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Multi-Objective Optimization of a Cost-Effective Modular Reconfigurable Manufacturing System: An Integration of Product Quality and Vehicle Routing Problem

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ABSTRACT A reconfigurable manufacturing system offers several manufacturing routes to produce the same product. Each manufacturing route considers different production, reconfiguration, and module changing time which can potentially impact the delivery time of a product to the customer location. This study considers the impact of different reconfigurable manufacturing routes and quality concerns on the efficiency of a vehicle routing problem. The reconfigurable manufacturing system produces different products while the vehicle routing problem distributes the products to different customer locations. The analysis is conducted by using two important reconfigurable manufacturing system characteristics i.e., modularity and scalability, to assess their impact on manufacturing and supply chain systems. A multi-objective model containing the objectives of the total cost, the total time, the scalability, and the modularity is proposed to analyze the problem. The model is subsequently implemented by using a two-phased meta-heuristic approach using automatic calibration. In the first phase, production analysis is examined by using different reconfigurable machines through the application of a non-sorting genetic algorithm embedded with an absorption policy and multiple crossover operators based on simulated annealing. The second phase considers the delivery of products to different customer locations through the application of a variable neighborhood search approach.

INDEX TERMS Modularity, non-sorting genetic algorithm, optimization, quality variation, reconfigurable manufacturing system, scalability, simulated annealing, variable neighborhood search, vehicle routing problem.

I. INTRODUCTION

Reconfigurable Manufacturing System (RMS) is an active field of research, and it has been regarded as one of the main challenges of the future by the Committee on Visionary Manufacturing Challenges [1]. RMS is distinguished from other manufacturing systems due to its ability to provide multiple machine settings. Each machine in a reconfigurable manufacturing system comprises a sequence of settings called configurations. Thus, a machine may have multiple configurations depending on the number of possible changes between configurations. For example, the settings of a machine can be changed from one configuration to another configuration by adding/removing/adjusting tools, modules, tool approach directions, etc. This aspect of manufacturing system is called reconfigurability. Due to several machine configurations, RMS is capable of accommodating product variety as well as high volume of production.

As RMS can provide a large variety of products, several customer classes, dispersed at different locations, can be anticipated. To meet the demand of all customer classes, a manufacturing system can either outsource or use an effective and responsive supply chain. A major concern of the RMS system is to carefully design the supply chain by taking maximum advantage of transportation and to avoid delay in delivery [2]. Any delay in delivering the product

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to the customer will affect customer satisfaction and future purchases.

The supply chain has gained increased research attention due to its role in business processes. A salient problem addressed in supply chain literature is the vehicle routing problem (VRP) which delivers the demand of various products to a set of customers. In the existing literature, the efficiency of VRP has been analyzed by using the objectives of travel distance, minimizing the number of vehicles by using different solution approaches [3]. However, the efficiency of VRP has not been analyzed in the context of a reconfigurable manufacturing system. In RMS, different sets of configurations can perform the same operation. It means that different production times, reconfiguration times, modular adjustment times can be anticipated depending on the set of configurations chosen for manufacturing. This may cause variability in the time to deliver the products to the depot and can influence the further dispatching time of products in a VRP problem. As shown in Figure 1, a product is to be created through the sequence of six operations (O_1-O_6). Each operation can be processed by the combination of different configurations. A variable delivery time to customer location can be observed depending on the sequencing of operations on machine configurations (also called process planning). In some cases, the delivery is made within the preferred time zone, whereas a penalty due to early/late arrival can be observed in other cases. The early arrival at the customer location is a cause of concern for the manufacturing system as the products will wait at the customer locations until the start of the preferred time windows. The late arrival of products to customer locations impacts both manufacturers as well as the customer. It is assumed in this study that the raw material is already available at the manufacturing facility and the vehicle routing problem examines only the distribution of products to different customer locations.

One way to avoid the time variability is by taking advantage of the scalability and modularity of a reconfigurable manufacturing system by installing extra machines in parallel which can produce an extra quantity of production to avoid such delays. For example, the capacity of RMS can be increased by installing machine configurations to produce more in a limited time, thereby, enabling the manufacturing system to reduce the anticipated delay.

The second cause of concern is machine disruption and quality variation of manufacturing systems. A machine with a pre-defined capacity can fulfill the required demand of 'd' units. However, in the presence of disruption and quality variation, few product units are discarded which necessitates an increase in the production capacity to meet demand.

RMS problems are NP-hard and are typically solved by evolutionary algorithms (e.g., non-sorting genetic algorithm). During the execution of an algorithm, crossover operators, such as order crossover, partially mapped crossover are used to refine the solutions. A random proportion of parent string is chosen to generate offspring. In contrast, this study uses a novel mechanism for the selection of a proportion of string to generate offspring.

This study considers the role of machine disruption, quality variation of a reconfigurable manufacturing system in the context of the overall supply chain. A manufacturing-routing (i.e., RMS-VRP) framework is analyzed by proposing a multi-objective model. Two important RMS characteristics i.e., modularity and scalability are integrated into the model. The model contains the objectives of the total cost (TC), the total time (TT), the scalability (S), and the modularity (M). A two-phased approach is implemented to solve the RMS-VRP problem. In the first phase, a modified version of the non-sorting genetic algorithm, embedded with an absorption policy and several crossovers is implemented to solve the RMS problem. In the second phase, a variable neighborhood search approach is used to address the vehicle routing problem.

The remaining study is organized as follows. Section II describes the literature related to reconfigurable manufacturing systems and vehicle routing problems. The literature on RMS is reviewed regarding two of its main characteristics i.e., scalability and modularity. Section III discusses the problem statement and mathematical model to optimize the cost, time, scalability, and modularity. Section IV describes the hybrid solution approach of NSGA-II-VNS, combining the strengths of the genetic algorithm and variable neighbourhood search approach. Section V describes the results and offers managerial implications. Finally, Section VI concludes the findings and contains future research recommendations.

II. LITERATURE REVIEW

A. SCALABILITY ANALYSIS IN RMS

Scalability is central to the performance of RMS, and it allows the rapid and cost-effective adjustment of a system to dynamic changes in demand. In this sense, the original RMS design is important for the optimal transition [4].

In [5], the authors proposed a mathematical model for upscaling the capacity of machines designed in series. In another study [6], authors optimized the number of machines needed for capacity scalability to meet demand. Reconfigurable and computerized numerical control machines were used for designing a scalable reconfigurable system. The focus was on meeting the revised market demand by rebalancing a manufacturing system.

In a subsequent study [7], a mathematical model was proposed for a system that contained storage buffers. The goal was to maximize the throughput once the system is reconfigured. In [8], the authors introduced a dynamic scalable model aimed at reducing delay in scaling a reconfigurable system.

Although there is enough emphasis on scalability in the design of RMS systems, the established literature does not consider the impact of machine disruption, product failure, and delayed transportation to the depot on the need to scale a manufacturing system. Intuitively, product failure can trigger extra production to meet the level of demand. In addition, different configurations will need different production, module

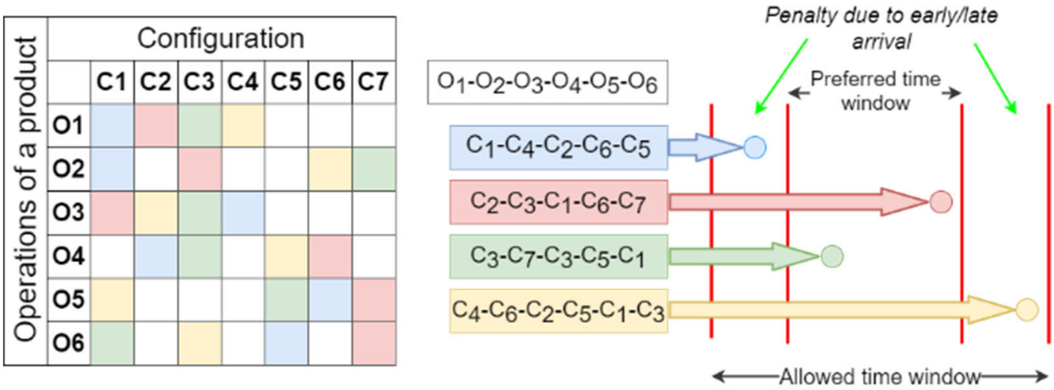

FIGURE 1. An illustration of assignment of operations to configurations and product delivery.

adjustment, configuration change time, etc. which means that the product may reach the depot with a delay, depending on the selection of the different sets of reconfigurable machines. An attempt is made through this study to analyze the need for scalability due to product failure and late delivery to depot. We embed scalability at the outset/initial RMS design as it is a standard practice in the established literature [6], [9].

B. MODULARITY ANALYSIS IN RMS

Modularity is an integral characteristic of RMS, and it allows the re-use, enhances the chances of fast-paced introduction of new techniques, and facilitates the allocation of resources with more ease [10]. In that sense, modularity is advantageous, and it helps in the reduction of manufacturing costs by minimizing the expenses needed in planning and shortens the changing time between different units [11].

Ref. [12] offered an approach to optimally select modular instances of a reconfigurable manufacturing system. A trade-off between the quality loss due to modularity and the reconfiguration cost was assessed by using a non-linear integer programming model. Ref. [8] discussed a trade-off between the responsiveness and the cost of a modular reconfigurable system. Ref. [9] studied modularity in the context of a scalable reconfigurable system. A mathematical model was used to consider the optimal number of modules in a scalable manufacturing system. The findings suggested a trade-off between the use of additional modules and the loss due to a decline in their availability.

Ref. [13] designed a cellular reconfigurable manufacturing system to group modular machines for performing several operations. Two objective functions were minimized by using an evolutionary solution approach. In [14], the authors proposed a mathematical model for a cellular reconfigurable manufacturing system. The approach was based on attaining a trade-off between the installation of the auxiliary module and the auxiliary module transportation/flow among different cells. The model optimized the objectives of the part travel time among cells, auxiliary module travel time, and the reconfiguration time needed to install and disassemble the auxiliary modules.

The performance of RMS has frequently been analyzed by modeling the modularity characteristic. However, the existing literature does not consider the extra modularity (modularity effort) needed in the presence of machine disruption (product failure) and to avoid the late arrival of product to depot. In this sense, this study considers the behavior of modularity in the context of the overall supply chain. By selecting different reconfigurable machines, we examine how modularity may be impacted under different circumstances. Like the application of scalability, modularity is embedded at the outset of the RMS design to reduce the life cycle costs and to synchronize the overall production [15], [16]. Ref. [17] suggested that a modular manufacturing system can prove to be more productive in the presence of equipment/machine failure.

Table 1 provides the summary of selected studies in RMS literature. Although scalability and modularity have been discussed in different studies, they have never been modeled keeping in view the quality defects and supply chain performance. These aspects are important as a defective RMS will discard few failed products and hence extra scalability and modularity will be needed to fulfill the demand. It can be observed from Table 1 that none of the existing studies has mathematically examined the role of RMS in the context of a supply chain. Lastly, genetic algorithms have been frequently used as solution approaches in solving the RMS problems and few studies have used more than one meta-heuristic in assessing the RMS performance. This study uses NSGA-II and VNS as solution approaches for assessing the performances of a reconfigurable manufacturing system and a vehicle routing problem. A novel mechanism is adopted to assess the impact of genetic operators on the performance efficiency of solution approaches.

C. VEHICLE ROUTING PROBLEM

VRP is a famous problem addressed in the supply chain literature, which was first proposed by [30]. In the VRP, a set of vehicles starts from one or multiple depots and visits

TABLE 1. Summary of selected studies in RMS literature.

Ref.	Objective function focus			Cost-Quality	Time-Quality	Scalability definition	Modularity definition	Supply chain analysis	Multiple heuristics			
	Cost	Time	Quality						GA family	MOPSO	VNS	Other
[6]	✓					Throughput			✓			
[18]	✓											
[19]	✓	✓							✓	✓		
[20]	✓					Scaling up RMS	Changing modules					AHP
[21]	✓	✓							✓			SPEA-II, e-constraint
[22]	✓	✓							✓			e-constraint
[2]	✓	✓							✓			
[23]		✓										
[24]	✓								✓			
[25]	✓								✓			
[26]		✓							✓			
[11]	✓	✓					Machine diversity					AMOSA
[27]	✓	✓										Weighted Goal Programming
[28]												Simulation
[29]	✓											Artificial Immune System

different customer nodes to fulfill demands and come back to their respective depot. In doing so, the VRP considers an optimal route to satisfy the requirements of different objective functions. In this section, we present an overview of the VRP literature regarding the production scheduling and quality focus.

The integration of production scheduling and product distribution is central to the performance of a supply chain. It is more important to closely monitor the production scheduling in RMS, as a particular schedule may impact the delivery time of a product. Though the existing literature lacks in integrating the reconfigurable manufacturing system scheduling and a vehicle routing problem, the integration of production scheduling and vehicle routing problem is well established in the literature of other manufacturing systems. For example, in [31], the authors studied a joint machine scheduling and VRP problem where the machine was switched between two products in a period. The objective of carbon emissions was optimized through the application of a tabu search algorithm.

Martins *et al.* [32] provided a co-ordinated framework for a hybrid flow shop production and a vehicle routing problem. A capacitated vehicle was used to deliver the products to different customer locations. The goal of the co-ordinated framework was to optimize the service time of the last customer. The model was implemented by using a biased-randomized variable neighbourhood descent metaheuristic. In [33], the authors offered an integrated approach for production scheduling and vehicle routing problem. The case of a make-to-order production was analysed by using a single machine and capacitated vehicles. The goal was to optimize the order delivery time. A genetic algorithm and a two-stage algorithm were used for obtaining the results.

Fu *et al.* [34] studied the integrated problem of production scheduling and vehicle routing problem. The production job was split onto unrelated machines, and the finished products were delivered to the customer locations by using heterogeneous vehicles. A two-phase iterative heuristic was used for optimizing the setup cost and the transportation cost. In [35], the authors considered the production and distribution of products to different customers in a routing problem. The aim was to decide the timing and the quantity of production and when to offer the products to different customers. The model was solved by using a heuristic designed in different phases. In another study [31], the objectives of cost and carbon emissions were minimized in an integrated manufacturing and distribution framework. A VRP model integrated with manufacturing capacity and driver regulations was studied in [36]. The goal was to establish routes for vehicles by fulfilling the delivery and collection needs of different customers.

To some extent, the VRP literature has emphasized on the quality of products. As an example, [37] addressed a closed-loop inventory routing problem by considering a mixed quality defects-based model. The model was applied to the e-commerce industry, and it analyzed the defective and non-defective returns. However, the study did not quantify the defective number of items during transportation or the role of disruptive manufacturing in the proposed model.

Table 2 summarizes the literature of selected studies in the VRP literature. Cost has repeatedly been used as an objective function in assessing the performance of a vehicle routing problem. Time and distance have also been selected to understand the behavior of vehicle routing problems. In the context of a production system, quality analysis and arrival time concerns at the depot and customer locations have not been studied for a changeable/reconfigurable manufacturing system. In other words, the existing literature does not consider the role of VRP in a reconfigurable manufacturing system. As RMS provides multiple production routes, the selection of a particular route may cause variation in the time to deliver the products to the customer locations.

The contributions offered by this study can be summarized as:

- A vehicle routing problem integrated with a reconfigurable manufacturing system (RMS-VRP) is analysed by considering the modularity and scalability RMS characteristics.
- A multi-objective model is proposed that considers the objectives of the total cost, the total time, the scalability, and the modularity in a joint manufacturing-routing problem.
- The model considers the role of quality variation/defects and the late arrival of products to the depot and customer locations.

TABLE 2. Summary of selected studies in vehicle routing problem literature.

	Objective function			Production system analysis			
Ref.	Cost	Distance	Time	Quality Analysis	Arrival time at depot	Changeability analysis	Solution approaches
[38]	√						
[39]	√						LNS
[40]	√						
[41]	√						LNS
[42]	√						LNS
[43]	√						ILS SP
[44]	√						NSGA-II
[45]			√				LNS
[46]	√						NSGA-III
[47]	√						NSGA-II
[48]		√	√				Clarke and Wright Saving Heuristic
[49]	√						LNS, SA
[50]		√					VNS, TS
[51]		√					SA
[52]	√						Artificial Fish Swarm
[53]		√					SA
[54]							LNS
[55]	√						SA, LNS
[56]			√				LNS
[57]	√						
[58]	√						GA

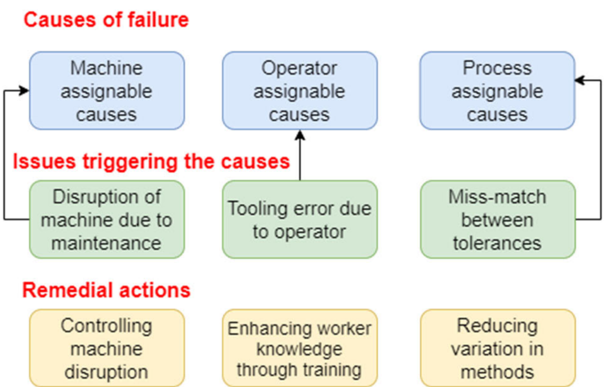

FIGURE 2. Manufacturing System Design Decomposition based quality variation and sources of defects [59].

- A novel solution approach based on a hybrid and automatically calibrated form of NSGA-II-VRP is implemented in the south asian manufacturing industry.

III. PROBLEM STATEMENT AND MATHEMATICAL MODEL

A. RMS PROBLEM STATEMENT

The manufacturing is performed by using a set of reconfigurable machines while the distribution is studied through a vehicle routing problem (VRP). Several product types (P), each comprising sequence of operations (O) are to be produced by using the available machine configurations (I). Due to quality variation, machine configuration i exhibits a disruptive profile and it produces failed operation units (fo_o^i). As shown in Figure 2, based on our previous framework of manufacturing system design decomposition (MSDD) [59], the quality variation can be attributed to poor maintenance, tolerance error, and tooling issues, etc. Thus, the number of operation units entering configuration i will always be greater than what enters configuration $i+1$ due to the removal of failed units. As the level of demand is to be respected, extra units are produced to compensate for the failed operation units. This will require scaling up the RMS and the need to use extra modularity. The products are shifted to a nearby depot once the required level of demand is produced. It is worth noticing that different configurations will consider different production times, module adjustment times, configuration change times, and extra production times to compensate for the failed products. Thus, the selection of different configurations may cause a delay in delivering the products to the depot.

B. VRP PROBLEM STATEMENT

From depot onwards, a vehicle routing problem (VRP) is analyzed where a set of customer locations (r, s) is to be visited to fulfill the demand of locations (d_p^s). All vehicles ($t \in T$) come back to the depot after completing the demand of customer locations.

The aim is to design the manufacturing-routing network by minimizing the effect of variation on production and the effect of late arrival to the depot on the efficiency of a vehicle routing problem. A set of machine configurations (i) is to be selected which can warrant the minimum number of failed operation units and a minimum delay in delivering the products to the customer locations. A multi-objective model is presented to optimize the total cost (TC), the total time (TT), the scalability (S), and the modularity (M) of a reconfigurable manufacturing system. The model description is given below.

INDEXES

Q	*index for quality characteristic* $q \in Q{:}q = \{1, 2, \ldots Q\}$
o	*index for operation* $o \in O{:}o = \{1, 2, \ldots O\}$
$i, \acute{i}$	*index for configuration* $i, \acute{i} \in I{:}i, \acute{i} = \{1, 2, \ldots I\}$
$m, \acute{m}$	*index for module* $m, \acute{m} \in M{:}m, \acute{m} = \{1, 2, \ldots M\}$
t	*index for vehicle* $t \in T{:}t = \{1, 2, \ldots T\}$
r, s	*index for customer location* $r, s \in S : r, s = \{1, 2, \ldots S\}$
p	*index for product type* $p \in P{:}p = \{1, 2, \ldots P\}$

PARAMETERS

ec_i	*exploitation cost of configuration i*
$cc_{i\acute{i}}$	*configuration change cost between conf.i and* $\acute{i}$
mac_i^m	*module adjustment cost of module m on conf.i*
sc_o^p	*scrap cost of operation o of product p*
wc_p^s	*waiting cost per product p at customer location s*
lc_p^s	*late arrival cost per product p at location s*
tc_p	*transportation cost per product p per km distance*
pc_o^p	*production cost of operation o of product p*
dc_p	*delay cost per product per minute at depot*
$ct_{i\acute{i}}$	*configuration change time between conf.i and* $\acute{i}$
mat_i^m	*module adjustment time of module m on conf.i*
$fr_i^{k,o}$	*failure rate of character is tick of op.o on on conf.i*
pt_o^p	*production time of operation o of product p*
e_p^d	*expected time of product p to arrive at depot*
$[et_p^s, lt_p^s]$	*time window of product p at customer location s*
v_t	*speed of vehicle t*
di_{rs}	*distance between customer locations r and s*
QC_q^o	1, *if characteristic q belongs to operation o, otherwise* 0
Zl_o^p	1, *if operation o belongs to product p, otherwise* 0
$L\acute{o}^p$	*precedence order of operation o in product p*
d_p^s	*demand of product p at customer location s*
cl_s^p	1, *if product p is needed by location s, otherwise* 0
NO_o^p	*number of operations in product p*
Ca_i	*production capacity of configuration i*
n_i	*quantity of operation units entering the RMS*
$NM_a^{o,\acute{o}}$	*number of modules added between op.o and* $\acute{o}$
$NM_s^{o,\acute{o}}$	*number of modules subtracted between op.o and* $\acute{o}$

DECISION VARIABLES

t_o^p	*time when product p arrives at depot*
x_i^o	1, *if operation o is assigned to conf.i, otherwise* 0
$y_{i,m,\acute{m}}^{o,\acute{o}}$	1, *if between ops.o and* $\acute{o}$, *there is a change of module from m to* $\acute{m}$ *on configuration i, otherwise* 0
$\omega_{i,\acute{i}}^{o,\acute{o}}$	1, *if between ops.o and* $\acute{o}$, *there is a change of conf. from i to* $\acute{i}$, *otherwise* 0
qo_o^i	*quantity of operation units o enterting conf.i*
fo_o^i	*failed operation units on configuration i*
t_s^p	*arrival time of product p at customer location s*
$g_{p,t}^{r,s}$	1, *if p is transported by k between r and s, otherwise 0*
$ma_i^{o,\acute{o}}$	*number of modules added between ops.o and* $\acute{o}$
$ms_i^{o,\acute{o}}$	*number of modules subtracted between ops.o and* $\acute{o}$

C. THE TOTAL COST

The objective function of the total cost (TC) examines the economic performance of RMS and VRP. Equation (1) contains the TC objective function which comprises ten (10) components. The first six (6) components are related to RMS while the remaining four components are related to VRP. These cost components are discussed below:

$$TC = CEC + CCC + PRC + MAC + EPC + SC + DCD + WC + LAC + TRC \tag{1}$$

The configuration exploitation cost (CEC) calculates the cost of using a machine setting, i.e., configuration. Each configuration has a cost value that depends on the number of tools, modules, etc. it offers.

$$CEC = \sum_{o\in O}\sum_{i\in I} x_i^o \times ec_i \tag{2}$$

The configuration change cost (CCC) (eq. 3) calculates the cost of reconfiguration if there is a change of configuration during processing the sequence of operations.

$$CCC = \sum_{o,\acute{o}\in O}\sum_{i,\acute{i}\in I} \omega_{i,\acute{i}}^{o,\acute{o}} \times cc_{i,\acute{i}} \tag{3}$$

The production cost (PRC) (eq. 4) expression calculates the production cost of the units entering configuration i.

$$PRC = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times qo_o^i \times pc_o^p \tag{4}$$

The module adjustment cost (MAC) (eq. 5) calculates the cost involved in changing modules on the same machine configuration. It will be calculated only if there is a change of modules between the sequence of operations.

$$MAC = \sum_{m,\acute{m}\in M}\sum_{o,\acute{o}\in O}\sum_{i\in I} y_{i,m,\acute{m}}^{o,\acute{o}} \times mac_i^m \tag{5}$$

The RMS produces extra quantity to compensate for the failed production. This extra quantity is exactly equal to the failed units produced (fo_o^i). Eq. 6 calculates the extra production cost (EPC) value.

$$EPC = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times fo_o^i \times pc_o^p \tag{6}$$

Eq. 7 calculates the scrap cost (SC) value associated with the production of failed units.

$$SC = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times fo_o^i \times sc_o^p \tag{7}$$

Eqs. (8-11) are the cost expressions associated with the VRP problem. Eq. 8 calculates the delay cost of transferring products to the depot (DCD). This delay is caused by the modular adjustments, changing configurations, etc. between the selected configurations and sequencing the operations.

$$DCD = \sum_{s\in S}\sum_{p\in P} max(0, t_o^p - ed_p) \times dc_p \times d_p^s \tag{8}$$

The products, if arrived early, will wait at the customer location until the start of preferred delivery time-window. Eq. (9) calculates the waiting cost (WC) at the customer location.

$$WC = \sum_{s\in S}\sum_{p\in P} cl_s^p \times max(0, et_p^s - t_s^p) \times wc_p^s \times d_p^s \tag{9}$$

There will be a penalty of late arrival if the products arrive at the customer location beyond the preferred time-window. Eq. (10) calculates the penalty cost of late arrival (LAC) at the customer location.

$$LAC = \sum_{s\in S}\sum_{p\in P} cl_s^p \times max(0, t_s^p - lt_p^s) \times lc_p^s \times d_p^s \tag{10}$$

Eq. (11) calculates the transportation cost (TRC) towards the customer locations. It considers the distance between customer locations r and s, and the speed of vehicle during transportation.

$$TRC = \sum_{r,s\in S}\sum_{t\in T}\sum_{p\in P} g_{p,t}^{r,s} \times d_p^s \times tc_p \times (\frac{di_{rs}}{v_t}) \tag{11}$$

D. THE TOTAL TIME

The objective function of the total time (TT) is given in eq. (12) and its components are detailed below.

$$TT = CCT + MAT + EPT + LPT + PRT + DTD + WT + TRT \tag{12}$$

The configuration change time expression (CCT) (eq. 13) calculates the time needed during changing the machine setting from one configuration to another configuration.

$$CCT = \sum_{o,\acute{o}\in O}\sum_{i,\acute{i}\in I} \omega_{i,\acute{i}}^{o,\acute{o}} \times ct_{i,\acute{i}} \tag{13}$$

The module adjustment time (MAT) on a configuration is calculated using eq. (14). It involves the addition/subtraction/re-adjustment of a module according to the operational needs of a product.

$$MAT = \sum_{m,\acute{m}\in M}\sum_{o,\acute{o}\in O}\sum_{i\in I} y_{i,m,\acute{m}}^{o,\acute{o}} \times mat_i^m \tag{14}$$

The extra production time (EPT) needed to compensate for the failed units is calculated using eq. (15).

$$EPT = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times fo_o^i \times pt_o^p \tag{15}$$

The production of failed units means that a useful time is lost. This component of time is calculated by the lost production time (LPT) expression (eq. 16).

$$LPT = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times fo_o^i \times L\acute{o}^p \times pt_o^p \tag{16}$$

The production time (PRT) required to meet the level of demand at different customer locations is calculated by using eq. (17).

$$PRT = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times qo_o^i \times pt_o^p \tag{17}$$

The time delay in transferring the product to the depot is calculated by the DTD expression (eq. 18).

$$DTD = \sum_{s\in S}\sum_{p\in P} max(0, t_o^p - ed_p) \times d_p^s \tag{18}$$

The waiting time (WT) at the customer location is calculated using eq. (19). The products will wait at the destination until the start of the preferred time-window.

$$WT = \sum_{s\in S}\sum_{p\in P} cl_s^p \times max(0, et_p^s - t_s^p) \tag{19}$$

The transportation time (TRT) needed to deliver the products to different customer locations is calculated using eq. (20).

$$TRT = \sum_{r,s\in S}\sum_{t\in T}\sum_{p\in P} g_{p,t}^{r,s} \times (\frac{di_{rs}}{v_t}) \tag{20}$$

E. SCALABILITY

There are two concerns that necessitate a scalable RMS, i.e., the arrival-related concerns, and the defective production. Eq. 21 contains the objective function of the scalability (S), and it comprises the number of extra machines required to meet demand due to failed units (NMD) and the number of extra machines required to avoid the late arrival at the depot (NML).

$$S = (\frac{1}{NMD}) + NML \tag{21}$$

The expressions for NMD and NML are provided in eq. 22 and eq. 23, respectively. NMD considers the decrease in production capacity due to failed products. Thus, the ratio of demand and effective production capacity (total capacity-failed products) is used to calculate the number of reconfigurable machines.

$$NMD = \sum_{p\in P}\sum_{s\in S}\sum_{o\in O}\sum_{i\in I} \left(\frac{x_i^o \times d_p^s \times NO_o^p}{Ca_i - fo_o^i} \right) \tag{22}$$

NML is expressed as the ratio of delay time and production time. For instance, if delay time has a value of 50 minutes and production time is 100 minutes, the production efficiency needs to be increased by 0.5. In other words, the production efficiency needs to be increased by 50% by installing a parallel production system that is half as much efficient as the original RMS system. The detailed expression for NML is given in eq. 24.

$$NML = \frac{DTD}{PRT} \tag{23}$$

$$NML = \sum_{s\in S}\sum_{p\in P}\sum_{o\in O}\sum_{i\in I}\left(\frac{max(0, t_o^p - ed_p) \times d_p^s}{x_i^o \times qo_o^i \times pt_o^p}\right) \tag{24}$$

F. MODULARITY

The objective function of the modularity (M) is given in eq. 25 and it is the sum of the extra modularity efforts to compensate the scrapped products (MES) and the extra modularity effort to avoid the late arrival at depot (MEL).

$$M = MES + MEL \tag{25}$$

The expression of MES is given in eq. 26. As extra quantity is produced which is equal to the number of failed products, MES calculates the extra modularity effort needed for this production. In eq. (26), $NM_a^{o,\acute{o}}$ and $NM_s^{o,\acute{o}}$ consider the modules added and subtracted between respective operations, in that order.

$$MES = \sum_{o,\acute{o}\in O}\sum_{i\in I} \begin{array}{l} x_i^o \times fo_o^i \times (\alpha \times NM_a^{o,\acute{o}} + \\ \beta \times NM_s^{o,\acute{o}}) \end{array} \tag{26}$$

The MEL component of modularity is given in Eqs. (27) and (28). MEL is the product of the number of machines required to avoid the late arrival (NML) and the associated modularity effort.

$$MEL = \sum_{o,\acute{o}\in O}\sum_{i\in I} NML \times (\alpha \times NM_a^{o,\acute{o}} + \beta \times NM_s^{o,\acute{o}}) \tag{27}$$

$$MEL = \sum_{s\in S}\sum_{p\in P} \begin{array}{l} \sum_{o,\acute{o}\in O}\sum_{i\in I}\left(\frac{\max(0, t_o^p - ed_p) \times d_p^s}{x_i^o \times qo_o^i \times pt_o^p}\right) \times \\ (\alpha \times NM_a^{o,\acute{o}} + \beta \times NM_s^{o,\acute{o}}) \end{array} \tag{28}$$

G. CONSTRAINTS

The actual time for a product to arrive at the depot is given in eq. 29. The products arrive at the depot once the production time, module adjustment time, extra production time, and configuration change time components of the total time are added.

$$t_o^p = PRT + MAT + EPT + CCT \tag{29}$$

All units entering the RMS system are fed to the first configuration (eq. 30).

$$qo_o^1 = n_o \tag{30}$$

For the remaining configurations, the incoming units are equal to the units coming from the previous configuration minus the failed units (eq. 31).

$$qo_o^i = Zl_o^p \times x_i^o \times (n_{i-1} - fo_o^{i-1}) \tag{31}$$

The number of failed units is calculated by using eq. 32.

$$fo_o^i = Qc_q^o \times x_i^o \times fr_i^{k,o} \times n_i \tag{32}$$

The time taken by the products to arrive at the customer location is calculated by using eq. 33 and it is the sum of the time to arrive at the depot and the transportation time. In this case, we compute the total time taken by a product from the state of raw material to its final delivery to the customer.

$$t_s^p = t_o^p + TRT \tag{33}$$

An operation is to be performed by only one machine configuration (eq. 34).

$$\sum_{i\in I} x_i^o = 1; \quad \forall o = \{1, 2, \ldots O\} \tag{34}$$

Between two operations, there can be at most one configuration change (eq. 35).

$$\sum_{i\in I} \omega_{i,\acute{i}}^{o,\acute{o}} \leq 1; \quad \forall o, \acute{o} = \{1, 2, \ldots O\} \tag{35}$$

The required level of demand should be fulfilled by balancing the produced quantity (PQ) and the failed products (FP) (eq. 36).

$$d_p^s \geq PQ - FP; \quad \forall s = \{1, 2, \ldots S\}, \quad \forall p = \{1, 2, \ldots P\} \tag{36}$$

The expressions for PQ and FP are provided in Eqs. 37 and 38, respectively.

$$PQ = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times (qo_o^i - fo_o^i) \tag{37}$$

$$FP = \sum_{p\in P}\sum_{o\in O}\sum_{i\in I} x_i^o \times fo_o^i \tag{38}$$

Eqs. 39 and 40 ensure that a vehicle starts and ends its trip at the depot, respectively.

$$\sum_{s\in S}\sum_{p\in P} g_{p,t}^{r,s} = 1; \quad \forall t = \{1, 2, \ldots T\} \tag{39}$$

$$\sum_{p\in P} g_{p,t}^{r,s} = 1; \quad \forall t = \{1, 2, \ldots T\} \tag{40}$$

Eq. 41 necessitates that each customer location should be visited exactly once while eq. 42 ensures that all customer locations should be visited.

$$\sum_{s\in S}\sum_{t\in T}\sum_{p\in P} g_{p,t}^{r,s} = 1; \quad \forall r = \{1, 2, \ldots S\} \tag{41}$$

$$\sum_{r\in S}\sum_{t\in T}\sum_{p\in P} g_{p,t}^{r,s} = 1; \quad \forall s = \{1, 2, \ldots S\} \tag{42}$$

Eq. 43 ensures that if an operation is assigned to a configuration, the Tool Approach Directions (TAD) of both operation and configuration need to be compatible.

$$x_i^o \times TAD\,[i] = TAD\left[o^P\right] \tag{43}$$

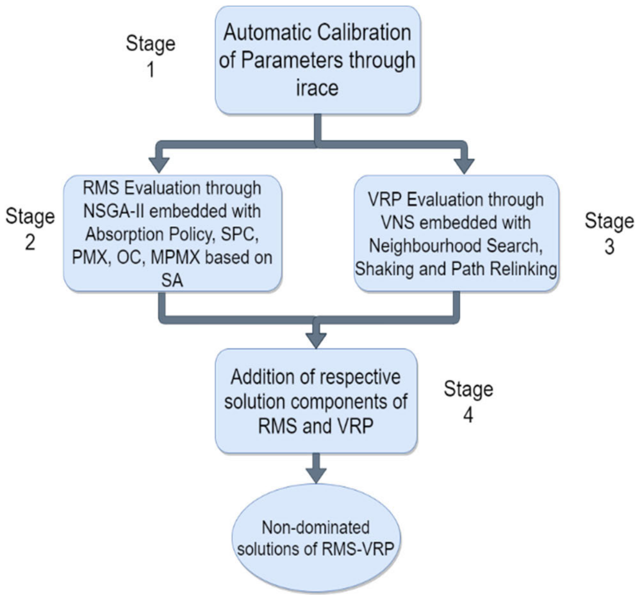

FIGURE 3. A stage-wise implementation of solution approach.

Lastly, Eqs. 44 and 45 are boundary constraints where eq. 44 states the binary variables while eq. 45 contains the non-negative variables.

$$x_i^o, y_{i,m,\acute{m}}^{o,\acute{o}}, \omega_{i,\acute{i}}^{o,\acute{o}}, g_{p,t}^{r,s} \in \{0, 1\} \tag{44}$$

$$t_o^p, qo_o^i, fo_o^i, t_s^p \geq 0 \tag{45}$$

IV. SOLUTION APPROACHES

A. A TWO-PHASE HYBRID SOLUTION APPROACH

Reconfigurable manufacturing system and vehicle routing problems are a non-polynomial hard set of problems as they involve complex analysis of different variables. Meta-heuristics are appropriate approaches for solving such complex problems. In addition, there has been a trend to hybridize several meta-heuristics to take advantage of the unique capabilities of each meta-heuristic. There are multiple examples in the literature where the hybridization of different approaches has been used to solve the relevant problems such as in [60]–[62]. In this study, a hybrid version of the genetic algorithm (NSGA-II) and variable neighborhood search (VNS) is used in different phases to solve the RMS-VRP problem. The framework of stage/phase-wise implementation of solution approaches is provided in Figure 3.

In stage 1, the input parameters of NSGA-II and VNS are automatically calibrated by using the budget, cost function, optimization, and statistical analysis (to be discussed later). In stage 2, a non-sorting genetic algorithm, embedded with an absorption policy and several crossover operators based on simulated annealing is used to solve the reconfigurable manufacturing system problem. Stage 3 assesses the vehicle routing problem through the application of a variable neighborhood search approach whereas stage 4 provides the consolidated result of a joint RMS-VRP problem.

The framework of NSGA-II-VNS for the RMS-VRP problem is presented in Figure 4. NSGA-II and VNS employ different search spaces for entirely different populations. The search space of NSGA-II is based primarily on the decision of assigning machine configurations to operations. Different components of cost, time, modularity, and scalability are evaluated because of the solutions attained in this search space.

The steps used in implementing a non-sorting genetic algorithm are provided in Algo. 1. The population of the RMS problem is selected by randomly assigning operations to configurations. This random assignment, however, should not violate the precedence and compatibility constraints. In such a case, the generated solution will not be feasible and will incur a penalty.

NSGA-II runs for an automatically tuned and defined number of iterations (gmax). At each iteration, the assignment of operation to configuration follows the compatibility and precedence checks. The algorithm uses a roulette wheel mechanism, probabilistic mutation, and several crossovers to assess the fitness of objective function values. The probabilistic tournament selection criterion is used for the selection of parents. In this approach, two candidate parents are selected for the potential parent population. Based on a probability value p, an improved solution is selected to become the parent solution for the crossover. In a contrary situation, the other solution is selected as a parent. It is worth noticing that the improved solution is selected based on non-domination principles.

This study uses a single-point crossover (SPC), order crossover (OC), partially mapped crossover (PMX), and a novel modified partially mapped crossover (MPMX). The illustration of SPC, OX, PMX and MPMX crossovers is presented in Figures 5, 6, 7, and 8, in that order. The steps to implement/use SPC, OX and PMX operators are provided in Algo. 5, 6 and 7, respectively. The steps to implement the novel MPMX crossover operator are provided in Algo. 2. The cut-point in crossovers is applied randomly, which can affect the proportion of string chosen for the procedure of crossover. MPMX either selects the proportion of string based on a pre-defined or random value. In Figure 8, two possible scenarios of string selection are presented against each probability/proportion value. The selection of the proportion of strings in OX, PMX and MPMX can potentially impact the objective function values. To this end, a simulated annealing (SA) procedure is embedded with the OX, PMX, and MPMX crossover operators. In this sense, SA ensures that in each iteration of NSGA-II, an appropriate portion of parent strings are selected to form offspring, resulting in the optimal values of objective functions. The execution steps of SA for crossover are provided between lines 15-29 in Algo 1.

An absorption policy is embedded in the NSGA-II to refine the non-dominated solutions. It controls the random absorption of solutions toward the dominant solution during the search. This practice ensures that high-quality solutions are obtained in each iteration of NSGA-II. Absorption policy considers the distance between solutions, the direction of

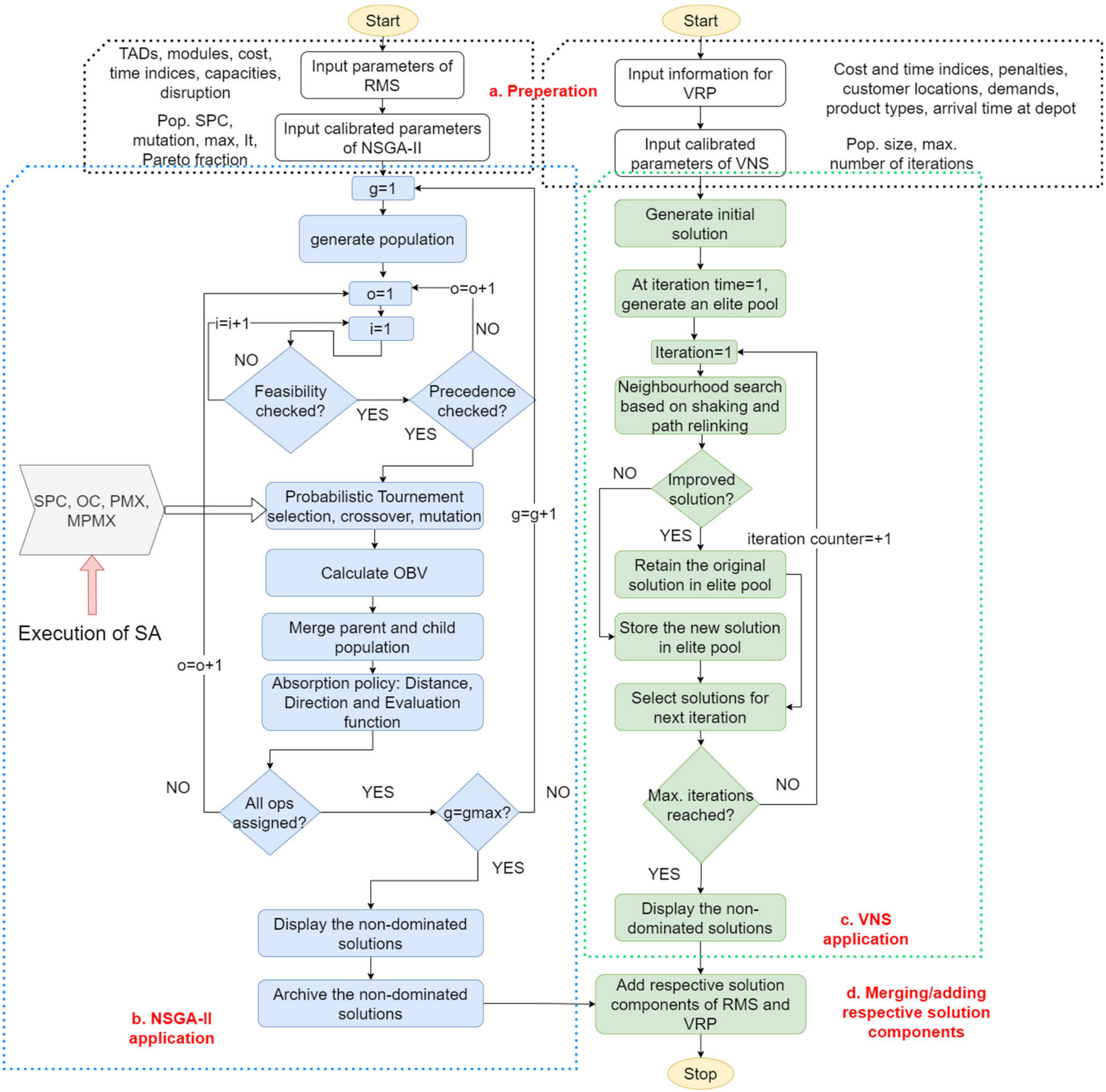

FIGURE 4. A joint framework of NSGA-II-VNS for RMS-VRP.

movement in radian, and advancement through evaluation function.

The merger and working of NSGA-II and VNS in the hybrid framework can be explained well through the representation of solutions. The complete array of solution of RMS problem is described in Figure 9. At each iteration of NSGA-II, an operation is assigned to a machine configuration by fulfilling the compatibility and precedence constraints. The information of product to which an operation belongs, and the number of machine configurations is archived. The objective function components of cost, time, scalability, and modularity related to RMS are calculated at each iteration, by assigning configurations to operations. In Figure 9, in one iteration, configuration M3 is assigned to the third operation of product 2 and five copies of machine configurations are needed to fulfil the demand, and so on.

Two important aspects of NSGA-II results are fed to the VNS. Firstly, the arrival time at the depot, disruption, extra machine requirements are archived to be used during the execution of VNS. Secondly, the type of products and their quantities produced by RMS is used during the execution

Algorithm 1 NSGA-II Embedded With Absorption Policy and Several Crossover Operators for RMS

```
Input: Parameters of RMS, including the information of TADs, modules, capacities, etc.
Input: irace tuned input parameters of genetic algorithm //Execution of irace
Output: Set of non-dominated solutions of process plan
For g = 1 to gmax do
    Generate initial solution
    Select an operation (o) and configuration (i)
    For i = 1: I, o = 1: O
        if compatibility o ≠ i
            i = i + 1
            Else if  precedence violated
                    o = o + 1
            End if
        End if
         Apply probabilistic Tournament, crossover, mutation //SPC, OC, PMX, MPMX
         Randomly generate an initial set of parents' strings //SA execution
         Set initial parent strings=best parent strings
         Set best parent strings=current parent strings
         Set initial temp, t = t_o
         Set final temperature t = t_min
        While       t_o > t_min
           Generate new parent strings from the current strings
           Generate a random value between 0-1 for proportion selection
           Validate the new strings in OX/PMX/MPMX
           Calculate the time function of current (T_c) and initial strings (T_i)
           If T_i > T_c
               Best string = new string
           Else If T_i < T_c
          Current string= initial string
        End While
        // Select the best string for OM/PMX/MPMX crossover
         Calculate fitness function of OBV's
         Merge parent and child population
         Apply Absorption policy
         Distance, Direction and Evaluation
    End For
End For
Stop
Display non-dominated solutions
Archive the solutions
```

of VNS. The former aspect affects the overall efficiency of the VRP problem, and the latter aspect is used as part of routing and satisfying the demand of different customers. An instance of the complete array of VRP solution representation is provided in Figure 10. A customer with a required quantity of a specific product is assigned to a route. This assignment is made in accordance with the constraints of the vehicle routing problem. The respective components of objective functions attained through VNS are archived. In stage 4 (Figure 3), these respective components are added to attain the non-dominated solutions of all objective functions.

In the VRP problem, a customer is randomly selected and assigned to a route based on the requirement of products at a particular customer location. VNS addresses the VRP problem, and its execution steps are provided in Algo. 3. It uses two important strategies, i.e., shaking and path relinking. Shaking is used to alter the direction of the search. It offers a starting point for the local search. A neighborhood solution is used for shaking by employing a one-one exchange. In

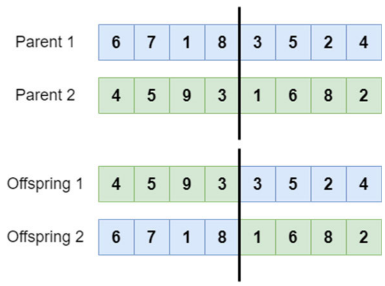

FIGURE 5. Single Point Crossover (SPC).

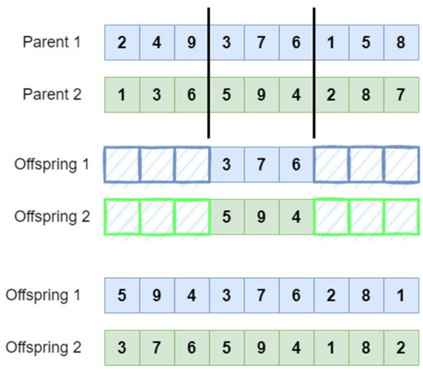

FIGURE 6. Order Crossover (OX).

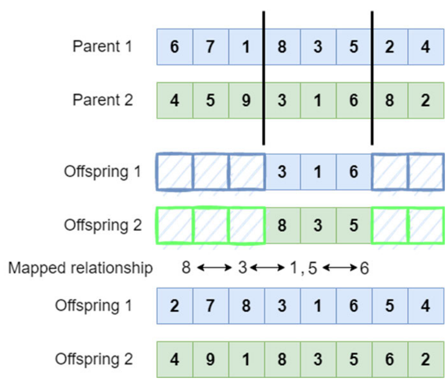

FIGURE 7. Partially Mapped Crossover (PMX).

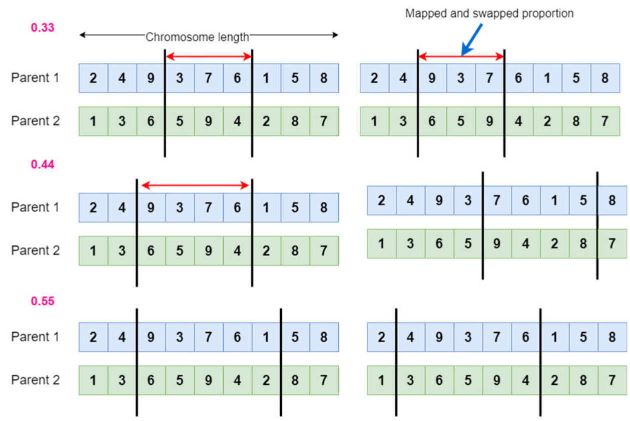

FIGURE 8. Modified Partially Mapped Crossover (MPMX).

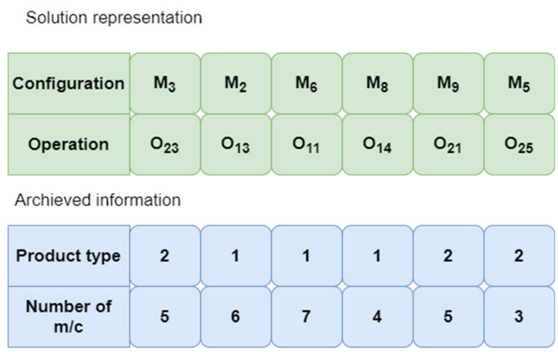

FIGURE 9. Solution representation for RMS using NSGA-II.

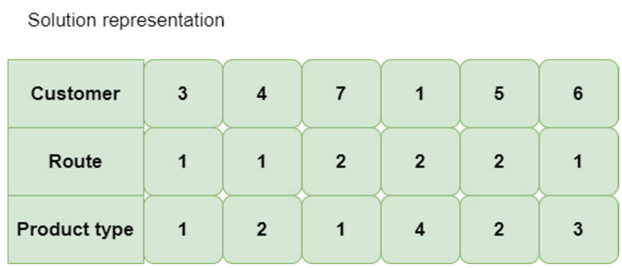

FIGURE 10. Solution representation for VRP using VNS.

one-one exchange, customer locations are selected from two routes and their positions are swapped. The shaking process is terminated if both new routes are feasible, otherwise, the process is repeated by selecting and swapping the order of two more customers, and so on. Path relinking is used to draw a connection between the current solution and the best solution. It helps in quickly attaining the best solutions. The current solution and the best (guiding) solution must share few properties to successfully implement the path relinking strategy. In the current context, both solutions share the properties of size, route length, common depot, etc. The algorithm runs for a maximum number of iterations, and in each iteration, local search techniques are employed to refine the solutions.

The input parameters of the algorithm are sensitive to changes and different values can impact the performance efficiency of their execution. Thus, the parameters of an algorithm need to be appropriately calibrated.

B. PARAMETERS TUNING THROUGH IRACE

The parameters of an algorithm are sensitive to changes and different values of parameters can result in different solutions. Thus, a careful selection of input parameters is necessary to obtain optimal values of objective functions. Traditionally, studies have been calibrating the input parameters of an algorithm by administering factorial design using Taguchi design of experiments [63], [64]. In this study, an automatic calibration procedure is used through irace package [65] for configuring the parameters of NSGA-II and VNS. Irace is a package used for automatic calibration/tuning of input parameters.

Algorithm 2 Steps for Modified Partially Mapped Crossover (MPMX)

Step 1 Randomly select two parent strings
Step 2 Input: Length of a chromosome/string
Step 3 Randomly generate a value between 0-1
Step 4 Select the proportion of string based on generated value (0.33, 0.44, 0.55, etc.)
Step 5 Exchange/Swap the sub-strings within the bound of cut points
Step 6 Identify the mapping relationship
Step 7 Copy the elements in the remaining places of the string
Step 8 If a configuration is already present in offspring 1 while copying from string 2,
its position is decided, and replacement is made based on the mapped relationship

Algorithm 3 VNS Embedded With Local Search for VRP

```
Input: Information for VRP including parameters,
  locations, demands, product types
Input: Automatically calibrated parameters of VNS:
  pop. size, iterations
Generate initial solution based on randomization
Zi = i^th solution in the population
For Iter = 1 to Max. Iter do
  | Generate an elite pool
  | Select a solution (N. Zi) about Zi
  | Execute the local search for a locally optimal
  | solution (L. Zi)
  | If L. Zi ≥ Zi
  |   | Store L. Zi as the new solution
  |   | Else retain Zi in the solution pool
  | End If
  |   Select a new random solution (NR. Zi) about Zi
  |   Iter = Iter +1
End For
    Display the non-dominated solutions for VRP
    Add respective components of RMS-VRP
     problems
    Consolidated non-dominated solutions
```

The underlying assumption of irace states that each parameter has its own sampling distribution which is independent from other parameters. The irace package implements an irace racing for sampling configurations of parameters, selecting optimal configurations, and updating the sample for acquiring the best solutions. The irace mitigates a premature convergence using a restart mechanism and employs an elitist procedure to ensure that the returned values are acquired after the highest number of instances.

The framework for automatic calibration through irace is given in Figure 11 and its pseudocode is presented in Algo. 4. The calibration uses a cost function (C), budget (B), and the number of iterations (Iter). At each iteration/race, the input parameter configurations are assessed through the cost function. Based on the cost performance, improved configurations are retained while the remaining are discarded. Following this, a statistical test is run to ascertain whether performing and non-performing parameters are statistically different. A range is defined to calibrate the input parameters of NSGA-II and VNS, as shown in Table 3. Due to the novel features of the RMS-VRP, a set of problems was generated to calibrate the input parameters. Each problem was defined by $i \times o \times s \times p$ where i = configurations, o = operations, s = number of customers, and p = product types. The second, third, and fourth columns of Table 3 show the input parameters, their range, and the optimal value selected through calibration, respectively. The irace was executed till the exhaustion of the allocated budget (B). The performance of tuned parameters based on irace was compared with another popular approach called Response Surface Methodology (RSM). The comparison was carried out by first tuning the input parameters of algorithms, followed by the assessment of the scalability objective function. The results are reported in Figure 12, stating that irace tuned parameters ensures a fast convergence of the solution to optimal values i.e., the parameters of NSGA-II-VNS take less iteration in providing stable results. This is because of the iterative, elitist procedure-based approach, exhaustive nature, and fine-tuning of parameters‘ through the statistical test in an irace package.

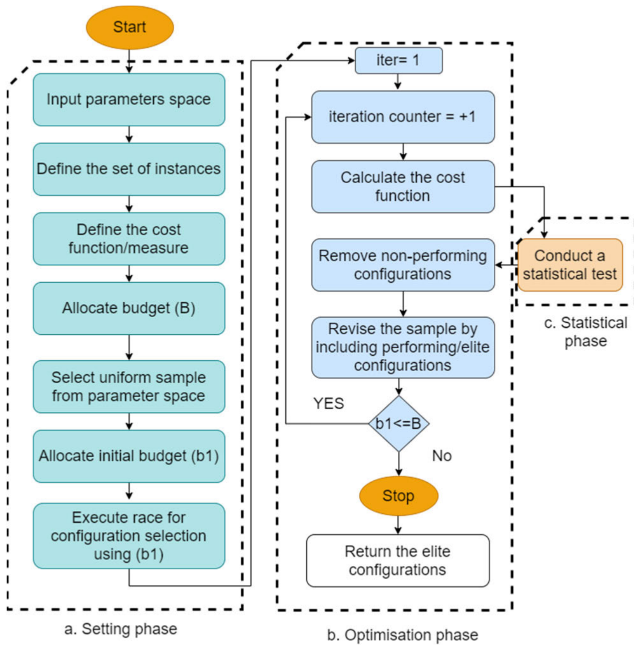

FIGURE 11. Automatic calibration (race) process for parameter selection.

The performance of NSGA-II-VRP is comparted with two alternate solution approaches, i.e., non-dominated ranked genetic algorithm (NRGA) and a simple non-sorting genetic algorithm (NSGA-II). NRGA, proposed by [66], is an elitist

TABLE 3. Input parameters, range and optimal values of NSGA-II and VNS.

Algorithm	Parameter	Range	Optimal value (irace)
NSGA-II	Crossover	[0.3-0.8]	0.72
	Mutation	[0.2-0.6]	0.2
	Number of iterations	[80-500]	300
	Population size	[80-150]	100
	Pareto fraction	[0.2-0.5]	0.4
VNS			
	Population size	[10-60]	40
	Maximum iterations	[50-500]	350

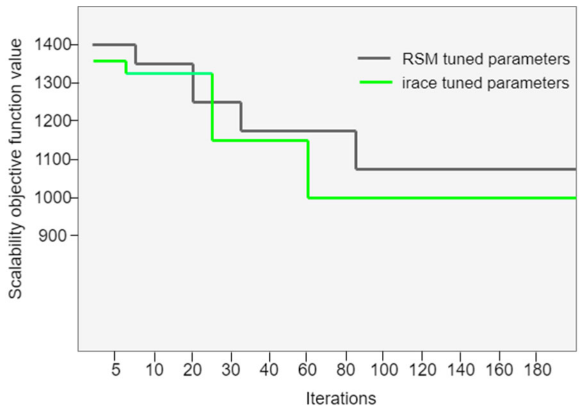

FIGURE 12. Performance comparison of solution approach based on RSM and irace tuned parameters.

Algorithm 4 Algorithm for Irace Implementation

Input: Parameter space
Output: Elite configuration set
Define: Set of instances, cost measure, budget
Select: Uniform sample from sample space
Allocate: An initial budget (b1)
Iter. = 1
While *b1 is less than B* **do**
    Iter = Iter + 1
    Value of cost function (C)
        Statistical significance test
        Update the sample set
End While
Stop
Elite configuration set

TABLE 4. Sixteen problem sets and their associated data.

Pr. Set	MC	CONF	PROD	OPS	CUST	MOD.
1	2	5	2	8	4	5
2	3	6	3	10	6	7
3	3	8	3	12	6	10
4	5	12	5	14	8	13
5	5	14	5	16	8	18
6	5	16	5	19	10	22
7	7	18	7	22	12	26
8	8	20	7	25	14	29
9	8	21	7	30	14	30
10	9	22	7	33	15	30
11	9	24	8	36	15	34
12	9	26	8	39	17	37
13	10	28	10	40	17	40
14	12	30	12	42	18	40
15	13	32	13	44	20	42
16	15	35	13	47	20	44

MC= machine, CONF= configuration, PROD= product, OPS= operations, CUST= customer, MOD= modules

multi-objective algorithm and it is based on non-sorting genetic algorithm. Unlike NSGA-II, NRGA selects the parent through a ranked-based roulette wheel mechanism. The hybrid approach was compared to the application of NSGA-II and NRGA by using the performance metrics of Error Ratio (ER) and Maximum Spread (MS). The Error Ratio (ER) metric, proposed by [67], evaluates the non-convergence of the Pareto approximated solutions. A smaller ER value represents an improved performance. The MS evaluates the diversification of solutions provided by the algorithm. It has been previously used in [68], [69]. This metric assesses the spread of the solutions, and a higher MS value is preferred.

V. RESULTS AND ANALYSIS

The mathematical model and the solution approaches were applied to a set of problems extracted from the practices of a south Asian mechanical products manufacturing industry and its associated collaborators. To this end, sixteen problem sets were attained, each containing a distinct number of machine configurations, operations of products, and several customers. Though the original data set was not extensive, extrapolation was used to extend its scope. This data set associated to the RMS-VRP is provided in Tables 4-12.

Figure 13 and 14 contains the ER and MS values of NSGA-II-VRP, NRGA, and NSGA-II against different problem sizes, respectively. The hybrid approach shows smaller error values and higher spread of solutions. The simulated annealing-based proportion selection in NSGA-II-VRP improves its performance and dominates it over the solutions provided by simple NSGA-II. In problem set 3, the MS value of NRGA is better than the value provided

TABLE 5. Production compatibility between machine configurations and operations of products.

		Operations																		
		P_1				P_2			P_3				P_4				P_5			
		O_{11}	O_{12}	O_{13}	O_{14}	O_{21}	O_{22}	O_{23}	O_{31}	O_{32}	O_{33}	O_{34}	O_{41}	O_{42}	O_{43}	O_{44}	O_{51}	O_{52}	O_{53}	O_{54}
Machine Configurations	1	x			X		x		X			x			x		x			x
	2	x		X		x		x			x			x			x		x	
	3		x		X		x		x	X			x		x			x		x
	4			X		x	x			X		x				x			x	
	5	x		X			x		x			x		x		x				x
	6		x			x		x		X			x		x			x		
	7			X			x		x		x				x		x			x
	8	x			x			x		X			x			x			x	
	9		x			x		x			x		x				x			
	10			X			x			X			x			x			x	
	11	x				x		x	x					x			x			x
	12		x		x		x			X		x	x		x			x		
	13	x			x	x			x		x			x		x			x	
	14		x				x	x			x		x	x				x		
	15			X		x		x		X		x			x	x			x	
	16	x			x		x		x		x			x			x	x		x

TABLE 6. Modules offered by different machine configurations and their exploitation costs.

Conf.	Modules	ec_i	Conf.	Modules	ec_i
1	m_3, m_4, m_{20}	320	9	m_{10}, m_{11}, m_{16}, m_{22}	250
2	m_1, m_3, m_5, m_{11}	190	10	m_{13}, m_{15}, m_{20}, m_{21}	320
3	m_2, m_4, m_7, m_9, m_{21}	450	11	m_{13}, m_{14}, m_{18}, m_{19}	350
4	m_1, m_{10}, m_{13}, m_{19}	400	12	m_2, m_8, m_6, m_{11}, m_{20}	270
5	m_8, m_9, m_{12}, m_{17}	325	13	m_3, m_{10}, m_{12}, m_{19}, m_{21}	500
6	m_6, m_8, m_{13}, m_{14}	285	14	m_4, m_6, m_9, m_{17}, m_{20}	400
7	m_{10}, m_{15}, m_{16}, m_{18}	300	15	m_5, m_7, m_{10}, m_{15}, m_{22}	440
8	m_3, m_{15}, m_{19}, m_{22}	300	16	m_9, m_{13}, m_{18}, m_{19}	230

TABLE 7. Operation precedence, production cost, production time and modular requirements of operations.

Ops.	$L\acute{o}^p$	pc_o^p	pt_o^p	Modules	Ops.	$L\acute{o}^p$	pc_o^p	pt_o^p	Modules
O_{11}	----	6	2.5	m_3, m_5, m_8	O_{33}	O_{32}	4.5	2.2	m_5, m_7, m_{11}, m_{14}
O_{12}	O_{11}	8	3.2	m_2, m_6, m_7	O_{34}	O_{33}	6.5	3.6	m_{10}, m_{12}, m_{15}
O_{13}	O_{12}	5.5	2.2	m_1, m_2, m_4	O_{41}	----	8.2	4.6	m_{17}, m_{19}, m_{20}, m_{22}
O_{14}	O_{12}	9	4.2	m_3, m_6, m_8	O_{42}	O_{41}	12	5.2	m_6, m_8, m_{12}, m_{18}
O_{21}	----	4.3	2	m_5, m_9, m_{16}, m_{19}	O_{43}	O_{41}	9	4	m_3, m_9, m_{13}, m_{17}, m_{21}
O_{22}	O_{21}	6.7	3	m_4, m_7, m_{18}, m_{20}	O_{44}	O_{42}, O_{43}	7	3.2	m_{10}, m_{16}, m_{19}, m_{20}
O_{23}	O_{21}	8.5	3.5	m_8, m_{11}, m_{18}, m_{21}	O_{51}	----	5.5	3	m_{13}, m_{16}, m_{18}, m_{22}
O_{31}	----	9	4	m_9, m_{13}, m_{17}, m_{22}	O_{52}	O_{51}	6.3	3.4	m_1, m_2, m_7, m_{11}, m_{14}
O_{32}	O_{31}	11	5.2	m_3, m_6, m_{13}, m_{15}	O_{53}	O_{52}	7.5	4.2	m_{11}, m_{13}, m_{17}, m_{20}
					O_{54}	O_{53}	8	4.8	m_{10}, m_{14}, m_{16}, m_{21}

by the hybrid framework, however, NSGA-II-VRP provide improved results in all other cases.

A discussion is presented in this section by considering the problem set 10. It contains 9 reconfigurable machines comprising a total number of 22 possible configurations. A total number of 30 modules are available on these configurations. These machines can be used to produce 7 product types by completing 33 sequences of operations. The products are to

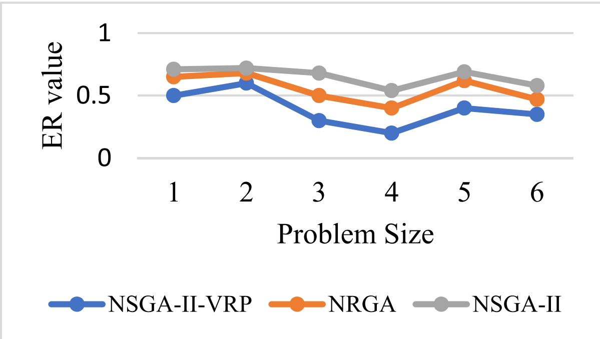

FIGURE 13. Error ratio (ER) metric values for different approaches.

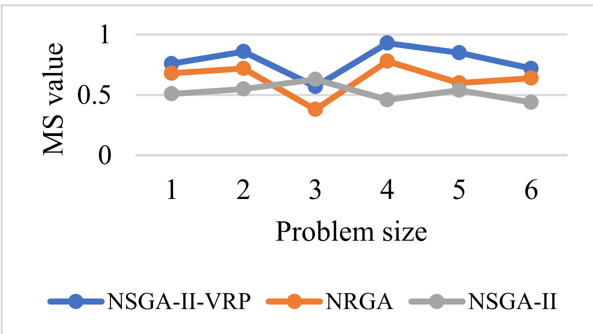

FIGURE 14. Maximum spread (MS) metric values for different approaches.

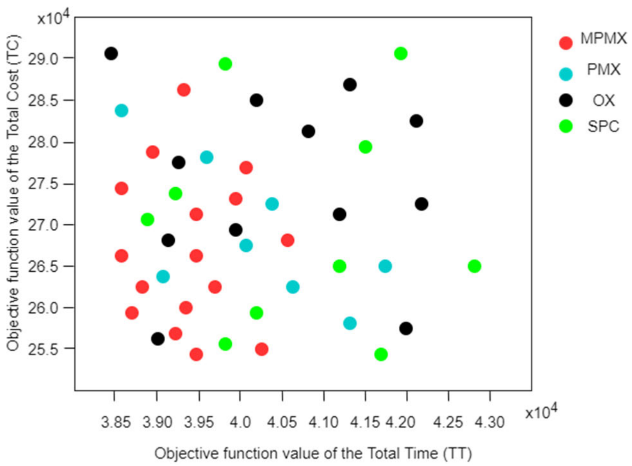

FIGURE 15. Non-dominated solutions of cost and time based on different crossover operators.

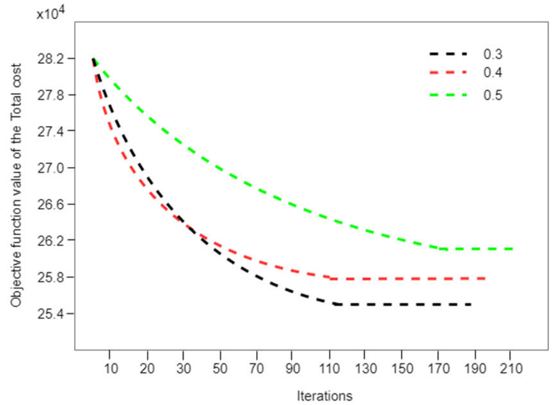

FIGURE 16. Number of iterations considered by the solution approach to gain stability against the different proportions of string selected in MPMX.

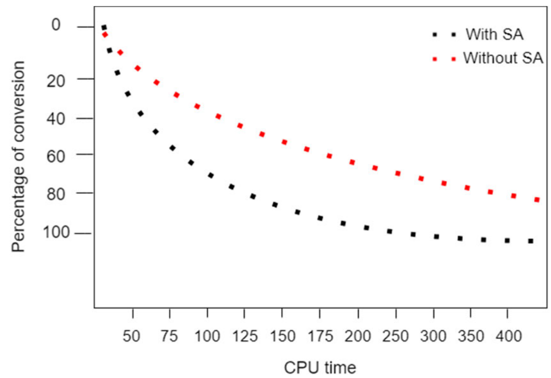

FIGURE 17. CPU time and percentage of convergence in the presence and absence of simulated annealing.

be delivered to 20 customer locations. The approaches were implemented in MATLAB on a computer core i5, 2.2 GHz with 8 GB RAM.

The performance assessment of objective functions by using different crossover operators is provided in Figures 15. It can be observed that the hybrid NSGA-II-VNS works well by using the modified partially mapped operator (MPMX) and it offers improved non-dominated solutions. This is because of the simulated annealing based refined selection of parent strings in the crossover operator to generate offspring. Thus, uniformly distributed and many non-dominated solutions are obtained.

Figure 16 shows the impact of different proportions of strings selected in the MPMX operator on the total cost solution. As the proportion of string selection increases, many iterations are taken by the solution approach to attain stability. In addition, the solution quality worsens, as reflected by the total cost value ($TC_{0.5} > TC_{0.4} > TC_{0.3}$). Thus, a small proportion of string select in MPMX will take fewer iterations in returning optimal solutions.

Figure 17 shows the significance of embedding SA in the framework. Accordingly, SA integrated into the framework will result in the fast convergence of solutions in less computation time (CPU). The convergence of solutions is impacted by many factors. The existing literature has discussed factors such as crossover rate, mutation rate, etc. The focus has been on selecting/tuning such input values that warrant optimal and convergent solutions. Our results show that the proportion of strings selected during crossover operation also impacts the quality and convergence of solutions. Thus, for a given crossover rate, a thoughtful selection of the chunk/proportion of a chromosome is important for mating purposes. Furthermore, the annealing phase (reduction of temperature) in

TABLE 8. Cost of change between different machine configurations and their production capacities.

Configuration	Configuration																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Ca_i
1		45	60														100
2			70														80
3																	130
4					80	100	75										110
5						50	60										100
6							120										65
7																	135
8									70								115
9																	130
10											130	75					80
11												60					90
12																	60
13														100	80	65	55
14															50	75	85
15																120	140
16																	85

TABLE 9. Arrival time information for customer locations of problem set 6.

Customer ID	Earliest arrival	Latest arrival
1	11:30	13:45
2	11:45	14:00
3	09:40	12:00
4	10:20	11:45
5	11:00	15:00
6	12:00	14:30
7	12:30	15:30
8	11:30	12:45
9	09:00	13:00
10	09:50	12:50

TABLE 10. Customer demand data for problem set 6.

Customer Number	Product demand				
	P_1	P_2	P_3	P_4	P_5
1	100	0	70	45	90
2	85	80	65	0	50
3	0	120	0	0	150
4	90	75	50	110	65
5	130	100	90	100	0
6	65	80	140	135	85
7	0	0	100	90	70
8	200	130	85	120	100
9	120	110	130	50	0
10	80	100	0	85	65

SA ensures that the convergent solutions are obtained after several iterations.

For the ease of understanding and without the loss of generality, the analysis is carried out by considering the following cases:

Case 1: The delayed cost and time of product delivery to the depot are not reduced by using extra modularity and scalability, i.e., NML $= 0$ and MEL $= 0$.

Case 2: Extra modularity and scalability are used to avoid the late arrival of products to the depot. This means that the RMS is scaled up to ensure that products reach on time to the depot. In this case, NML $\neq 0$, MEL $\neq 0$, DCD $= 0$ and DTD $= 0$.

Case 3: RMS is free of any quality-related defects, i.e., NMD $= 0$ and MES $= 0$.

The analysis is presented by firstly considering case 1. The top 5 clusters of assigning operations to different configurations are provided in Figure 18. These clusters result in different objective function values of the total cost, the total time, the modularity, and the scalability. In some clusters, fewer modular changes are needed while a higher number of failed products (due to machine disruption) are produced in other clusters.

TABLE 11. **Operation names, codes and tool(s) needed for operations of product 1 and 3.**

Product	Ops.	Operation names	Standard code	Tool(s) needed
1	O_{11}	Drilling, Boring	B94.11	Drill
	O_{12}	Straight turning, Chamfering		Turner
	O_{13}	Drilling, Boring, Reaming	B94.11, B94.2	Drill, Reamer, Chamfer mill
	O_{14}	Facing, Boring, Cutting	B94.11	Miller, Drill, Cemented Carbide tool
3	O_{31}	Milling	B5.9	Face and end miller
	O_{32}	Straight turning	B5.9	Engine lathe tool
	O_{33}	Milling, Boring, Drilling	B5.9, B94.11	Face and end millers, Drill
	O_{34}	Drilling, Boring, Milling	B5.9, B94.11	Millers, Drill

TABLE 12. **Modular analysis in cluster 1.**

Configuration	Operations	Available modules	Needed modules	Subtracted modules	Added modules
C_1	O_{14}, O_{13}	m_3, m_4, m_{20}	m_3, m_6, m_8, m_9, m_{13}, m_{17}, m_{22}	m_4, m_{20}	m_6, m_8, m_9, m_{13}, m_{17}, m_{22}
C_3	O_{22}, O_{32}, O_{52}	m_2, m_4, m_7, m_9, m_{21}	m_3, m_4, m_6, m_7, m_{11}, m_{13}, m_{15}, m_{17}, m_{18}, m_{20}	m_2, m_9, m_{21}	m_3, m_6, m_{11}, m_{13}, m_{15}, m_{17}, m_{18}, m_{20}
C_7	O_{13}, O_{54}	m_{10}, m_{15}, m_{16}, m_{18}	m_1, m_2, m_4, m_{10}, m_{14}, m_{16}, m_{21}	m_{15}, m_{18}	m_1, m_2, m_4, m_{14}, m_{21}
C_8	O_{11}, O_{23}, O_{41}	m_3, m_{15}, m_{19}, m_{22}	m_3, m_5, m_8, m_{11}, m_{17}, m_{18}, m_{19}, m_{20}, m_{21}, m_{22}	m_{15}	m_5, m_8, m_{11}, m_{17}, m_{18}, m_{20}, m_{21}
C_{10}	O_{44}, O_{53}	m_{13}, m_{15}, m_{20}, m_{21}	m_{10}, m_{11}, m_{13}, m_{16}, m_{17}, m_{19}, m_{20}	m_{15}, m_{21}	m_{10}, m_{11}, m_{16}, m_{17}, m_{19}
C_{12}	O_{12}, O_{34}, O_{43}	m_2, m_6, m_8, m_{11}, m_{20}	m_2, m_3, m_6, m_7, m_9, m_{10}, m_{12}, m_{13}, m_{15}, m_{17}, m_{21}	m_8, m_{11}, m_{20}	m_3, m_7, m_9, m_{10}, m_{12}, m_{13}, m_{15}, m_{17}, m_{21}
C_{13}	O_{21}, O_{33}, O_{42}	m_3, m_{10}, m_{12}, m_{19}, m_{21}	m_5, m_6, m_7, m_8, m_9, m_{11}, m_{12}, m_{14}, m_{16}, m_{18}, m_{19}	m_3, m_{10}, m_{21}	m_5, m_6, m_7, m_8, m_9, m_{11}, m_{14}, m_{16}, m_{18}

The configuration instances and their frequency of use are provided in Figure 19. A comparison is provided between cluster 1 and cluster 5. Cluster 5 uses a smaller number of machine configurations. In addition, in many cases, it uses a higher frequency of a specific configuration.

Figure 20 shows the configuration exploitation cost (CEC), scrap cost (SC), waiting cost at the customer location (WC) and transportation cost (TRC) values of clusters 1, 2 and 5. Cluster 1 contains the highest CEC, SC and TRC values compared to other clusters. This is because it uses a higher number of machine configurations for production which increases the machine exploitation cost. In addition, it results in more quality variation and defects which elevates the scrap cost value. Cluster 5 has the highest value of waiting cost. This is due to the smaller number of configurations used in cluster 5 and hence a limited need for configuration and modular changes. Thus, production can be completed earlier, resulting in delivering the products well before the preferred time-window and hence more waiting cost at the customer locations. A similar pattern is shown by configuration change time (CCT), lost production time (LPT), waiting time (WT), and transportation time (TRT) values (Figure 21).

The cost components related to case 1, case 2, and case 3 are provided in Figure 22. The perfect quality-based RMS (case 3) has the lowest configuration, extra production, and late arrival cost values. This is because it focuses on 'doing it right the first time' and hence there is no need for excessive production and the use of additional machine configurations for such production. Case 2 uses additional scalability and modularity to avoid the delayed cost of transferring the products from manufacturing to distribution (DCD = 0). However, this results in the increased values of configuration exploitation cost and production cost. The distribution of cost components in the operation-configuration cluster highlights the component which contributes most in elevating the overall cost. If cluster 1 is selected, more effort will be needed to reduce the extra production cost, scrap cost, and transportation cost. Within cluster 1, case 2 has the highest value of scrap cost whereas case 1 has the highest transportation cost.

Although monumental savings can be achieved through a defect-free RMS (case 3), it is extremely hard to design such a system. Every manufacturing system is subject to defects and decay during its operation. In the wake of Industry 4.0, manufacturing systems need to be more responsive by providing optimal quality and on-time delivery of products. A Reconfigurable Integrated Manufacturing System (RIMS) can be installed to readily monitor the behavior of a manufacturing system and to identify the sources of quality-related issues.

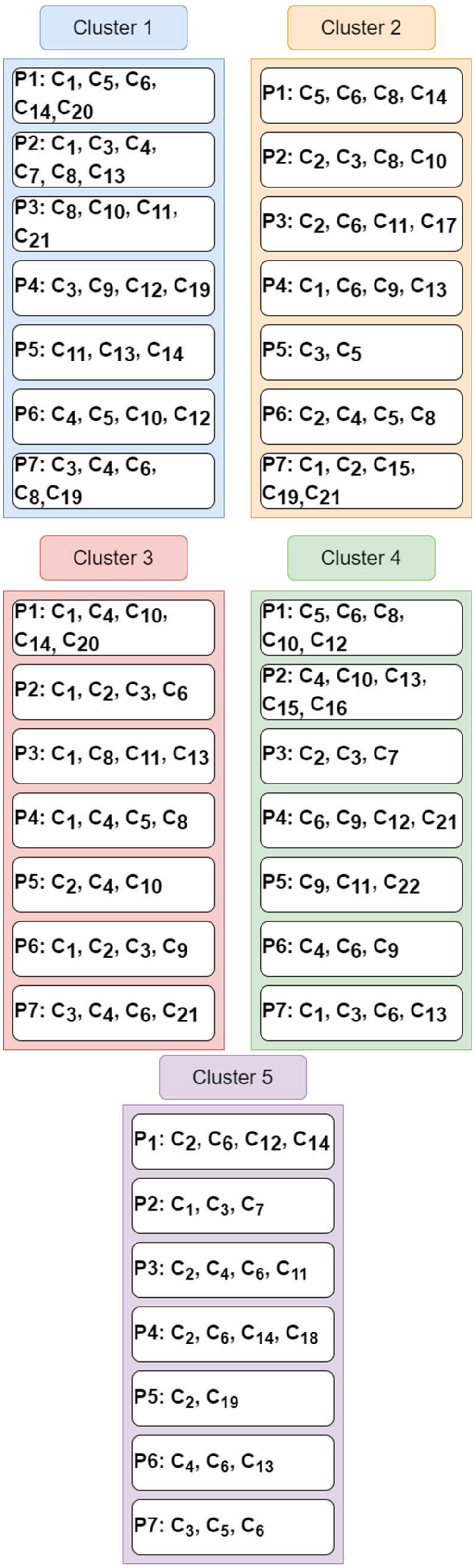

FIGURE 18. Clusters of operations assignments in Case 1.

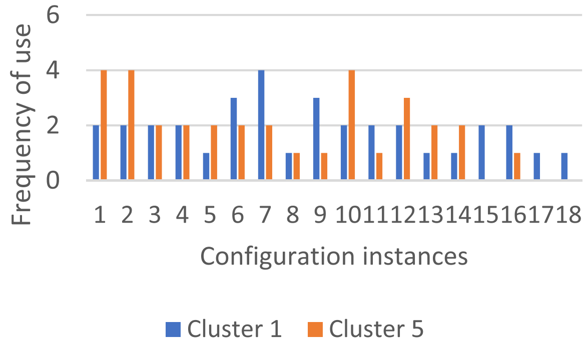

FIGURE 19. Configuration instances and their frequency of use in Clusters 1 and 5.

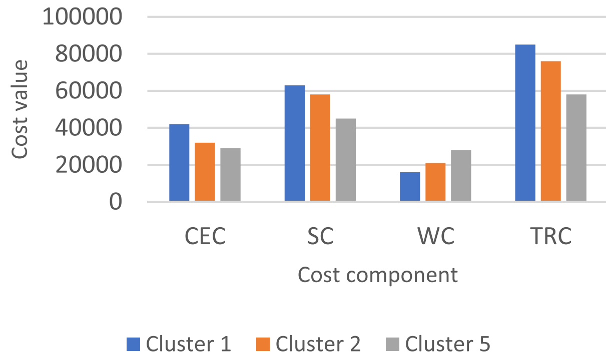

FIGURE 20. Cost components of Clusters 1, 2 and 5.

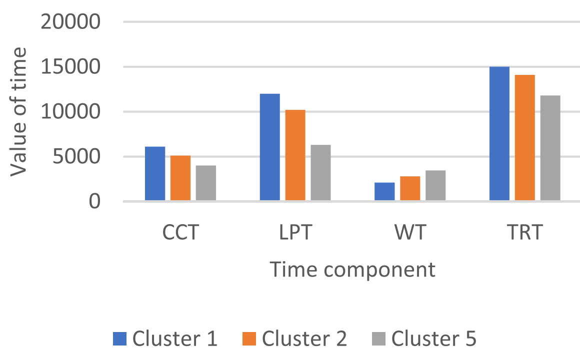

FIGURE 21. Time components of Clusters 1, 2 and 5.

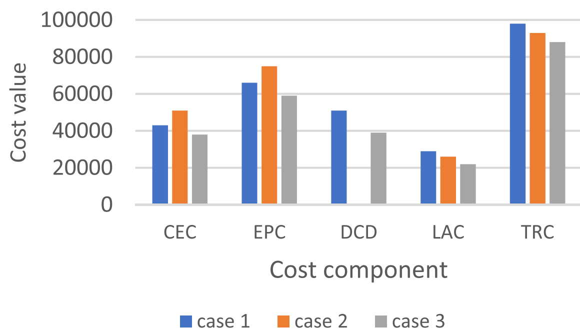

FIGURE 22. Cost comparison among Cases 1, 2, and 3.

Following implications can be drawn, based on the presented analysis for researchers and managers working in reconfigurable/changeable manufacturing and supply chains:

1) Different operation-configuration clusters can impact the time to deliver products to customers. Thus, a considerate selection of machine configurations (process

planning) is required to ensure the on-time delivery of product to customers.

2) More focus needs to be provided to ensure a defect-free manufacturing system. Defects have manifold consequences, and they increase the cost/time and scalability, and modularity requirements.
3) The need to control the production of failed products and late arrival concerns will demand investment in more scalable and modular manufacturing systems. Thus, the overall cost will increase. In this sense, there is a trade-off among cost, time, modularity, and scalability in the presence of defective production and late arrival concerns.
4) Customer satisfaction can be enhanced by offering variety, throughput, and on-time delivery. The variety and throughput requirements can be met by using a reconfigurable manufacturing system. However, the on-time delivery of products can be a challenging task. Practitioners working in a reconfigurable/changeable manufacturing system can closely monitor the path followed by a product during production to ensure on-time delivery.
5) The irace tuned parameters of the hybrid algorithm work well and return stable solutions in less computation time.
6) The integration of simulated annealing ensures the fast convergence of solutions. For the crossover, a thoughtful selection of the chunk/proportion of a chromosome is important for mating purposes. The annealing phase (reduction of temperature) in SA ensures that the convergent solutions are obtained after several iterations.
7) MPMX crossover operator in NSGA-II offers many non-dominated solutions, showing uniform distribution and compactness. In addition, a small proportion of string selection provides optimal solutions in a smaller number of iterations.

VI. CONCLUSION

The reconfigurable manufacturing system is a promising manufacturing paradigm. It can cost-effectively provide variety as well as throughput. However, it still faces multiple challenges of which defective production and responsive delivery are prominent issues. RMS offers several manufacturing routes to produce the same product which can impact the production time and delivery time of a product. Motivated by such issues, in the first, this study attempted to design a reconfigurable manufacturing system in the context of a supply chain i.e., a vehicle routing problem. The aim was to understand the impact of product failure and late delivery on the need to scale up a reconfigurable manufacturing system with extra modularity.

A multi-objective model was proposed to solve the joint manufacturing-routing (RMS-VRP) problem. The model contained the objectives of the total cost, the total time, the scalability, and the modularity. Each objective function modeled the behavior of RMS and VRP. A hybrid and automatically tuned framework of NSGA-II-VNS, integrated with SA was used to analyze the problem.

Multiple clusters and cases were analyzed to provide meaningful implications. These findings will assist practitioners in understanding the analysis of cost in different cases and the trade-off between different components of the proposed model. It is important to closely monitor the scheduling of operations on different configurations for responsive delivery.

This study has the following limitations and suggestions for future research. The failure rate was restricted to specific value for the deterministic problem. It is a stochastic phenomenon that can be well examined by modeling as a probability value. The presented analysis was based on production according to the operational precedence. Future research can define a priority rule such as First-In-First-Out (FIFO) for the production purpose. In addition, other RMS characteristics such as diagnosability, integrability can be modeled to better understand the behavior of a reconfigurable manufacturing system. In continuation to a vehicle routing problem, other supply chain problems such as a closed-loop supply chain can be analyzed in the context of a reconfigurable manufacturing system. Sustainability and emission-related objectives, besides the objectives of cost and time, can be defined which are quite practical in a vehicle routing problem. In addition, social well-being concerns related to high vehicle speeds can be mathematically examined. Lastly, exact approaches and other evolutionary approaches can be used for comparative purposes.

APPENDIX

Algorithm 5 Steps of Single Point Crossover (SPC)

Step 1 Randomly select two parent strings
Step 2 Cut each string into two halves
Step 3 Select the left or right sub-string to the cut point and exchange it with the right or left sub-string of another string

Algorithm 6 Steps of Ordered Crossover (OX)

Step 1 Randomly select two parent strings
Step 2 Randomly cut the selected parent strings at two points
Step 3 Maintain the sub-strings within the cut bound in the offspring
Step 4 Select the sub-string after the second cut point in the second chromosome and paste it in the first string/chromosome.
Step 5 During paste, ensure the order by removing any repeated value of the configuration
Step 6 Select the sub-string after the second cut point in the first chromosome and paste it into the second string/chromosome
Step 7 Repeat step 5.

Algorithm 7 Steps of Partially Mapped Crossover (PMX)

Step 1 Randomly select two parent strings
Step 2 Randomly select two cut points in each string
Step 3 Exchange/Swap the sub-strings within the bound of cut points
Step 4 Identify the mapping relationship
Step 5 Copy the elements in the remaining places of the string
Step 6 If a configuration is already present in offspring 1 while copying from string 2, its position is decided, and replacement is made based on the mapped relationship

LIST OF ABBREVIATIONS

RMS	Reconfigurable Manufacturing System.
VRP	Vehicle Routing Problem.
NP	Non-Polynomial.
TC	Total Cost.
TT	Total Time.
S	Scalability.
M	Modularity.
M1	Model 1.
M2	Model 2.
NSGA-II	Non-Sorting Genetic Algorithm.
VNS	Variable Neighborhood Search.
PRP	Production Routing Problem.
MSDD	Manufacturing System Design Decomposition.
AHP	Analytical Hierarchical Process.
SPEA-II	Strength Pareto Evolutionary Algorithm.
GA	Genetic Algorithm.
MOPSO	Multi-Objective Particle Swarm Optimization.
AMOSA	Archived Multi-Objective Simulated Annealing.
WGP	Weighted Goal Programming.
LNS	Local Neighborhood Search.
ILS	Iterated Local Search.
SA	Simulated Annealing.
TS	Tabu Search.
CEC	Configuration Exploitation Cost.
CCC	Configuration Change Cost.
PRC	Production Cost.
MAC	Module Adjustment Cost.
EPC	Extra Production Cost.
SC	Scrap Cost.
DCD	Delay Cost and Depot.
WC	Waiting Cost.
LAC	Late Arrival Cost.
TRC	Transportation Cost.
CCT	Configuration Change Time.
MAT	Module Adjustment Time.
EPT	Extra Production Time.
LPT	Lost Production Time.
PRT	Production Time.
DTD	Delayed Time Delivery.
WT	Waiting Time.
TRT	Transportation Time.
NMD	Machines required for failed products.
NML	Machines required for avoiding late arrival.
MES	Modularity for compensating failed products.
MEL	Modularity for avoiding late arrival.
PQ	Produced Quantity.
FP	Failed Products.
TAD	Tool Approach Direction.
SPC	Single Point Crossover.
OC	Order Crossover.
PMX	Partially Mapped Crossover.
MPMX	Modified Partially Mapped Crossover.
C	Cost function.
B	Budget.
RSM	Response Surface Methodology.
RO	Robust Optimization.
CPU	Computation Time.
RISM	Reconfigurable Integrated Manufacturing System.
FIFO	First-In-First-Out.

REFERENCES

[1] S. K. Moghaddam, M. Houshmand, K. Saitou, and O. F. Valilai, "Configuration design of scalable reconfigurable manufacturing systems for part family," *Int. J. Prod. Res.*, vol. 58, no. 10, pp. 2974–2996, May 2020, doi: 10.1080/00207543.2019.1620365.

[2] A. Chaube, L. Benyoucef, and M. K. Tiwari, "An adapted NSGA-2 algorithm based dynamic process plan generation for a reconfigurable manufacturing system," *J. Intell. Manuf.*, vol. 23, no. 4, pp. 1141–1155, Aug. 2012, doi: 10.1007/s10845-010-0453-9.

[3] G. Laporte, "An overview of exact and approximate algorithms," *Eur. J. Oper. Res.*, vol. 59, no. 3, pp. 345–358, Jun. 1992, doi: 10.1016/0377-2217(92)90192-C.

[4] S. Ariafar and N. Ismail, "An improved algorithm for layout design in cellular manufacturing systems," *J. Manuf. Syst.*, vol. 28, no. 4, pp. 132–139, Dec. 2009, doi: 10.1016/j.jmsy.2010.06.003.

[5] 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, no. 5, pp. 2231–2249, Mar. 2017, doi: 10.1007/s00170-016-9243-7.

[6] W. Wang and Y. Koren, "Scalability planning for reconfigurable manufacturing systems," *J. Manuf. Syst.*, vol. 31, no. 2, pp. 83–91, Apr. 2012, doi: 10.1016/j.jmsy.2011.11.001.

[7] Y. Koren, W. Wang, and X. Gu, "Value creation through design for scalability of reconfigurable manufacturing systems," *Int. J. Prod. Res.*, vol. 55, no. 5, pp. 1227–1242, Mar. 2017, doi: 10.1080/00207543.2016.1145821.

[8] A. M. Deif and W. H. ElMaraghy, "A control approach to explore the dynamics of capacity scalability in reconfigurable manufacturing systems," *J. Manuf. Syst.*, vol. 25, no. 1, pp. 12–24, Jan. 2006.

[9] P. Spicer, D. Yip-Hoi, and Y. Koren, "Scalable reconfigurable equipment design principles," *Int. J. Prod. Res.*, vol. 43, no. 22, pp. 4839–4852, Nov. 2005, doi: 10.1080/00268970500183042.

[10] H. A. ElMaraghy, "Changing and evolving products and systems-models and enablers," in *Changeable and Reconfigurable Manufacturing Systems*. London, U.K.: Springer, 2009, pp. 25–45, doi: 10.1007/978-1-84882-067-8_2.

[11] H. H. Benderbal, M. Dahane, and L. Benyoucef, "Modularity assessment in reconfigurable manufacturing system (RMS) design: An archived multi-objective simulated annealing-based approach," *Int. J. Adv. Manuf. Technol.*, vol. 94, no. 1, pp. 729–749, Jan. 2018, doi: 10.1007/s00170-017-0803-2.

[12] A. S. Yigit and A. Allahverdi, "Optimal selection of module instances for modular products in reconfigurable manufacturing systems," *Int. J. Prod. Res.*, vol. 41, no. 17, pp. 4063–4074, Jan. 2003, doi: 10.1080/0020754031000149220.

[13] L. N. Pattanaik, P. K. Jain, and N. K. Mehta, "Cell formation in the presence of reconfigurable machines," *Int. J. Adv. Manuf. Technol.*, vol. 34, no. 3, pp. 335–345, Sep. 2007, doi: 10.1007/s00170-006-0592-5.

[14] M. Bortolini, E. Ferrari, F. G. Galizia, and A. Regattieri, "An optimisation model for the dynamic management of cellular reconfigurable manufacturing systems under auxiliary module availability constraints," *J. Manuf. Syst.*, vol. 58, pp. 442–451, Jan. 2021, doi: 10.1016/j.jmsy.2021.01.001.

[15] P. J. Gurumurthy, "Life-cycle modularity in product design," Ph.D. dissertation, Univ. Alabama, Tuscaloosa, AL, USA, 1998.

[16] P. Fredriksson, "Mechanisms and rationales for the coordination of a modular assembly system: The case of Volvo cars," *Int. J. Oper. Prod. Manage.*, vol. 26, no. 4, pp. 350–370, Apr. 2006, doi: 10.1108/01443570610650530.

[17] S. Hsieh and C. R. Hung, "Feasibility study of modular plant for 300 mm-IC fabrications," *J. Intell. Manuf.*, vol. 15, no. 2, pp. 233–244, Apr. 2004, doi: 10.1023/B:JIMS.0000018035.69841.61.

[18] 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, doi: 10.1016/j.jmsy.2013.05.002.

[19] 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, May 2020.

[20] 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, doi: 10.1080/00207543.2020.1756511.

[21] E. Massimi, A. Khezri, H. H. Benderbal, and L. Benyoucef, "A heuristic-based non-linear mixed integer approach for optimizing modularity and integrability in a sustainable reconfigurable manufacturing environment," *Int. J. Adv. Manuf. Technol.*, vol. 108, nos. 7–8, pp. 1997–2020, Jun. 2020.

[22] J. Dou, C. Su, and X. Zhao, "Mixed integer programming models for concurrent configuration design and scheduling in a reconfigurable manufacturing system," *Concurrent Eng.*, vol. 28, no. 1, pp. 32–46, Mar. 2020.

[23] Y. C. Choi and P. Xirouchakis, "A holistic production planning approach in a reconfigurable manufacturing system with energy consumption and environmental effects," *Int. J. Comput. Integr. Manuf.*, vol. 28, no. 4, pp. 379–394, Apr. 2015.

[24] J. Dou, X. Dai, and Z. Meng, "Optimisation for multi-part flow-line configuration of reconfigurable manufacturing system using GA," *Int. J. Prod. Res.*, vol. 48, no. 14, pp. 4071–4100, Jul. 2010.

[25] 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, doi: 10.1080/00207543.2011.599345.

[26] H. H. Benderbal, M. Dahane, and L. Benyoucef, "Flexibility-based multi-objective approach for machines selection in reconfigurable manufacturing system (RMS) design under unavailability constraints," *Int. J. Prod. Res.*, vol. 55, no. 20, pp. 6033–6051, Oct. 2017, doi: 10.1080/00207543.2017.1321802.

[27] A. Khezri, H. H. Benderbal, and L. Benyoucef, "A sustainable reconfigurable manufacturing system designing with focus on environmental hazardous wastes," in *Proc. 24th IEEE Int. Conf. Emerg. Technol. Factory Autom. (ETFA)*, Sep. 2019, pp. 317–324, doi: 10.1109/ETFA.2019.8869380.

[28] P. Renna, "Capacity reconfiguration management in reconfigurable manufacturing systems," *Int. J. Adv. Manuf. Technol.*, vol. 46, nos. 1–4, pp. 395–404, Jan. 2010, doi: 10.1007/s00170-009-2071-2.

[29] L. K. Saxena and P. K. Jain, "A model and optimisation approach for reconfigurable manufacturing system configuration design," *Int. J. Prod. Res.*, vol. 50, no. 12, pp. 3359–3381, Jun. 2012, doi: 10.1080/00207543.2011.578161.

[30] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Manage. Sci.*, vol. 6, no. 1, pp. 80–91, 1959, doi: 10.1287/mnsc.6.1.80.

[31] J. Wang, S. Yao, J. Sheng, and H. Yang, "Minimizing total carbon emissions in an integrated machine scheduling and vehicle routing problem," *J. Cleaner Prod.*, vol. 229, pp. 1004–1017, Aug. 2019.

[32] L. D. C. Martins, E. M. Gonzalez-Neira, S. Hatami, A. A. Juan, and J. R. Montoya-Torres, "Combining production and distribution in supply chains: The hybrid flow-shop vehicle routing problem," *Comput. Ind. Eng.*, vol. 159, Sep. 2021, Art. no. 107486.

[33] X. Zou, L. Liu, K. Li, and W. Li, "A coordinated algorithm for integrated production scheduling and vehicle routing problem," *Int. J. Prod. Res.*, vol. 56, no. 15, pp. 5005–5024, Aug. 2018.

[34] L.-L. Fu, M. A. Aloulou, and C. Triki, "Integrated production scheduling and vehicle routing problem with job splitting and delivery time windows," *Int. J. Prod. Res.*, vol. 55, no. 20, pp. 5942–5957, 2017.

[35] O. Solyalı and H. Süral, "A multi-phase heuristic for the production routing problem," *Comput. Oper. Res.*, vol. 87, pp. 114–124, Nov. 2017, doi: 10.1016/j.cor.2017.06.007.

[36] J. Oesterle and T. Bauernhansl, "Exact method for the vehicle routing problem with mixed linehaul and backhaul customers, heterogeneous fleet, time window and manufacturing capacity," *Proc. CIRP*, vol. 41, pp. 573–578, Jan. 2016, doi: 10.1016/j.procir.2015.12.040.

[37] S. Deng, Y. Li, H. Guo, and B. Liu, "Solving a closed-loop location-inventory-routing problem with mixed quality defects returns in E-commerce by hybrid ant colony optimization algorithm," *Discrete Dyn. Nature Soc.*, vol. 2016, pp. 1–12, Jan. 2016, doi: 10.1155/2016/6467812.

[38] P. C. Pop, I. Kara, and A. H. Marc, "New mathematical models of the generalized vehicle routing problem and extensions," *Appl. Math. Model.*, vol. 36, no. 1, pp. 97–107, 2012, doi: 10.1016/j.apm.2011.05.037.

[39] S. Mancini, "The hybrid vehicle routing problem," *Transp. Res. C, Emerg. Technol.*, vol. 78, pp. 1–12, May 2017, doi: 10.1016/j.trc.2017.02.004.

[40] Z. Wang and J. B. Sheu, "Vehicle routing problem with drones," *Transp. Res. B, Methodol.*, vol. 122, pp. 350–364, Apr. 2019, doi: 10.1016/j.trb.2019.03.005.

[41] R. Raeesi and K. G. Zografos, "The electric vehicle routing problem with time windows and synchronised mobile battery swapping," *Transp. Res. B, Methodol.*, vol. 140, pp. 101–129, Oct. 2020, doi: 10.1016/j.trb.2020.06.012.

[42] R. Eshtehadi, E. Demir, and Y. Huang, "Solving the vehicle routing problem with multi-compartment vehicles for city logistics," *Comput. Oper. Res.*, vol. 115, Mar. 2020, Art. no. 104859, doi: 10.1016/j.cor.2019.104859.

[43] A. Subramanian, P. H. Penna, E. Uchoa, and L. S. Ochi, "A hybrid algorithm for the heterogeneous fleet vehicle routing problem," *Eur. J. Oper. Res.*, vol. 221, no. 2, pp. 285–295, Sep. 2012, doi: 10.1016/j.ejor.2012.03.016.

[44] P. Amorim and B. Almada-Lobo, "The impact of food perishability issues in the vehicle routing problem," *Comput. Ind. Eng.*, vol. 67, pp. 223–233, Jan. 2014, doi: 10.1016/j.cie.2013.11.006.

[45] P. Kitjacharoenchai, B.-C. Min, and S. Lee, "Two echelon vehicle routing problem with drones in last mile delivery," *Int. J. Prod. Econ.*, vol. 225, Jul. 2020, Art. no. 107598, doi: 10.1016/j.ijpe.2019.107598.

[46] Y. Wang, Q. Li, X. Guan, M. Xu, Y. Liu, and H. Wang, "Two-echelon collaborative multi-depot multi-period vehicle routing problem," *Expert Syst. Appl.*, vol. 167, Apr. 2021, Art. no. 114201, doi: 10.1016/j.eswa.2020.114201.

[47] G. Srivastava, A. Singh, and R. Mallipeddi, "NSGA-II with objective-specific variation operators for multiobjective vehicle routing problem with time Windows," *Expert Syst. Appl.*, vol. 176, Aug. 2021, Art. no. 114779, doi: 10.1016/j.eswa.2021.114779.

[48] S. Erdoğan and E. Miller-Hooks, "A green vehicle routing problem," *Transp. Res. E, Logistics Transp. Rev.*, vol. 48, no. 1, pp. 100–114, Jan. 2012, doi: 10.1016/j.tre.2011.08.001.

[49] A. Felipe, M. T. Ortuño, G. Righini, and G. Tirado, "A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges," *Transp. Res. E, Logistics Transp. Rev.*, vol. 71, pp. 111–128, Nov. 2014, doi: 10.1016/j.tre.2014.09.003.

[50] M. E. H. Sadati and B. Çatay, "A hybrid variable neighborhood search approach for the multi-depot green vehicle routing problem," *Transp. Res. Em Logistics Transp. Rev.*, vol. 149, May 2021, Art. no. 102293, doi: 10.1016/j.tre.2021.102293.

[51] C. Koç and I. Karaoglan, "The green vehicle routing problem: A heuristic based exact solution approach," *Appl. Soft Comput.*, vol. 39, pp. 154–164, Feb. 2016, doi: 10.1016/j.asoc.2015.10.064.

[52] M.-X. Song, J.-Q. Li, Y.-Q. Han, Y.-Y. Han, L.-L. Liu, and Q. Sun, "Metaheuristics for solving the vehicle routing problem with the time Windows and energy consumption in cold chain logistics," *Appl. Soft Comput.*, vol. 95, Oct. 2020, Art. no. 106561, doi: 10.1016/j.asoc.2020.106561.

[53] I. Iihan, "An improved simulated annealing algorithm with crossover operator for capacitated vehicle routing problem," *Swarm Evol. Comput.*, vol. 64, Jul. 2021, Art. no. 100911, doi: 10.1016/j.swevo.2021.100911.
[54] N. Azi, M. Gendreau, and J. Y. Potvin, "A dynamic vehicle routing problem with multiple delivery routes," *Ann. Oper. Res.*, vol. 199, no. 1, pp. 103–112, Oct. 2012, doi: 10.1007/s10479-011-0991-3.
[55] M. Keskin, B. Çatay, and G. Laporte, "A simulation-based heuristic for the electric vehicle routing problem with time Windows and stochastic waiting times at recharging stations," *Comput. Oper. Res.*, vol. 125, Jan. 2021, Art. no. 105060, doi: 10.1016/j.cor.2020.105060.
[56] A. A. Kovacs, B. L. Golden, R. F. Hartl, and S. N. Parragh, "The generalized consistent vehicle routing problem," *Transp. Sci.*, vol. 49, no. 4, pp. 796–816, Nov. 2015, doi: 10.1287/trsc.2014.0529.
[57] A. Mingozzi, R. Roberti, and P. Toth, "An exact algorithm for the multitrip vehicle routing problem," *INFORMS J. Comput.*, vol. 25, no. 2, pp. 193–207, May 2013, doi: 10.1287/ijoc.1110.0495.
[58] M. Abbasi, M. Rafiee, M. R. Khosravi, A. Jolfaei, V. G. Menon, and J. M. Koushyar, "An efficient parallel genetic algorithm solution for vehicle routing problem in cloud implementation of the intelligent transportation systems," *J. Cloud Comput.*, vol. 9, no. 1, pp. 1–4, Dec. 2020, doi: 10.1186/s13677-020-0157-4.
[59] 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, pp. 1421–1444, May 2021.
[60] C. Qian, Y. Yu, and Z. H. Zhou, "Pareto ensemble pruning," in *Proc. 29th AAAI Conf. Artif. Intell.*, Feb. 2015, pp. 2935–2941.
[61] P. Côté, T. Wong, and R. Sabourin, "A hybrid multi-objective evolutionary algorithm for the uncapacitated exam proximity problem," in *Proc. Int. Conf. Pract. Theory Automated Timetabling*, Aug. 2004, pp. 294–312, doi: 10.1007/11593577_17.
[62] T. Wong, P. Cote, and R. Sabourin, "A hybrid MOEA for the capacitated exam proximity problem," in *Proc. Congr. Evol. Comput.*, Jun. 2004, pp. 1495–1501.
[63] J. Sadeghi, S. Sadeghi, and S. T. A. Niaki, "A hybrid vendor managed inventory and redundancy allocation optimization problem in supply chain management: An NSGA-II with tuned parameters," *Comput. Oper. Res.*, vol. 41, pp. 53–64, Jan. 2014, doi: 10.1016/j.cor.2013.07.024.
[64] K. Sarrafha, S. H. A. Rahmati, S. T. A. Niaki, and A. Zaretalab, "A bi-objective integrated procurement, production, and distribution problem of a multi-echelon supply chain network design: A new tuned MOEA," *Comput. Oper. Res.*, vol. 54, pp. 35–51, Feb. 2015, doi: 10.1016/j.cor.2014.08.010.
[65] M. López-Ibáñez, J. Dubois-Lacoste, T. Stützle, L. P. Cáceres, and M. Birattari, "The irace package: Iterated racing for automatic algorithm configuration," *Oper. Res. Perspect.*, vol. 3, pp. 43–58, Sep. 2016, doi: 10.1016/j.orp.2016.09.002.
[66] J. O. Al, L. Rajamani, and C. R. Rao, "Non-dominated ranked genetic algorithm for solving multiobjective optimization problems," *NRGA J. Theor. Appl. Inf. Technol.*, vol. 4, no. 1, pp. 60–67, Jan. 2008.
[67] D. A. Van Veldhuizen, "Multiobjective evolutionary algorithms: Classifications, analyses, and new innovations," Ph.D. dissertation, Air Force Inst. Technol., Jan. 1999.
[68] R. Tavakkoli-Moghaddam, M. Azarkish, and A. Sadeghnejad-Barkousaraie, "A new hybrid multi-objective Pareto archive PSO algorithm for a bi-objective job shop scheduling problem," *Expert Syst. Appl.*, vol. 38, no. 9, pp. 10812–10821, 2011.
[69] M. Yazdani, M. Zandieh, and R. Tavakkoli-Moghaddam, "Evolutionary algorithms for multi-objective dual-resource constrained flexible job-shop scheduling problem," *Opsearch*, vol. 56, no. 3, pp. 983–1006, Sep. 2019.

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