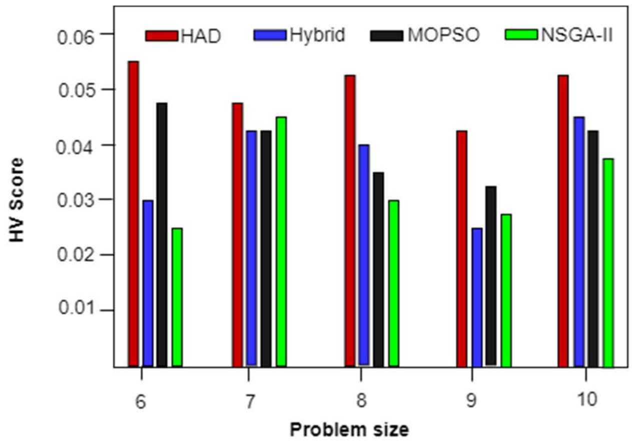

FIGURE 11. HV values for large problem sizes.

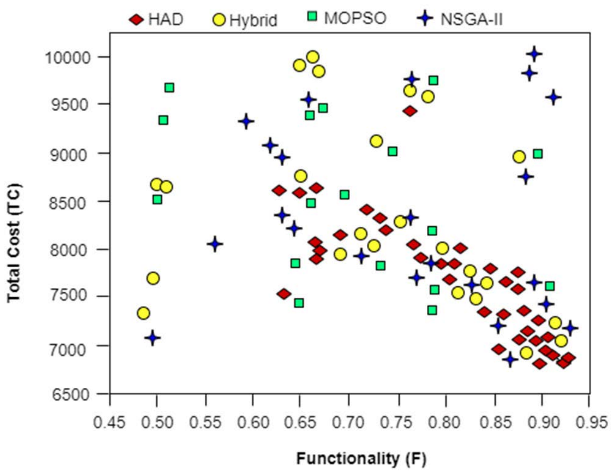

FIGURE 12. Non-dominated solutions concerning functionality and cost for different heuristics (small size problems).

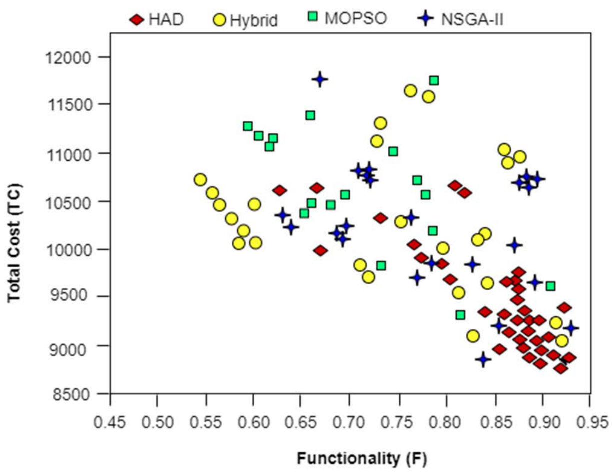

FIGURE 13. Non-dominated solutions concerning functionality and cost for different heuristics (large size problems).

minimum cost (TC) is preferred and is a potential candidate for the optimal solution. In other words, any solution in Figure 12 and Figure 13 that lies at the right bottom will be

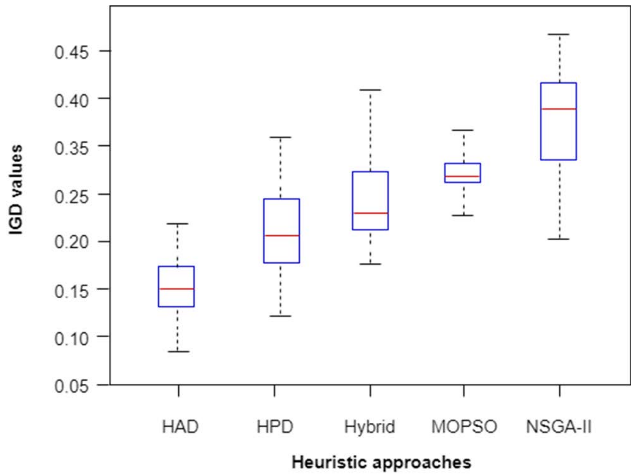

FIGURE 14. The boxplot of IGD values using different heuristics.

preferred. According to this criterion, the HAD heuristic has more non-dominated solutions and it shows more compactness for small as well as large problem sizes. As a result, it has a higher NPS score compared to all other approaches. The hybrid heuristic also performs well, and it has a better NPS score compared to MOPSO and NSGA-II. To summarize, the HAD heuristic has a good performance w.r.t the HV and NPS criteria. However, it is custom designed (specific to the problem) which can impact its generalizability towards other problems in a reconfigurable manufacturing system.

The performance of all approaches was further assessed by using the criteria of the Inverse Generational Distance (IGD). The boxplot of IGD values of several approaches is provided in Figure 14. A smaller value of IGD is preferred and it can be observed that the HAD heuristic outperforms other approaches and it had the lowest IGD average values. This indicates that the solutions provided by the HAD heuristic have improved quality and can be trusted to be accurate.

B. CASE STUDY

The deterministic problem setting is discussed at first for a specific case study and then the results of the stochastic problem setting are discussed. The heuristics for the deterministic problem and SBO were implemented in MATLAB 2016a by using a system comprising the specification Core i5, 2.8 GHz processor, and 16 GB RAM. A product from our previous study [5] (as shown in Figure 15) comprising 17 operations is to be processed by using any combination of five reconfigurable machines. The time to process an operation varies between 6-19 minutes. In addition, the total working time of each configuration (TRT_i) is 480 minutes. The functionality profiles of all machine configurations in the absence and presence of distinguishability are provided in Figure 16 and Figure 17, respectively.

It can be observed in Figure 16 that configuration 1 ($i = 1$) works perfectly in the detectability phase up until time = 92 minutes. Henceforth, its performance starts deteriorating

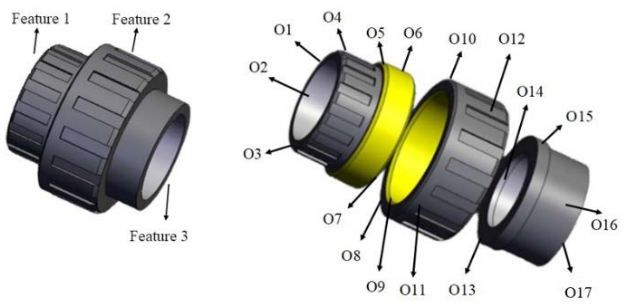

FIGURE 15. Features and operations of a mechanical product (based on our previous study [5]).

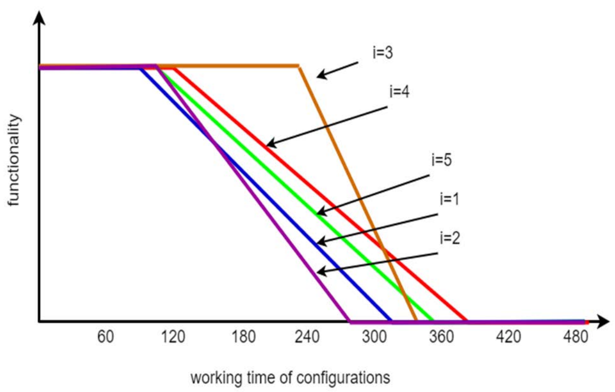

FIGURE 16. Configurations working profiles in the absence of distinguishability.

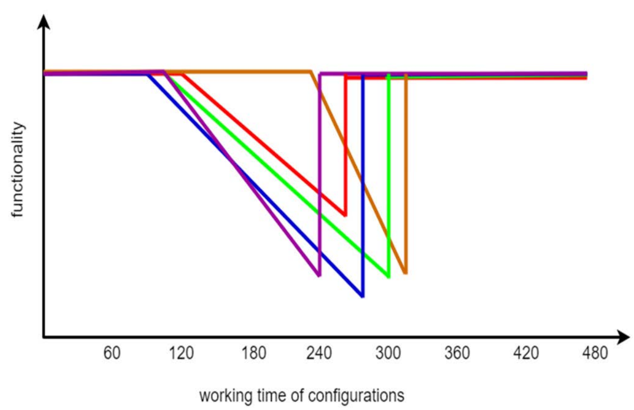

FIGURE 17. Configurations working profiles in the presence of distinguishability.

and a complete system failure is anticipated at time = 315 minutes. The remaining configuration profiles can be similarly interpreted. In the presence of distinguishability (Figure 17), $i = 1$ is restored at time = 287 minutes by replacing the LRUs so that the complete failure can be avoided. This set of figures provides the input data for the deterministic problem setting.

The results of HAD and HPD heuristics, in the absence and presence of distinguishability, are provided in Figure 18 and Figure 19, respectively. The horizontal axis refers to the operation time of different configurations whereas the vertical axis shows the functionality. Four alternative solutions are provided in Figure 18 wherein each solution, several machine configurations are selected to perform the operations.

For example, in solution #1, configuration five (C_5) is selected twice, in the beginning as well as at the end, to process the operations sets $\{O_1, O_3, O_5, O_6\}$ and $\{O_{12}, O_{15}, O_{17}\}$. The colored bars in each solution show the time when configurations work in the predictability phase, thus producing failed products. The summation of colored bars (i.e., cumulative inventory to be used) is provided at the top of each solution. Among the presented solutions (#1 to #4), the #3 solution is a better candidate as it results in the minimum inventory used during production. The potential reason is that it makes use of such configurations which have better functionality profiles. Next to it, the #4 solution has a slight increase in the level of inventory needed. However, it can be preferred as it uses only three machine configurations (C_2, C_5, and C_3) compared to the #3 solution which uses four configurations (C_1, C_4, C_3, and C_5). The existing literature on RMS emphasizes minimizing the reconfiguration effort (RE) during production [14], [57], [61]. The value of RE can be minimized by selecting such a solution that contains a smaller number of configurations (or less transition between configurations). A manager may select the #4 solution over the #3 for its less reconfiguration effort at the expense of a slight increase in failed products.

The results of the HPD heuristic (for the same case study) are provided in Figure 19. A smaller quantity of inventory items is used in each solution. This is due to the distinguishability phase which uses LRUs as replacement units to restore the functionality of reconfigurable machines. Hence, fewer failed units are produced, and consequently small portion of inventory is needed. Among the given solutions, #4 is the best solution as not only does it use the minimum quantity of inventory items but also, #4 completes the total production in the least time. The presence of the distinguishability phase though helps in minimizing the use of inventoried items; however, it is pertinent to examine the cost analysis, especially when the LRUs are added to the manufacturing system.

The cost analysis of different solutions provided by HAD and HPD heuristics is provided in Figure 20. The first four solutions to the left are provided by HAD whereas the last four solutions are provided by HPD. It can be observed that in the absence of distinguishability, the penalty cost of failed units (CP) and inventory cost (CI) have roughly the same values. This is because an inventory equal to failed units is used to fulfil the customer demand (eq. 6). The penalty cost of failed units is reduced in the distinguishability phase due to the use of LRUs. However, it can be observed that the inventory costs have drastically increased.

Thus, the combined cost of penalty and inventory is much higher in the presence of distinguishability as compared to the cost values in the absence of distinguishability. The investment and running costs of a reconfigurable manufacturing

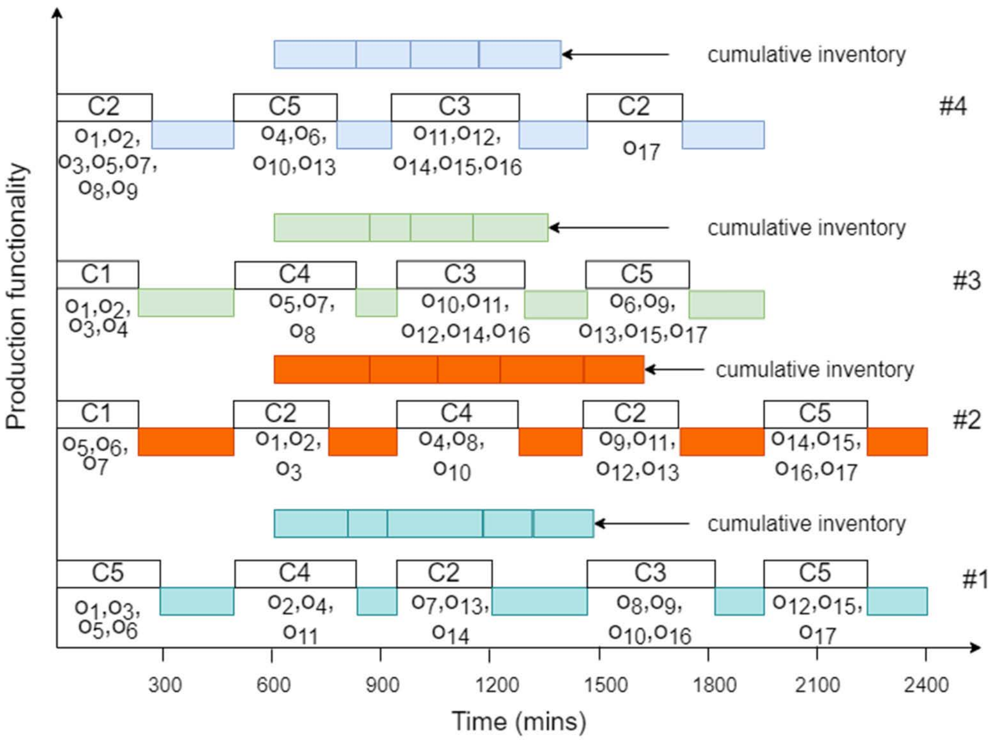

FIGURE 18. Different alternative solutions in the absence of distinguishability by using HAD heuristic.

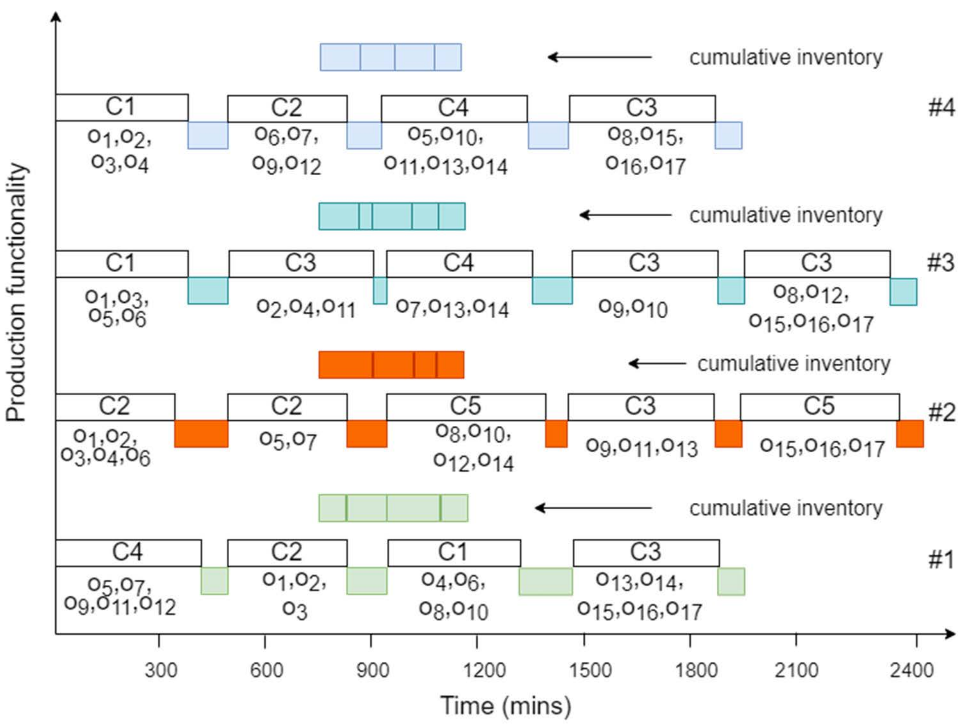

FIGURE 19. Different alternative solutions in the presence of distinguishability by using HPD heuristic.

system are much higher as compared to the cost of a dedicated manufacturing line or a flexible manufacturing system [18], [62]. To restore the reconfigurable manufacturing system performance, line replacement units (i.e., fixtures, tools,

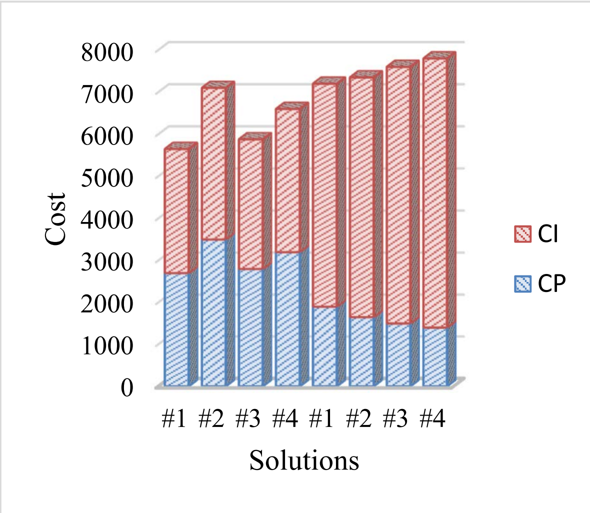

FIGURE 20. Cost analysis of different solutions.

TABLE 3. Simulation results for different combinations in the absence of distinguishability.

S. No	α	γ	L_{AD} (%)	$pX(t)$	CP	CI	Total Cost
1	1.3	10	60	12%	3120	3120	6240
2	1.3	10	75	9.40%	2735	2735	5470
3	1.3	12	60	13.68%	3245	3245	6490
4	1.3	12	75	10.33%	2865	2865	5730
5	1.5	10	60	15.21%	3429	3429	6858
6	1.5	10	75	11.89%	2973	2973	5946
7	1.5	12	60	16.77%	3576	3576	7152
8	1.5	12	75	13.05%	3048	3048	6096

modules, etc.) are added which may add to the total cost value.

The simulation results were replicated for different combinations of input values of shape and scale parameters and failure threshold. Two values of shape parameters i.e., α = 1.3 and 1.5, two values of scale parameters γ = 10 and 12, and two failure thresholds L = 60% and 75% were used in the replications. The value of L = 60% means that the failure occurs once 60% of the configuration run-time is elapsed. The results of different combinations of input values in the absence and presence of distinguishability are provided in Table 3 and Table 4, respectively. The last four columns in each table comprise the proportion of failed units (pX(t), in percentage), penalty cost of failed products (CP), cost of using inventory (CI), and the total cost value (i.e., CP+CI).

Figure 21 shows the cost values in the presence and absence of distinguishability. The following points can be extracted from Table 3, Table 4, and Figure 21.

- There are fewer failed units, less penalty, and inventory cost values for a higher threshold limit (LAD=75%). From Table 3, it can be observed that LAD=75% on average results in 3.248% fewer failed product units and 436.25 USD less penalty cost value as compared to LAD=60%. Though the results are interesting, it requires more effort and investment to enhance the failure threshold limit of a reconfigurable manufacturing system.
- The higher values of shape and scale parameters in the gamma process result in more deterioration and hence a higher proportion of defective product units and higher penalty cost values.
- On average, the penalty cost of failed units is 60% less in the presence of distinguishability as compared to the model in the absence of distinguishability.

TABLE 4. Simulation results for different combinations in the presence of distinguishability.

S. No	α	γ	L_D (%)	$pX(t)$	CP	CI	Total Cost
1	1.3	10	60	5.23%	1230	6104	7334
2	1.3	10	75	3.45%	965	5276	6241
3	1.3	12	60	6.21%	1345	5938	7283
4	1.3	12	75	4.67%	1054	5413	6467
5	1.5	10	60	7.43%	1485	6354	7839
6	1.5	10	75	5.93%	1189	5647	6836
7	1.5	12	60	8.21%	1532	6513	8045
8	1.5	12	75	6.08%	1307	5790	7132

In addition, the average inventory cost in the presence of distinguishability is almost 47% more compared to the model in the absence of distinguishability. As a result, the average total cost of the model in the presence of distinguishability is 13% more than the model in the absence of distinguishability. These findings are consistent with the deterministic model findings. Thus, both models reinforce each other, and the findings are equally applicable to deterministic and stochastic problem settings.

VII. MANAGERIAL IMPLICATIONS

The following constitute the list of implications for managers working in a changeable/reconfigurable manufacturing environment:

- The functionality and performance of a reconfigurable manufacturing system change in each stage. Thus, it is important to examine the functionality of a reconfigurable manufacturing system before putting it into use.
- In the absence of distinguishability, higher inventory levels are needed which may require storage capacity and can potentially increase the storage/inventory costs. However, the use of LRUs though may reduce the level of inventory, the findings show that the overall costs will increase.
- Managers are interested in reducing the effort while changing from one configuration to another. The diagnosability-driven findings of this study imply that a solution selected based on minimum cost and/or inventory levels may not warrant minimum effort in

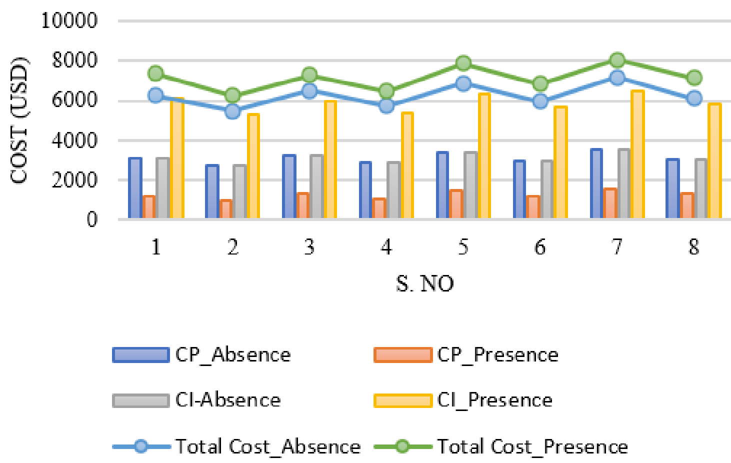

FIGURE 21. **Cost analysis of different simulation model solutions.**

reconfiguration. The results are self-sufficient to help managers in selecting a solution based on cost, inventory, functionality, or minimum requirement of reconfiguration.

- #4 solution in the presence of distinguishability completes the production in minimum time (1860 minutes). Managers are more often triggered by the time taken while replace defective/problematic parts. There is a possible arrangement of reconfigurable machines which will complete the production in minimum time while replacing the LRUs during production.
- The model is equally applicable to deterministic and/or stochastic settings. Modern-day practices are volatile, and uncertain and can be effectively examined by using randomness in the processes. The results suggest that both deterministic and stochastic setting findings reinforce each other.

The considered problem addressed the diagnostics of a reconfigurable manufacturing system. This problem remained unexplored in the concerned literature. The presented problem has multiple applications in the real-life situations, ranging from reconfigurable supply chains [63], single-unit process plans [64], multi-unit process plans [65], reconfiguration in emergency response systems [66], integrated production scheduling and process control [67], and performance evaluation of reconfigurable integrated manufacturing system (RIMS) [3]. Table 5 summarizes the applications of the on-hand problem. The considered problem can be analyzed in the reconfiguration of healthcare emergency response systems where ad-hoc production of emergency units is required, especially in the times of COVID-19. A well-diagnosed production system can ensure that the delivered healthcare units are of adequate quality. Another noteworthy application of this problem is in integrated production scheduling and process control. More often, managers are interested in joint scheduling and process planning. In such events, process control and diagnostics can enhance production efficiency and can schedule units on well-diagnosed machines which results in minimum loss and less use of inventory.

The proposed models and solution approaches have manifold benefits. Firstly, they will enable the managers to simultaneously analyze the cost and functionality of manufacturing. Secondly, they will help a manager in accessing the level of required inventory in different phases of production. Managers are normally concerned about the cost of maintenance and downtime during maintenance. Our models show that the maintenance and replacement of LRUs do not compromise the production completion time.

To the best of our knowledge, complex decision-making problems involving cost, functionality, inventory, and deterioration have not been studied in the published literature. Managers working in a changeable/reconfigurable working environment can adapt the proposed approaches to their specific needs. The model is simple and primarily based on the input information of operations, configurations, and functionalities. Thus, it can be easily applied to practical problems. Moreover, the heuristic approaches are also simple and can easily be implemented. The results suggest that the HAD heuristic is more effective in offering good solutions in less time. However, the heuristics are custom designed for the on-hand problem. Advanced skills in evolutionary approaches maybe needed to modify these heuristics. The mathematical model is designed to produce a single product type. RMS is an expensive manufacturing system, and it is more often designed to produce a variety of products. This also delimits the application of the proposed models and approaches to the RMS part-family design problems. Lastly, the proposed model uses inventory based on a Just-In-Time (JIT) approach. Any disruption in the supply chain and inventory policy was not considered. These results can be replicated for the case of a disruptive supply chain.

TABLE 5. Application of the considered problem.

S. No	Applications	Description
1	Reconfigurable or X- Supply Chains [63]	An analysis of the role of diagnostics in the design of proactive manufacturing and reconfigurable supply chain.
2	Reconfiguration in healthcare emergency response systems [66]	Examination of diagnosability in the ad-hoc reconfigurable production of emergency healthcare units.
3	Single unit process plans [64]	Efficient diagnostics and production design for single unit process planning.
4	Multi-unit process plans [65]	Assessing the impact of time-based diagnostics for multi-unit and variety of products-based process planning.
5	Integrated production scheduling and process control [67]	Diagnostics and process control for a reconfigurable integrated production scheduling.
6	Performance evaluation of Reconfigurable Integrated Manufacturing System (RIMS) [3]	A joint working mechanism of diagnostics, inspection, and production in the form of a Reconfigurable Integrated Manufacturing System (RIMS).

VIII. CONCLUSION

This study examined the diagnosability RMS characteristic both from a system as well as a product perspective. Mathematical models, heuristic approaches, and simulation frameworks were proposed to study the deterministic, as well as stochastic behavior of reconfigurable manufacturing system performance. The solution efficiency of the proposed heuristic approaches was compared with the published approaches in the literature. The results suggest that the proposed approaches work effectively in resolving the problem. The results of deterministic and simulation models reinforced each other, meaning that the findings are equally applicable to a manufacturing system working under stable and/or dynamic/stochastic working conditions. The simulation results are quite sensitive to changes in shape/scale parameters, and hence any change in the input values of these parameters can impact the significance of obtained results.

Each manufacturing phase of the RMS offers distinctive opportunities as well as threats. The penalty cost of failed products and the use of inventory is much less in the distinguishability phase. A manufacturing system with a higher threshold of failure works more effectively. In practice, enhancing the threshold limit of the production system needs more effort and investment. A trade-off between the use of the Line Replacement Units (LRUS) and inventory needs was also highlighted. On average, the use of LRUs can potentially increase the total cost of manufacturing. However, it warrants optimal quality products in less time. The proposed results can help practitioners in assessing the performance of a reconfigurable/changeable manufacturing system in different phases of production. In addition, these results can address the concerns of practitioners to examine the trade-off between inventory, the functionality of manufacturing system performance, and costs.

Future research may extend this discussion by simultaneously modeling other RMS characteristics with diagnosability, such as modularity, scalability, etc. This will help in attaining a multi-dimensional view of the performance of a reconfigurable manufacturing system. These results can be replicated/validated by using evolutionary solution approaches such as the advanced versions of genetic algorithms (NSGA-III/NSGA-IV) and other popular metaheuristics. The proposed RMS framework can be extended toward the production of a variety of products. The findings of other deterioration processes such as the Markov process and the Wiener process can be compared with the current results.

REFERENCES

[1] M. G. Mehrabi, A. G. Ulsoy, and Y. Koren, "Reconfigurable manufacturing systems: Key to future manufacturing," *J. Intell. Manuf.*, vol. 11, no. 4, pp. 403–419, Aug. 2000.
[2] M. Bortolini, F. G. Galizia, and C. Mora, "Reconfigurable manufacturing systems: Literature review and research trend," *J. Manuf. Syst.*, vol. 49, pp. 93–106, Oct. 2018.
[3] R. Pansare, G. Yadav, and M. R. Nagare, "Reconfigurable manufacturing system: A systematic bibliometric analysis and future research agenda," *J. Manuf. Technol. Manage.*, vol. 33, no. 3, pp. 543–574, Mar. 2022.
[4] P. P. Singh, J. Madan, and H. Singh, "Composite performance metric for product flow configuration selection of reconfigurable manufacturing system (RMS)," *Int. J. Prod. Res.*, vol. 59, no. 13, pp. 3996–4016, Jul. 2021.
[5] A. S. Khan, L. Homri, J. Y. Dantan, and A. Siadat, "Modularity-based quality assessment of a disruptive reconfigurable manufacturing system—A hybrid meta-heuristic approach," *Int. J. Adv. Manuf. Technol.*, vol. 115, nos. 5–6, pp. 1421–1444, Jul. 2021.
[6] Y. Kuo, "Optimal adaptive control policy for joint machine maintenance and product quality control," *Eur. J. Oper. Res.*, vol. 171, no. 2, pp. 586–597, Jun. 2006.
[7] K. Kang and V. Subramaniam, "Integrated control policy of production and preventive maintenance for a deteriorating manufacturing system," *Comput. Ind. Eng.*, vol. 118, pp. 266–277, Apr. 2018.
[8] J. M. Van Noortwijk, "A survey of the application of gamma processes in maintenance," *Rel. Eng. Syst. Saf.*, vol. 94, no. 1, pp. 2–21, Jan. 2009.
[9] B. Lu, Z. Chen, and X. Zhao, "Data-driven dynamic predictive maintenance for a manufacturing system with quality deterioration and online sensors," *Rel. Eng. Syst. Saf.*, vol. 212, Aug. 2021, Art. no. 107628.
[10] Y. Koren and M. Shpitalni, "Design of reconfigurable manufacturing systems," *J. Manuf. Syst.*, vol. 29, no. 4, pp. 130–141, Oct. 2010.
[11] C. Renzi, F. Leali, M. Cavazzuti, and A. O. Andrisano, "A review on artificial intelligence applications to the optimal design of dedicated and reconfigurable manufacturing systems," *Int. J. Adv. Manuf. Technol.*, vol. 72, nos. 1–4, pp. 403–418, Apr. 2014.
[12] Y. Koren, X. Gu, and W. Guo, "Reconfigurable manufacturing systems: Principles, design, and future trends," *Frontiers Mech. Eng.*, vol. 13, no. 2, pp. 121–136, 2018.
[13] S. Borgo, A. Cesta, A. Orlandini, and A. Umbrico, "A planning-based architecture for a reconfigurable manufacturing system," in *Proc. 26th Int. Conf. Automated Planning Scheduling*, Mar. 2016, pp. 1–9.

[14] K. K. Mittal and P. K. Jain, "An overview of performance measures in reconfigurable manufacturing system," *Proc. Eng.*, vol. 69, pp. 1125–1129, Jan. 2014.

[15] I. Maganha, C. Silva, and L. M. D. F. Ferreira, "The layout design in reconfigurable manufacturing systems: A literature review," *Int. J. Adv. Manuf. Technol.*, vol. 105, nos. 1–4, pp. 683–700, Nov. 2019.

[16] X. Wei, S. Yuan, and Y. Ye, "Optimizing facility layout planning for reconfigurable manufacturing system based on chaos genetic algorithm," *Prod. Manuf. Res.*, vol. 7, no. 1, pp. 109–124, Jan. 2019.

[17] F. Musharavati and A. S. M. Hamouda, "Enhanced simulated-annealing-based algorithms and their applications to process planning in reconfigurable manufacturing systems," *Adv. Eng. Softw.*, vol. 45, no. 1, pp. 80–90, Mar. 2012.

[18] H. A. El Maraghy, "Flexible and reconfigurable manufacturing systems paradigms," *Flexible Service Manuf. J.*, vol. 17, no. 4, pp. 261–276, 2006.

[19] G. Kumar, K. K. Goyal, and N. K. Batra, "Evolution, principles and recent trends in reconfigurable manufacturing system," *J. Phys., Conf. Ser.*, vol. 1240, no. 1, Jul. 2019, Art. no. 012161.

[20] K. Rezaie, M. Dehghanbaghi, and V. Ebrahimipour, "Performance evaluation of manufacturing systems based on dependability management indicators—Case study: Chemical industry," *Int. J. Adv. Manuf. Technol.*, vol. 43, no. 5, pp. 608–619, 2009.

[21] J. Dou, J. Li, D. Xia, and X. Zhao, "A multi-objective particle swarm optimisation for integrated configuration design and scheduling in reconfigurable manufacturing system," *Int. J. Prod. Res.*, vol. 59, no. 13, pp. 3975–3995, Jul. 2021.

[22] O. Battaïa, A. Dolgui, and N. Guschinsky, "Optimal cost design of flow lines with reconfigurable machines for batch production," *Int. J. Prod. Res.*, vol. 58, no. 10, pp. 2937–2952, May 2020.

[23] M. Bortolini, F. G. Galizia, C. Mora, and F. Pilati, "Reconfigurability in cellular manufacturing systems: A design model and multi-scenario analysis," *Int. J. Adv. Manuf. Technol.*, vol. 104, nos. 9–12, pp. 4387–4397, Oct. 2019.

[24] D. Prasad and S. C. Jayswal, "Scheduling in reconfigurable manufacturing system for uncertainty in decision variables," *Mater. Today*, vol. 5, no. 9, pp. 18451–18458, 2018.

[25] A. Kumar, L. N. Pattanaik, and R. Agrawal, "Multi-objective scheduling model for reconfigurable assembly systems," in *Innovations in Soft Computing and Information Technology*. Singapore: Springer, 2019, pp. 209–217.

[26] A. S. Khan, "Multi-objective optimization of a cost-effective modular reconfigurable manufacturing system: An integration of product quality and vehicle routing problem," *IEEE Access*, vol. 10, pp. 5304–5326, 2022.

[27] K. Gumasta, S. K. Gupta, L. Benyoucef, and M. K. Tiwari, "Developing a reconfigurability index using multi-attribute utility theory," *Int. J. Prod. Res.*, vol. 49, no. 6, pp. 1669–1683, Mar. 2011.

[28] A. Khezri, H. H. Benderbal, L. Benyoucef, and A. Dolgui, "Diagnosis on energy and sustainability of reconfigurable manufacturing system (RMS) design: A bi-level decomposition approach," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage. (IEEM)*, Dec. 2020, pp. 141–145.

[29] A. Napoleone and A. L. Andersen, "Reconfigurable manufacturing: How shop floor digitalisation supports operators in enhancing diagnosability," in *Proc. SPS Conf.*, 2020, pp. 1–12.

[30] F. A. Touzout and L. Benyoucef, "Multi-objective sustainable process plan generation in a reconfigurable manufacturing environment: Exact and adapted evolutionary approaches," *Int. J. Prod. Res.*, vol. 57, no. 8, pp. 2531–2547, Apr. 2019.

[31] A. S. Khan, L. Homri, J. Y. Dantan, and A. Siadat, "An analysis of the theoretical and implementation aspects of process planning in a reconfigurable manufacturing system," *Int. J. Adv. Manuf. Technol.*, vol. 119, pp. 1–32, Jan. 2022.

[32] M. A. Saliba, S. Azzopardi, C. Pace, and D. Zammit, "A heuristic approach to module synthesis in the design of reconfigurable manufacturing systems," *Int. J. Adv. Manuf. Technol.*, vol. 102, nos. 9–12, pp. 4337–4359, Jun. 2019.

[33] A. Azab, G. Perusi, H. A. El Maraghy, and J. Urbanic, "Semi-generative macro-process planning for reconfigurable manufacturing," in *Digital Enterprise Technology*. Boston, MA, USA: Springer, 2007, pp. 251–258.

[34] A. Bensmaine, M. Dahane, and L. Benyoucef, "A new heuristic for integrated process planning and scheduling in reconfigurable manufacturing systems," *Int. J. Prod. Res.*, vol. 52, no. 12, pp. 3583–3594, Jun. 2014.

[35] H. H. Benderbal, M. Dahane, and L. Benyoucef, "Exhaustive search based heuristic for solving machine layout problem in reconfigurable manufacturing system design," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 78–83, 2018.

[36] H. Haddou-Benderbal, M. Dahane, and L. Benyoucef, "Hybrid heuristic to minimize Machine's unavailability impact on reconfigurable manufacturing system using reconfigurable process plan," *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 1626–1631, 2016.

[37] A. Lamghari and R. Dimitrakopoulos, "Hyper-heuristic approaches for strategic mine planning under uncertainty," *Comput. Oper. Res.*, vol. 115, Mar. 2020, Art. no. 104590.

[38] M. H. Z. Sabegh, A. Mirzazadeh, E. C. Maass, Y. Ozturkoglu, M. Mohammadi, and S. Moslemi, "A mathematical model and optimization of total production cost and quality for a deteriorating production process," *Cogent Math.*, vol. 3, no. 1, Dec. 2016, Art. no. 1264175.

[39] C. H. Kim, Y. Hong, and S. Y. Chang, "Optimal production run length and inspection schedules in a deteriorating production process," *IIE Trans.*, vol. 33, no. 5, pp. 421–426, May 2001.

[40] M. J. Rosenblatt and H. L. Lee, "Economic production cycles with imperfect production processes," *IIE Trans.*, vol. 18, no. 1, pp. 48–55, Mar. 1986.

[41] M. Hariga and M. Ben-Daya, "Note: The economic manufacturing lot-sizing problem with imperfect production processes: Bounds and optimal solutions," *Nav. Res. Logistics*, vol. 45, no. 4, pp. 423–433, Jun. 1998.

[42] L. Jafari and V. Makis, "Optimal lot-sizing and maintenance policy for a partially observable production system," *Comput. Ind. Eng.*, vol. 93, pp. 88–98, Mar. 2016.

[43] E. H. Aghezzaf, M. A. Jamali, and D. Ait-Kadi, "An integrated production and preventive maintenance planning model," *Eur. J. Oper. Res.*, vol. 181, no. 2, pp. 679–685, Sep. 2007.

[44] A. Khatab, C. Diallo, and I. B. Sidibe, "Optimizing upgrade and imperfect preventive maintenance in failure-prone second-hand systems," *J. Manuf. Syst.*, vol. 43, pp. 58–78, Apr. 2017.

[45] C.-H. Wang, "Integrated production and product inspection policy for a deteriorating production system," *Int. J. Prod. Econ.*, vol. 95, no. 1, pp. 123–134, Jan. 2005.

[46] M. Ben-Daya, S. M. Noman, and M. Hariga, "Integrated inventory control and inspection policies with deterministic demand," *Comput. Oper. Res.*, vol. 33, no. 6, pp. 1625–1638, Jun. 2006.

[47] C.-K. Chen and C.-C. Lo, "Optimal production run length for products sold with warranty in an imperfect production system with allowable shortages," *Math. Comput. Model.*, vol. 44, nos. 3–4, pp. 319–331, Aug. 2006.

[48] B. C. Giri and T. Dohi, "Inspection scheduling for imperfect production processes under free repair warranty contract," *Eur. J. Oper. Res.*, vol. 183, no. 1, pp. 238–252, Nov. 2007.

[49] M. Zhang, O. Gaudoin, and M. Xie, "Degradation-based maintenance decision using stochastic filtering for systems under imperfect maintenance," *Eur. J. Oper. Res.*, vol. 245, no. 2, pp. 531–541, 2015.

[50] A. M. A. Youssef and H. A. El Maraghy, "Assessment of manufacturing systems reconfiguration smoothness," *Int. J. Adv. Manuf. Technol.*, vol. 30, nos. 1–2, pp. 174–193, Aug. 2006.

[51] K. Khanna and R. Kumar, "Reconfigurable manufacturing system: A state-of-the-art review," *Benchmarking, Int. J.*, vol. 26, no. 8, pp. 2608–2635, Sep. 2019.

[52] N. Xie, A. Li, and L. Xu, "Research on diagnosability technique for reconfigurable manufacturing system (RMS)," *Zhongguo Jixie Gongcheng, China Mech. Eng.*, vol. 16, no. 17, pp. 1545–1549, 2005.

[53] J. Liu, Z. Luo, and K. Chen, "Diagnosability of rapidly reconfigurable manufacturing systems," *J. Tsinghua Univ., Sci. Technol.*, vol. 40, no. 8, pp. 14–17, 2000.

[54] G. X. Wang, S. H. Huang, Y. Yan, and J. J. Du, "Reconfiguration schemes evaluation based on preference ranking of key characteristics of reconfigurable manufacturing systems," *Int. J. Adv. Manuf. Technol.*, vol. 89, pp. 2231–2249, Mar. 2017.

[55] J. P. Liu, Z. B. Luo, L. K. Chu, and Y. L. Chen, "Manufacturing system design with optimal diagnosability," *Int. J. Prod. Res.*, vol. 42, no. 9, pp. 1695–1714, May 2004.

[56] C. Rösiö, T. Aslam, K. B. Srikanth, and S. Shetty, "Towards an assessment criterion of reconfigurable manufacturing systems within the automotive industry," *Proc. Manuf.*, vol. 28, pp. 76–82, Jan. 2019.

[57] K. K. Goyal, P. K. Jain, and M. Jain, "Optimal configuration selection for reconfigurable manufacturing system using NSGA II and TOPSIS," *Int. J. Prod. Res.*, vol. 50, no. 15, pp. 4175–4191, Aug. 2012.

[58] I. Khettabi, L. Benyoucef, and M. A. Boutiche, "Sustainable reconfigurable manufacturing system design using adapted multi-objective evolutionary-based approaches," *Int. J. Adv. Manuf. Technol.*, vol. 115, nos. 11–12, pp. 3741–3759, Aug. 2021.

[59] A. S. Khan, L. Homri, J. Y. Dantan, and A. Siadat, "Cost and quality assessment of a disruptive reconfigurable manufacturing system based on MOPSO Metaheuristic," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 10431–10436, 2020.

[60] L. While, P. Hingston, L. Barone, and S. Huband, "A faster algorithm for calculating hypervolume," *IEEE Trans. Evol. Comput.*, vol. 10, no. 1, pp. 29–38, Jan. 2006.

[61] K. K. Goyal, P. K. Jain, and M. Jain, "A novel methodology to measure the responsiveness of RMTs in reconfigurable manufacturing system," *J. Manuf. Syst.*, vol. 32, no. 4, pp. 724–730, Oct. 2013.

[62] P. Renna, "Capacity reconfiguration management in reconfigurable manufacturing systems," *Int. J. Adv. Manuf. Technol.*, vol. 46, nos. 1–4, pp. 395–404, Jan. 2010.

[63] A. Dolgui, D. Ivanov, and B. Sokolov, "Reconfigurable supply chain: The X-network," *Int. J. Prod. Res.*, vol. 58, no. 13, pp. 4138–4163, Jul. 2020.

[64] N. Cai, L. Wang, and H.-Y. Feng, "GA-based adaptive setup planning toward process planning and scheduling integration," *Int. J. Prod. Res.*, vol. 47, no. 10, pp. 2745–2766, May 2009.

[65] F. A. Touzout and L. Benyoucef, "Multi-objective multi-unit process plan generation in a reconfigurable manufacturing environment: A comparative study of three hybrid metaheuristics," *Int. J. Prod. Res.*, vol. 57, no. 24, pp. 7520–7535, Dec. 2019.

[66] B. I. Epureanu, X. Li, A. Nassehi, and Y. Koren, "An agile production network enabled by reconfigurable manufacturing systems," *CIRP Ann.*, vol. 70, no. 1, pp. 403–406, 2021.

[67] M. Baldea and I. Harjunkoski, "Integrated production scheduling and process control: A systematic review," *Comput. Chem. Eng.*, vol. 71, pp. 377–390, Dec. 2014.

ABDUL SALAM KHAN received the B.S. degree in mechanical engineering from UET Peshawar, Pakistan, in 2012, the M.S. degree in engineering management from the college of E&ME, NUST, Islamabad, Pakistan, 2014, and the Ph.D. degree in industrial engineering, related to the optimization of manufacturing system performance, France.

Since 2012, he has been teaching courses related to engineering and business management, to undergraduate, master's, and MBA students. He is currently working as an Assistant Professor with the Department of Operations and Supply Chain, NUST Business School (NBS), NUST. His research interests include the domain of manufacturing systems and supply chains. His conferences and journal articles have been published on the platforms of IEEE, Elsevier, Springer, and ACM. He has served as a reviewer for Taylor & Francis and IEEE Access. In addition, he has chaired sessions on topics, such as supply chain management at IEEE conferences.