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A NSGA-II based approach for multi-objective optimization of a reconfigurable manufacturing transfer line supported by Digital Twin: A case study

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A B S T R A C T

In response to the wide range of customer demands, the concept of reconfigurable manufacturing systems (RMS) was introduced in the industrial sector. RMS enables producers to meet varying volumes of demand over varying time periods by swiftly adjusting its production capacity and functionality within a part family in response to abrupt market changes. In these circumstances, RMS are made to swiftly reconfigure their Reconfigurable Machine Tools (RMTs). RMTs are designed to have a variety of configurations that may be conditionally chosen and reconfigured in accordance with specific performance goals. However, the reconfiguration process is not an easy process, which entails optimization of several objectives and many of which are inherently conflictual. As a result, it necessitates real-time monitoring of the RMS's condition, which may be achieved by digital twinning, or the real-time capture of system data. The concept of using a digital replica of a physical system to provide real-time optimization is known as digital twin. This work considered a case study of discrete parts manufacturing on a reconfigurable single manufacturing transfer line (SMTL). Six manufacturing operations are required to be performed on the parts at six production stages. This work uses the Digital Twin (DT) based approach to assist a discrete multi-objective optimization problem for a reconfigurable manufacturing transfer line. This multi-objective optimization problem consists of four objective functions which is illustrated by using DT-based Non-dominated Sorting Genetic Algorithm-II (NSGA-II). The innovative aspect of the current study is the use of a DT-based framework for RMS reconfiguration to produce the best optimum solutions. The produced real-time solutions will be of great assistance to the decision maker in selecting the appropriate real-time optimal solutions for reconfigurable manufacturing transfer lines.

A R T I C L E I N F O

Keywords:
Reconfigurable manufacturing system;
Digital twin;
Multi-objective optimization;
Evolutionary computation;
Evolutionary algorithm;
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1. Introduction

Manufacturing has ushered in the digital era thanks to developments in data-acquisition systems, information technology (IT), and network technologies. With the fast progress of digital technology, the industrial sector is confronting global issues against a backdrop of digitalization. In the present-day production environment, sophisticated manufacturing initiatives have been launched, including Industry 4.0, Industrial Internet of Things (IIoT), etc. Achieving smart manufacturing, usually referred to as intelligent manufacturing, which is the unifying goal of these initiatives [1]. Since the 1980s, intelligent manufacturing has been used to describe the nexus of manufacturing and artificial intelligence (AI) [2] . Nowadays, knowledge-based intelligent manufacturing is being replaced by data-driven and knowledge-enabled smart manufacturing, where "smart" refers to the collection and usage of data [2]. Moreover, with the evolution of AI, Internet of Things (IoT), the Digital twins (DTs) and Reconfigurable manufacturing systems (RMS) are considered among the smart technologies that are adopting a vital role in the new generation manufacturing [2], [3].

1.1 Reconfigurable manufacturing systems

An emerging area in the era of Industry 4.0 is Reconfigurable Manufacturing Systems (RMS). Past two decade ago, this new paradigm of manufacturing systems has emerged in order to cope with circumstances where the capacity and productivity of the system must respond to fluctuation [4]. RMS offer customized flexibility through scalability and reconfiguration as needed in order to meet customer demand [5]. An RMS is built from the ground up to accommodate quick structural, software, and hardware changes in order to quickly adjust production capacity and functionality [4].

An RMS is designed around a part family and manufactures all the variants of the part family. The system require reconfiguration when switching from one part family to another, which is a labour and financially-intensive operation. The difficulty and expense of changing configurations relies on the original configuration already in place and the new configuration needed to produce orders in the future that belong to a different part family [6]. Hence, RMS is a component of industry 4.0 which is based upon digitization [7] where all parts of an industry are connected and have real-time communication capabilities. Digital Twin (DT) is one such technology that emerged as a tool for achieving intelligent production through RMS [8].

1.2 Digital Twin

Digital Twin (DT) is considered as a new data-driven vision that brings together real-time data analytics, optimization, and simulation. DT is composed of two major components (physical and virtual), with real-time data transfer between them, i.e., each system consists of two parts, a physical part and a virtual one that contains all of the information about the physical part [8]. DT analyzes, and evaluates the massive quantity of data gathered (in real-time/offline mode), resulting in improved system transparency [18]. As a result, a wide range of information may be gathered and used for a variety of purposes, including tracking system condition, generating predictions, diagnosing, simulating, and optimizing the system [9].

1.3 Digital twinning of RMS

Reconfigurable machine tools (RMTs) are an integral part of RMS. These RMTs are required to be reconfigured from time to time as per the system requirements. The reconfiguration of RMTs can be done by keeping the basic modules of RMTs as it is and adding/replacing/rearranging the auxiliary modules according to the system needs. However, the reconfiguration of RMTs is a complex process which requires a lot of technical support from the technology like Digital Twin (DT). By simulating the reconfiguration on a virtual environment, DT enables the solution of the challenging RMT reconfiguration issues [20]. As a result, this work suggests the idea of the DT-based selection of RMTs and its respective configurations for RMS.

A digital twin of an RMT consists of both its physical and virtual counterparts as well as continuous data transfer between them. The virtual RMT is updated with the most recent states of the physical RMT thanks to the data flow from the physical RMT to the virtual RMT, which keeps the virtual RMT in a high-fidelity condition. Hence, the virtual RMT may be used to check on the functionality of the actual RMT [10].

Moreover, a DT is composed up of four layers, which correspond to data collecting, data transmission, data aggregation, and decision-making. This is based on the DT's anticipated functionality. The third and fourth layers of a DT focuses areas pertaining to reconfiguration process in RMS. The DT models must be changing in real-time while executing concurrently with the reconfiguration process.

Since, Digital Twinning of RMS involve gathering a range of information and using it for a variety of purposes like for simulating and optimizing the system [11]. This work presented a framework that addresses the fourth layer of DT that involve simulation of a multi-objective optimal configuration selection problem for a Single Manufacturing Transfer Line (SMTL). The problem has been illustrated by using non-dominated sorting Genetic algorithm (NSGA-II). In a SMTL, a family of raw materials enters the production line at one end, it undergoes various number of operations which are generally being performed at various stages and finally leaves the production line at the other end after finished product. At each stage, a reconfigurable manufacturing tool with different changeable RMT configurations having capability to perform variety of operations has been switched over. When one product family type gets finished, the RMT configurations at the stages are changed (if needed) for processing/manufacturing another product family [12]. A Multi-objective optimization problem (MOOP) based on best optimal configuration selection of machines in a SMTL is considered which comprises four conflicting parameters, i.e., one parameter (cost) that should be minimised and three other parameters (reconfiguration factor, process feasibility, and reliability) which should be maximised simultaneously till optimized level.

2. Literature review

2.1 Beginning and advacements in Digital Twins

As defined in [13], "A Digital twin can be defined as a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making". In 2003 lecture, Michael Grieves coined the word "Digital Twin" for the first time [14]. Due to the constraints and initial stages of the technology at the time, there was essentially no pertinent research or applications [14]. The development of DTs is currently made possible by new IT advancements. Product design [15], manufacturing [16], manufacturing line design [17], prognosis [18], health management, retail and water supply [16] are just a few of the recent uses of DTs in a variety of sectors. Several significant companies, including General Electric, Siemens, etc. adopt DT industrial methods to boost their product performance. This viewpoint reveals how widespread DT's technical uses are. DT is hence comparable to an engineering category as compared to CPS. In this context, Tao *et al*. [19] suggested a method for product design and manufacturing driven by DT, the application methods and frameworks were investigated and case studies were illustrated for future applications of DT. Qi *et al*. [20] found that through integration of the physical and digital worlds in production, DT offers a potential chance to adopt smart manufacturing and industrial 4.0. A DT of a cutting tool was provided by Botkina *et al*. [21], they discussed the data format and structure, information flows, and data management of the digital version of a physical tool as well as potential future applications and productivity analyses. A decision support system for the order management process in manufacturing systems was studied by Kunath & Winkler [22] based on the DT-based conceptual framework and prospective applications. Durão *et al.* [23] conducted a study aiming to address two research inquiries, i.e., what are the main criteria involved in creating a DT, and how does the industry comprehend the concept of DT? Their work provided an explanation and evaluation of the requirements for DT. Luo *et al*. [24] described a modelling method of DT for CNC machine tools and provided a demonstration of DT application scenarios in CNC machine tool era. Another similar work presented types of data and technology required to build the DT of each stage for an injection moulding industry and how to integrate these DT models [25]. Twin [26] discussed a DT demonstrator method involving the design and implementation for privacy enhancement mechanisms in the automotive industry.

2.2 Integration of Digital Twin with RMS

In this context, a method for designing and simulating an RMS by employing the DT technique was proposed [27]. Another RMS-DT based modular structure [9] was reported to predict the condition of a system at any given time while enabling comprehensive system visibility to enhance performance and allowing flexible decision-making. Tang *et al*. [28] introduced the DT-RMS idea, which allowed for high levels of transparency about data, performance, and pertinent reconfiguration decisions by creating a dynamic cyber-replica of the physical production environment. A DT based analytical model for performance evaluation of manufacturing system integrating evaluation of joint parameter fluctuations was introduced that focused in particular on the advantages of an integrated system model that may provide tactical decision makers [29]. The functionality of a simulation program with a DT simulation program was compared by some academicians [30] for incorporation of DT into RMS. Two simulation models were compared by using the Plant simulation 11 for a normal simulation model and Visual components for a DT model. The idea of a creating DT of an RMT was presented to carry out reconfiguration experiments on a high-fidelity virtual RMT in order to tackle complicated reconfiguration challenges. Three components for the RMT-DT were explored, considering the design processes of RMT during reconfiguration. Another idea [10] of Digital twinning of an RMT was presented for carrying out reconfiguration experiments on a high-fidelity virtual RMT in order to address complicated reconfiguration challenges.

2.3 Optimal configuration selection in RMS

One of the emerging area in the era of Industry 4.0 is RMS which offers customized flexibility through reconfiguration and scalability as needed in order to meet consumer needs [5]. When switching from one part family to another, the system may need to be reconfigured, which is a labour and money-intensive procedure. The difficulty and expense of changing configurations relies on the original configuration already in place and the new configuration needed to produce orders in the future that belong to a different part family [6]. For producing multiple part families, RMS optimal configurations at production stages must be identified. In relation to that Hasan *et al.* [6] determined the best optimal configuration of an RMS required by multiple part family orders.

2.4 Multi-objective optimization

In the present days, several kinds of Multi-objective optimization problems (MOOP) are correlated with manufacturing systems [31]. These problems are often solved by using a range of evolutionary algorithms. In this relation, Yu *et al.* developed a tailored instruction method in combination with the notion of non-dominated sorting [32]. In a discrete MOOP, Ashraf *et al.* considered the multiple conflicting objectives for RMT configuration rearrangement [12]. Dou *et al.* [33] suggested the multi-objective particle swarm optimization (MoPSO) technique for RMS's integrated configuration design and scheduling. Liu *et al.* [34] investigated a multi-module RMS for multi-product manufacturing. A mixed-integer programming model was presented in order to minimise the total cost and minimise the cycle time simultaneously. This work compared the efficiency of the proposed algorithm with a classic NSGA. Xu *et al.* [35] developed NSGA-III algorithm to address the multi-objective model and reported that the designed multi-objective model successfully decreases system downtime. Another work [36] optimized multiple objectives in the estimation of heat transfer coefficients while numerically simulating the quenching process of cylindrical steel samples. The proposed approach reported that it outperformed the results of existing works in terms of faster convergence time. Umer *et al.* [37] investigated four parameters with three levels of machining performance variables while machining Aluminium based composites, the utilization of the NSGA-II enabled the achievement of multi-response optimization objectives. Amjad *et al.* [38] proposed a four-layered genetic algorithm (GA) for a flexible job shop scheduling problem, while Xu *et al.* [39] investigated a scheduling problem in manufacturing by applying standard GA.

From the above literature review, it can be concluded that several continuous MOOPs has been solved by using NSGA-II. However, no research addressed the DT-based application of NSGA-II for a discrete kind of optimal configuration selection problem for RMS.

3. Problem formulation

3.1 Evolutionary multi-objective optimization

Many real-life problems comprise multiple performance parameters, or objectives, which should be optimized simultaneously. These performance parameters are termed as objective functions. Such kind of optimization problems which consist of multiple objective functions are called as Multi-Objective Optimization Problems (MOOPs). A MOOP comprises simultaneous optimization of certain objective functions which have to be maximized or minimized. It may enclose several constraints which any viable solution (i.e., all optimal solutions) need to satisfy. Since all the objectives can either be maximized or minimized, thus, the MOOP can be represented in its generalised form as defined in Eqs. 7 and 8. The MOOPs become more challenging when the objectives are conflicting in nature [40], i.e., the objectives are generally contradictory in nature, preventing optimization of each objective concurrently and most of the real engineering problems actually do have conflicting multiple-objectives which are unified into one objective [41].

3.2 Revised Non-Dominanted Sorting Genetic Algorithm

Revised Non-dominated Sorting Genetic Algorithm (NSGA-II) is found an effective tool for solving MOOPs. It is reported that when compared to other evolution techniques, NSGA-II is found to have significantly greater distribution of solutions and superior convergence near Pareto-optimal front [4]. A key aspect of NSGA-II is that the best members are chosen from a pool of parent and offspring solutions (produced by parent crossover and mutation) and are further used as the parents of the subsequent generation. It maintains elitism, which limits the variety of the solutions and retain the ones having greater fitness over the generations together with the other solutions, while the solutions with lower fitness are swept away with the passing of generations. The best solutions are produced in the first pareto-front, that is how NSGA-II implements the idea of choosing non-dominated solutions.

3.3 DT-based MOOP in RMS

This work considered a case study of discrete parts (see Fig. 1 in Section 6) manufacturing on a reconfigurable single manufacturing transfer line (SMTL). Six manufacturing operations, i.e., Milling, Grinding, Drilling, Boring, Surface finishing, and Assembly are required to be performed on the parts at six production stages, S-I, S-II,….,S-VI.

It involves four performance parameters, i.e., operating cost, reconfiguration factor, process feasibility factor and reliability factor in a SMTL that involve discrete MOOP for developing a decisive criterion in selecting machine tool and its corresponding configuration. For a SMTL, the assignment of machine and its configuration on the stages is carried out based on the four aforementioned objectives by applying NSGA II, the notations used in the problem definition are presented in Tables 1-4.

Table 1 General notations for SMTL modelling

M_t	Cluster of all machine tools engaged in a SMTL.
M_c	Cluster of all machine tool configurations engaged in a SMTL $\|\forall M_c \in M_t$.
P_c	Cluster of processes required to be performed on the parts.
MC_p	Cluster of feasible alternative RMT configurations essential to execute p_{th} operation $\|\forall p \in P_c$.
MC_m^c	A specific machine tool m in its c^{th}configuration $\|$ $\forall\ m \in M_t$ and $\forall\ c \in M_c$
MC_i^j	A possible alternative configuration of an i^{th} machine in its j^{th} configuration
J_i	Maximum possible number of configurations of a machine tool $MC_i \mid \forall MC_i \in M_t$.
D_r	Demand rate (parts/hr)
s	Production stage of a reconfigurable Serial product transfer line $\|1 \le s \le S$.
ψ	Power index for Process feasibility
N_i^j	Number of machine tools required to meet the demand when a specific machine tool in its configuration $MC_i^j$is selected $\|$ $\forall\ i \in M_t$ and $\forall j \in M_c$.
CM_i^j	Cost of a specific machine tool in its configuration $MC_i^j \mid\ \forall\ i \in M_t\ and\ \forall j \in M_c$
$P_i^{j_o}$	Capacity (parts/hour) of i^{th}machine with its j^{th}configuration for performing the o^{th}operation $\|$ $\forall\ o \in O,\ \forall\ i \in M_t\ and\ \forall\ j \in M_c$

Table 2 Decision variables for SMTL modelling

CO_i^j	Cost of operating machine tool configuration MC_i^j from the alternative feasible machine tools and its respective feasible configurations for the execution of a process at demand rate $D_r \mid \forall i \in M_t$ and $j \in M_c$
MR_i^j	Machine reconfiguration factor for allocating MC_i^j from the alternative feasible machines with its respective feasible configurations for the execution of a process at a demand rate $D_r \mid \forall i \in M_t$ and $j \in M_c$.
PF_i^j	Process feasibility of a RMT configuration for allocating MC_i^j on SMTL from the alternative feasible machines with its configuration for the execution of a process at the demand rate $D_r \mid \forall i \in M_t$ and $j \in M_c$
RL	Reliability of the SMTL
$R_{i_s}^{j_s}$	Reliability of allocating MC_i^j on the s^{th} stage from the alternative feasible machine tools with its respective feasible configurations for executing a process at a demand rate $D_r \mid \forall i \in M_t$ and $j \in M_c$.

Table 3 Notations for machine reconfiguration factor (MRF)

γ	Machine reconfiguration index
λ	Weightage for the number of modules that need to be added while changing RMT configurations.
μ	Weightage for the number of modules that need to be eliminated while changing RMT configurations.
δ	Weightage for the number of modules that need to be readjusted while changing RMT configurations.
A_i^j	Set of auxiliary modules needed in i^{th} machine with its j^{th} configuration $\mid \forall\ i \in M_t\ and\ \forall j \in M_c$.
$\Phi_{i,o}^j$	$\begin{cases} 1, \text{if } o^{th} \text{operation can be performed selecting } i^{th} \text{ machine with its } j^{th} \text{ configuration} \mid \forall\ i \in M_t\ and\ \forall j \in M_c \\ 0, \text{otherwise} \end{cases}$
Y	Secondary modules set up in the i^{th} existing feasible machine with its j^{th} configuration
Z	Secondary modules set up in the i^{th} configured feasible machine with its k^{th} configuration

Table 4 Optimization and ranking parameters

$\mathrm{F}_1, \mathrm{F}_2, \mathrm{F}_3, \mathrm{F}_4$	Objective functions
f_i	The i^{th} objective function which is to be minimized $\mid 1 \leq i \leq I$.
I	Maximum number of objective functions.
$g_j(x) \geq 0$	Inequality constraint.
x	Decision variable vector representing a feasible solution, i.e., satisfying the J inequality constraints and K equality constraints.

4. Performance parameters

The allocation of a feasible machine and its optimal configuration on the production stages of SMTL for execution of a process is based upon four performance factors: (1) Operating cost, (2) Machine Reconfiguration factor (MRF) (3) Process feasibility of a RMT configuration, and (4) Reliability of the system. Here, the operating cost refers to operating cost of the RMT configuration which is an attribute that is to be minimised. The other three attributes, i.e., Process feasibility, Reconfiguration factor and Reliability are beneficial attributes which have to be maximised. The Process feasibility is the ability of a RMT configuration to perform certain number of processes, MRF represent the responsiveness of a machine and Reliability refers to the reliability of the SMTL.

In the previous works, no such all-inclusive work has been done considering these four performance parameters for searching an all-inclusive suitability of a possible alternative RMT configuration in a SMTL. In the succeeding section, four performance factors [4]are discussed for determining a comprehensive fitness of a possible alternative RMT configuration.

4.1 Operating cost

The operating cost of a feasible alternative RMT configuration for performing the o^{th} process at a certain demand rate D_r is evaluated from Eqs. 1 and 2:

$$CO_i^j = N_i^j \times CM_i^j \tag{1}$$

$$N_i^j = ceil(D_r/P_i^{jo}) \cdot \left[D_r/P_i^{jo}\right] \tag{2}$$

4.2 Machine reconfiguration factor

Machine Reconfiguration factor (MRF) indicates the feasibility of Reconfiguration of machine, that can be accomplished by adding, deleting, or readjusting the auxiliary modules in addition to maintaining the primary modules in the current configuration. In the present work, the number of modules to be included/discarded/rearranged are evaluated along with the total modules while changing machine from one of its configuration to other configuration say from c_1 to c_2. It also shows the auxiliary module set-Y which involve the secondary modules of machine m in its c_1 configuration, i.e., $MC_m^{c_1}$ and auxiliary module set-Z consist of the auxiliary modules of machine m in its c_2 configuration, i.e., $MC_m^{c_2}$. The machine $MC_m^{c_1}$ is reconfigured by eliminating unnecessary secondary modules from set-Y, adding modules from set-Z, and changing or keeping the shared auxiliary modules between set-Y and set-Z. Thus, the reconfiguration of RMTs is evaluated by using Eq. 3.

$$MR_i^j = \frac{[J_i - 1]^\gamma}{\left\{N_i^j \times \sum_{k=1,k\neq j}^{J_i}\left[\lambda \times \frac{\left|A_i^k - A_i^j\right|}{\left|A_i^j \cup A_i^k\right|} + \mu \times \frac{\left|A_i^j - A_i^k\right|}{\left|A_i^j \cup A_i^k\right|} + \delta \times \frac{\left|A_i^j \cap A_i^k\right|}{\left|A_i^j \cup A_i^k\right|}\right]\right\}} \tag{3}$$

4.3. Process feasibility

An o^{th}process is performed such that $\forall\ o \in O$, the Process feasibility of a viable alternative RMT configuration is formulated on the basis of variety of processes that can be executed by the machine in its existing configuration. Increase in number of processes performed by a machine, increases the process feasibility. Hence, the aim of this research is to maximise the process feasibility of an RMT. The process feasibility of a viable alternative RMT configuration to accomplish certain process with ψ as power index, is determined by using Eq. 4.

$$PF_i^j = \left[\left(\sum_{o=1}^{O} \Phi_{i,o}^j\right) - 1\right]^\psi \tag{4}$$

4.4 Reliability

In a SMTL, at each stage a machine performs certain process which indicates, all the machines are linked in series. For the series linking of machines, reliability of the whole SMTL can be calculated by using Eq. 5.

$$RL = \prod_{s=1}^{S} R_{i_s}^{j_s} \tag{5}$$

5. Multi-objective optimization function

The multiple objective functions comprising four objective function for the present problem are defined in Eq. 6. The overall optimization problem is transformed into a minimization problem by multiplying the beneficial objective functions F_2, F_3, and F_4 with a negative sign.

$$\left.\begin{array}{l}
\text{Minimize, } \mathrm{F}_1 = \sum_{s=I}^{S} CO_{i_s}^{j_s} \\
\text{Maximize, } \mathrm{F}_2 = \sum_{s=I}^{S} MR_{i_s}^{j_s} \Leftrightarrow \text{Minimize, } \mathrm{F}_2 = -\sum_{s=I}^{S} MR_{i_s}^{j_s} \\
\text{Maximize, } \mathrm{F}_3 = \sum_{s=I}^{S} PF_{i_s}^{j_s} \Leftrightarrow \text{Minimize, } \mathrm{F}_3 = -\sum_{s=I}^{S} PF_{i_s}^{j_s} \\
\text{Maximize, } \mathrm{F}_4 = \prod_{s=I}^{S} R_{i_s}^{j_s} \Leftrightarrow \text{Minimize, } \mathrm{F}_4 = -\prod_{s=I}^{S} R_{i_s}^{j_s}
\end{array}\right\} \tag{6}$$

Since, the present work has considered the performance and optimization of four objectives as mentioned in Eq. 6 hence, the formulated problem is a multi-objective optimization problem (MOOP) with conflicting objectives, where Operating cost has to be minimized and other three objectives have to be maximized. For a MOOP, it is impossible to have a single particular solution which concurrently optimizes all objectives. Therefore, NSGA-II is used for finding the non-dominated solutions. Most of the MOOPs use concept of domination where two solutions are selected for comparison on the basis of whether one solution dominates other solution or not [12]. The common representation of a MOOP consists of a certain objectives and several equality and inequality constraints which are defined in Eqs. 7 and 8:

$$min(f_i(x)) = [f_1(x), f_2(x), \ldots, f_n(x)], \tag{7}$$

$$\text{Subjected to:} \begin{Bmatrix} g_j(x) \geq 0 & , j = 1,2,\ldots,m \\ h_k(x) = 0 & , k = 1,2,\ldots,n \end{Bmatrix} \tag{8}$$

x is the decision variable vector that satisfy m inequality constraints and h equality constraints representing a feasible solution, f_i is the i^{th} objective function to be minimized, and n is the number of objective functions.

6. Selection of optimal RMT configurations in SMTL

A Serial Manufacturing Transfer Line (SMTL) following an operation sequence 2 → 5 → 7 → 15 → 8 → 16 is considered (Fig. 2). Raw materials are processed at various stages from one stage to the next stage performing variety of operations at the stages. A SMTL permits paralleling of identical machines where each process is consigned to a stage as per the precedence constraint of an operation sequence. After assigning an operation to each stage, a suitable machine type and its configuration to each stage is designated for performing that operation. Various sets of viable alternative RMT configurations MC_p are logged at each stage, performing o^{th}operation at the corresponding stages. Each feasible alternative MC_i^j has two characteristic parameters, i.e., machine number 'i' and its configuration number 'j' from the respective set of its RMT configurations M_c. Each configuration is built with some primary modules as well as secondary auxiliary modules. Generally, the basic modules within a machine remains same while the auxiliary modules are changed while switching from one RMT configuration to the other as presented in the Table 5. Each configuration has its configuration cost and its own capacity to perform variety of operations at prescribed capacity which is termed as the Process feasibility of a RMT configuration as well as Reliability that is being mentioned in Table 6 and Table 7, respectively.

Eq. 6 represents four performance parameters, taken into consideration for present work applied to a SMTL. The optimal RMT configuration assignment is tackled by NSGA-II, taking cost, reconfigurability, process feasibility and reliability as the objective functions of the MOOP.

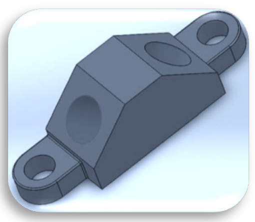

Fig. 1 Finished product

Feasible Solution no.	Feasible machine configuration for the operation sequence 2→5→7→15→8→16					
	2	5	7	15	8	16
1	MC_2^2	MC_1^2	MC_1^3	MC_2^2	MC_1^1	MC_1^1
2	MC_2^4	MC_2^4	MC_2^4	MC_3^2	MC_2^3	MC_1^3
3	MC_3^3	MC_3^2	MC_5^3	MC_3^3	MC_3^2	MC_4^3
4	MC_4^3	-	MC_3^4	-	MC_4^3	MC_3^2

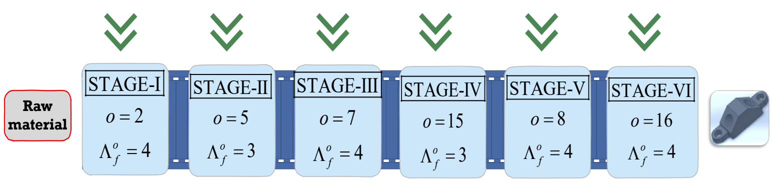

Fig. 2 RMT configuration assignment to the stages in a SMTL

Table 5 RMT configurations, process feasibility and cost of RMT configuration

RMT	RMT configurations	Operations performed	Operation cost (in SAR (x103))
M1	MC_1^1	{4,8,12,16}	85
	MC_1^2	{5,18,9}	132
	MC_1^3	{7,3,16}	89
	MC_1^4	{19,10}	145
M2	MC_2^1	{12,1,6,20}	133
	MC_2^2	{15,2,13}	121
	MC_2^3	{3,17,8,11}	200
	MC_2^4	{2,7,5,14}	158
	MC_2^5	{4,18,13,20}	175
M3	MC_3^1	{2,12,9,17}	140
	MC_3^2	{8,1,4,15,11,19,17}	252
M4	MC_4^1	{10,6,18}	192
	MC_4^2	{17,1,20,12}	202
	MC_4^3	{13,2,8,4,19,16}	188
M5	MC_5^1	{14,1,11,7,18}	173
	MC_5^2	{5,3,17,20,10}	153
	MC_5^3	{9,4,15}	216
	MC_5^4	{14,1,7,6,19,16}	180

Table 6 Capacity (parts/h) RMT configurations for performing operations

o	Capacity (in parts/h)																	
	MC_1^1	MC_1^2	MC_1^3	MC_1^4	MC_2^1	MC_2^2	MC_2^3	MC_2^4	MC_2^5	MC_3^1	MC_3^2	MC_4^1	MC_4^2	MC_4^3	MC_5^1	MC_5^2	MC_5^3	MC_5^4
1	-	-	-	-	20	-	-	-		-	12	-	22	-	25	-	-	13
2	-	-	-	-	-	24	-	25	-	15	-	-	-	17	-	-	-	-
3			24		-	-	17	-	-	-	-	-	-	-	-	14	-	-
4	18	-	-	-	-	-	-	-	16	-	19	-	-	21	-	-	17	-
5	-	20	-	-	-	-	-	19	-	-	-	-	-	-	-	25	-	-
6					16	-	-	-	-	-	-	16	-	-	-	-	-	27
7	-	-	18	-	-	-	-	20	-	-	-	-	-	-	18	-	-	12
8	16	-	-	-	-	-	28	-	-	-	29	-	-	24	-	-	-	-
9	-	12	-	-	-	-	-	-	-	23	-	-	-	-	-	-	10	-
10	-	-	-	18	-	-	-	-	-	-	-	18	-	-	-	22	-	-
11	-	-	-	-	-	-	21	-	-	-	22	-	-	-	16	-	-	-
12	10	-	-	-	22	-	-	-	-	18	-	-	24	-	-	-	-	-
13	-	-	-	-	-	19	-	-	-	-	-	-	-	16	-	-	-	-
14	-	-	-	-	-	-	-	16	-	-	-	-	-	-	10	-	-	18
15	-	-	-	-	-	20	-	-	-	-	17	-	-	-	-	-	14	-
16	15	-	22	-	-	-	-	-	-	-	-	-	-	26	-	-	-	21
17	-	-	-	-	-	-	30	-	-	20	24	-	19	-	-	19	-	-
18	-	20	-	-	-	-	-	-	14	-	-	22	-	-	28	-	-	-
19	-	-	-	23	-	-	-	23		-	24	23	-	-	-	-	-	15
20	-	-	-	-	26	-	-	-	23	-	-	-	15	-	-	30	-	-

Table 7 Reliability of RMT configuration for performing operations

o	Reliability ($\times 10^{-2}$)																	
	MC_1^1	MC_1^2	MC_1^3	MC_1^4	MC_2^1	MC_2^2	MC_2^3	MC_2^4	MC_2^5	MC_3^1	MC_3^2	MC_4^1	MC_4^2	MC_4^3	MC_5^1	MC_5^2	MC_5^3	MC_5^4
1	-	-	-	-	97	-	-	-	-	-	91	-	94	-	-	94	-	95
2	-	-	-	-	-	95	-	75	-	98	-	-	-	97	-	-	-	-
3			80		-	-	93	-	-	-	-	-	-	-	-	96	-	-
4	88	-	-	-	-	-	-	-	96	-	87	-	-	94	-	-	97	-
5	-	80	-	-	-	-	-	98	-	-	-	-	-	-	-	85	-	-
6	-	-	-	-	84	-	-	-	-	-	-	93	-	-	-	-	-	96
7	-	-	98	-	-	-	-	72	-	-	-	-	-	-	88	-	-	82
8	76	-	-	-	-	-	98	-	-	-	79	-	-	84	-	-	-	-
9	-	88	-	-	-	-	-	-	-	92	-	-	-	-	-	-	94	-
10	-	-	-	97	-	-	-	-	-	-	-	88	-	-	-	96	-	-
11	-	-	-	-	-	-	95	-	-	-	97	-	-	-	96	-	-	-
12	95	-	-	-	96	-	-	-	-	94	-	-	96	-	-	-	-	-
13	-	-	-	-	-	88	-	-	-	-	-	-	-	93	-	-	-	-
14	-	-	-	-	-	-	-	88	-	-	-	-	-	-	86	-	-	97
15	-	-	-	-	-	72	-	-	-	-	87	-	-	-	-	-	84	-
16	95	-	92	-	-	-	-	-	-	-	-	-	-	86	-	-	-	75
17	-	-	-	-	-	-	95	-	-	96	87	-	95	-	-	95	-	-
18	93	-	-	-	-	-	-	-	86	-	-	94	-	-	86	-	-	-
19	-	-	-	91	-	-	-	91	-	-	81	97	-	-	-	-	-	94
20	-	-	-	-	97	-	-	-	95	-	-	-	89	-	-	93	-	-

6.1 Machine feasibility

The Fig. 2 shows a SMTL where allocation of RMT configurations (MC_i^j) is to be done at several stages by chromosome encoding and decoding technique. A random gene value in the range [0.01 1.00] is assigned to each stage forming a set of gene values called as chromosome. Since, it has already been established that Real Encoded chromosome (REC) are superior to Binary Encoded chromosome (BEC) for optimization problems as established in previous works [42], therefore, REC along with NSGA II has been implemented in the present research for finding the non-dominated solutions of the proposed optimal machine allocation problem. The length of the chromosome is equal to the number production stages, and on each stage an o^{th} operation has been performed following an operation precedence constraint. At each stage, the gene values are multiplied to the number of respective alternative feasible RMT configurations (Λ_f^o) and the rational number is rounded off to the higher digit because the RMT configuration can't be rational and thus it gives the suitable RMT configuration number from the set of alternative feasible RMT configurations (Λ_f^o) which can be traced from Fig. 2. Thus how, a chromosome representing various stages in a SMTL can be decoded into a solution vector of the assigned RMT configuration at various stages of the SMTL.

6.2 Problem illustration

In this case study, a reconfigurable SMTL having six manufacturing stages with six different variety of operations are performed at each stage thereby, requiring allocation of the suitable RMT configuration at each stage. Chromosomes having six random gene values in the range [0.01 1.00] is generated for each stage. Each gene value corresponds to a stage performing a specific operation. Based upon this procedure the feasible RMT configurations are allocated at each stage for performing the desired operation on the respective stages. In order to allocate feasible and best optimal RMT configuration for each stage, number of alternative RMT configurations are evaluated for each stage, following the defined operation sequence by fetching the necessary data from Fig. 2. Further, the gene values of respective stages are multiplied with their counterpart number of feasible alternative RMT configurations, the obtained value are rounded off to the higher digit which gives the feasible RMT configuration number at various stages in a SMTL. Then, the corresponding feasible RMT configurations are allocated for each stage.

The objective function values of operating cost (CO_i^j), MRF (MR_i^j), process feasibility (PF_i^j) and reliability (RL) are evaluated at each stage for the corresponding allocated RMT configurations by using Eqs. 1 to 5. Further, the obtained objective function values for all stages for a SMTL from S-I to S-VI are summed up and the MOOP criterion formulation is considered using Eq. 6.

7. Results and discussion

Following the process outlined in the previous sections, the DT-based MATLAB program using NSGA-II algorithm is run for 200 population size and 100 generation runs. The objective functions are sorted in a non-dominated manner to provide optimal solutions using the MOOP criteria specified in Eq. 6. Out of the large number of non-dominated solutions presented in Fig. 3(a)-(f), only few alternative solutions have been presented in Table 8 for different manufacturing scenarios. These solutions may aid production planners in crucial decision-making tasks by assisting in RMT configuration selection strategy through selecting the best suitable optimal solutions. However, the selection of only one optimal solution out of the 12 alternative solutions for each production stage can be made by the enterprise management as per the facility requirements and the constraints. The results presented in Table 8 depicts 12 alternative non-dominated solutions which represents the viable RMT configurations allocated to RMS manufacturing stages from stage S-I to S-VI. Moreover, the corresponding objective functions values are evaluated based on the MOOP criterion using the DT-based NSGA-II algorithm.

The Viable RMT configurations required to be allocated to manufacturing stages can be understood in this way, i.e., the first digit signifies the RMT number and another digit represent its respective feasible RMT configuration. Furthermore, the best optimal objective function values that have been evaluated reveals that Machine 5 in its 2nd configuration, i.e., MC_5^2 and Machine 2 in its 4th configuration, i.e., MC_2^4 are the only two feasible optimal RMT configurations that are allocated to production stage S-II. Likewise, Machine 2 in its 2nd configuration, i.e., MC_2^2 and Machine 3 in its 2nd configuration, i.e., MC_3^2 are the two most likely feasible optimal RMT configurations that are allocated to production stage S-IV. As for the production stage S-V, MC_2^3 and MC_4^3 are the most likely allocated best suitable optimal RMT configurations on the SMTL.

Table 8 Optimal configuration solutions obtained after 100 simulation runs

	Produc-tion	Alternative solutions 1	2	3	4	5	6	7	8	9	10	11	12
Feasible RMT configuration allocated to production stages	S-I	24	24	24	43	43	22	22	43	24	24	22	22
	S-II	52	52	24	52	24	52	24	52	52	24	24	24
	S-III	13	24	24	13	51	24	51	51	51	24	13	13
	S-IV	22	32	53	32	32	22	32	32	22	22	22	22
	S-V	23	32	23	43	32	23	23	43	43	23	11	23
	S-VI	11	54	43	11	11	13	43	13	13	54	13	11
Corresponding objective function values	CO_i^j	38.24	34.79	41.8	25.26	38.59	37.42	28.19	31.55	23.21	26.54	34.93	33.82
	MR_i^j	59.52	47.68	59.69	39.40	39.65	61.41	49.24	39.51	53.46	64.02	57.17	59.78
	PF_i^j	23	33	25	31	33	22	29	32	26	25	20	21
	RL (%)	41.88	23.66	37.46	56.1	54.62	37.74	60.07	48.78	31.21	28.01	45.93	61.16

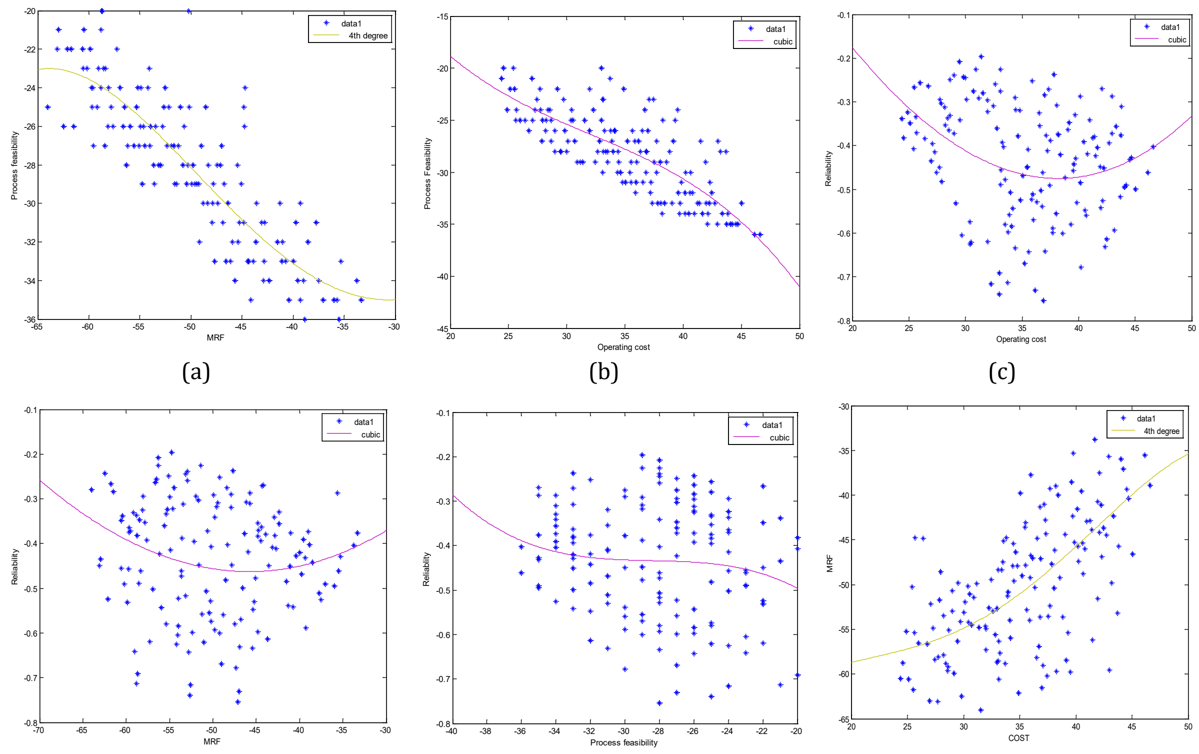

Fig. 3 (a) Process feasibility vs MRF; (b) Process feasibility vs operating cost; (c) Reliability vs operating cost; (d) Reliability vs MRF; (e) Reliability vs process feasibility; (f) MRF vs operating cost

Moreover, the relationship variation between objective function values are presented in Fig. 3a-f. The process feasibility found to have inverse proportional relationship with rest of all the parameters, i.e., the process feasibility drops with the rise of another parameter or vice-versa as shown in Fig. 3(a)-(b) and Fig. 3(e). The objectives MRF and Operating cost have direct proportional relationship, Fig. 3(f), and thus both parameters increase or decrease altogether. Reliability have Bath-tub curve relationship with operating cost and Machine Reconfiguration factor, Fig. 3(c)-(d).

In relation to the present work, another study [43] presented a simulation-based MOOP technique for optimizing the configuration of a Multi-Part Production Flow Line by applying NSGA-II algorithm for only two factors, i.e., (1) assigning tasks to workstations and (2) allocating buffers to achieve maximum throughput (THP) while minimizing the total buffer capacity required. Non-dominated solutions so obtained with a THP higher/lower than 60 in numbers were presented by different colours. Further, a bi-objective minimization problem in RMS [44] obtained the pareto front using the proposed multi-objective simulated annealing algorithm. The effectiveness of the proposed algorithm was compared with NSGA-II that was reported outperformed in several aspects. However, this work considered a bi-objective optimization problem with no conflicting objectives and moreover, the results revealed lowly crowded solutions. Kurniadi *et al*. [30] considered an RMS problem and compared a conventional simulation program with a DT-based simulation program, results showed that total Reconfiguration Planning cost of RMS using Visual Components was found lower while using Plant Simulation software. Xu *et al*. [35] developed a selective maintenance model. In order to assess the efficacy of the devised strategy, the NSGA-II and NSGA-III algorithms were employed to address two maintenance decision-making models. The first model aimed to minimize maintenance and maximize the probability of the system completing the next task, while the second model included an objective of minimizing system downtime. The findings affirmed that the three-objective decision-making model, which considered minimizing downtime, effectively reduced system downtime. From the past studies, it can be concluded that NSGA-II is an effective algorithm that can be used in solving the MOOP related to DT-based works in RMS.

8. Conclusion and future work

This case study addressed a DT-based reconfiguration planning problem for RMS, particularly with regards to configuration selection of machines needed to meet future demands. The research demonstrated how DTs may be used in the configuration planning of RMTs used in RMS. RMT configuration selection is among the most crucial factors required for the successful and efficient planning of RMS. Every time new demands are raised to the system, machine reconfigurations are quite likely to occur. Thus, one of the most crucial factors in achieving a successful and efficient RMS is the RMT configuration selection. The integration of DT technology into RMS make real-world applications conceivable, and by integrating all the operators, physical equipment, and data, the system will be able to function more efficiently and logically. A novel DT-based MOOP technique is proposed for RMS which is based on four objective functions—Operation cost, MRF, process feasibility, and machine reliability. The best optimum configuration for the six-stage reconfigurable SPFL has been evaluated. To create a virtual environment, a DT-based optimization cum simulation model is developed in order to evaluate the non-dominated solutions for the optimal RMT configuration selection problem for RMS. The authors developed a MATLAB simulation program using NSGA-II algorithm. This research will aid production planners in crucial decision-making tasks for DT-based RMS production planning by assisting in RMT configuration selection strategy through evaluating the best suitable optimal solutions. As for limitations of the study, this work is only limited for the case of single reconfigurable manufacturing transfer line. The complexity of the problem may increase with the increase in (1) The number of parallel reconfigurable manufacturing transfer lines and (2) Number of conflicting objectives considered in the Multi-objective optimization problem. Hence, this work can be extended for the DT-based integrated production planning of (1) multiple reconfigurable flow lines (2) considering more multiple conflicting objectives and (3) solving the MOOP with the help of more powerful optimization algorithms.

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Conflicts of interest

The authors declare no conflict of interest.

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