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Modeling and Optimization of Assembly Line Balancing Type 2 and E (SLBP-2E) for a Reconfigurable Manufacturing System

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Abstract: This study undertakes the line balancing problem while allocating reconfigurable machines to different workstations. A multi-objective model is used to analyze the position of workstations, assignment of configurations to workstations, and operation scheduling in a reconfigurable manufacturing environment. A model is presented that comprises the objectives of the Total Time (*TT*), the Line Efficiency Index (*LEI*), and the Customer Satisfaction Index (*CSI*). The objective is to minimize the completion time and maximize the efficiency of a production line. The proposed model combines the Simple Line Balancing Problems Type 2 and Type E in the form of SLBP-2E. The presented problems are addressed by using a heuristic solution approach due to non-polynomial hard formulation. The heuristic approach is designed to assess different solutions based on no repositioning, separate repositioning of workstations and configuration, and simultaneous repositioning of workstations and configurations. A detailed assessment is presented regarding the efficiency as well as the effectiveness of proposed approaches. Finally, conclusions and future research avenues are outlined.

Keywords: reconfigurable manufacturing system; line balancing; scheduling; optimization; multi-objective; heuristic

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1. Introduction

Modern manufacturing systems need to be robust and adaptive to the agile and ever-changing dynamics of the market. COVID-19 has made the marketplace more challenging and demanding in terms of the changing needs of customers. Reconfigurable Manufacturing System (RMS), as a change agent, has the potential to respond to the changing needs of the market [1]. It uses a Reconfigurable Manufacturing Tool (RMT) which enables it to quickly change from one state of manufacturing (configuration) to another configuration [2]. Though it is robust in terms of changing production needs, however, line balancing of a reconfigurable manufacturing system can be a major concern for practitioners. The assignment of reconfigurable machines to several workstations can be visualized in Figure 1. Each workstation (1, 2, . . . , n) can accommodate a set of reconfigurable machines to be used for production. These workstations are arranged in series, meaning that a product may pass through some/all workstations to be completed. A product may pass through a set of successive configurations assigned to different workstations to get the final shape desired by the customer. If a reconfigurable machine assigned to (n-1)th workstation takes more (less) time in production, it will cause the concern of idle-time (bottleneck) at the nth workstation. As a result, the production line will become inefficient and imbalanced.

Thus, machines can be repositioned across the workstations so that the equal distribution of workload and line balancing can be ensured.

The existing literature assumes that the processing time of an operation is the same regardless of the selection of configuration to operate. This may not be an accurate assumption due to the differential attributes of workers or robots processing the operation. Thus, the operation time may vary from configuration to configuration due to the skill set and experience of workers or the inaccuracy and variable speeds of robots. In addition, a reconfigurable machine may be needed to re-adjust its configuration and modules to meet the dynamic production requirements. Combining these aspects, a product may take less time in the n-1th production stage as compared to the nth production stage. This may cause an increased burden on the worker/robot operating in the nth production stage and may originate the issue of line balancing. The earlier studies consider the time, cost, responsiveness, process planning, etc. [3,4], attributes of a reconfigurable manufacturing system; however, to the best of our knowledge, none of the existing studies consider the line-balancing problem in a reconfigurable manufacturing system.

RMS is the most appropriate manufacturing system to be designed, keeping the balancing problem in view. It can be reconfigured from one configuration to another configuration by adding, subtracting, and readjusting the existing modules. The addition of modules is a pure assembling task, subtraction is disassembling, while module readjustment is both assembling as well as disassembling. Each module may require different time values of addition, subtraction, and readjustment. Considering these aspects in mind, RMS is at the same time an assembling as well as a disassembling line balancing problem. Both assembling and disassembling problems have attained much research attention (e.g., refer to [5–7] for assembling problems, and [8,9] for disassembling problems); however, they have been independently applied in most cases. One of the goals of the current study is to understand the impact of module assembling/disassembling efforts on the line balancing efficiency of a reconfigurable manufacturing system.

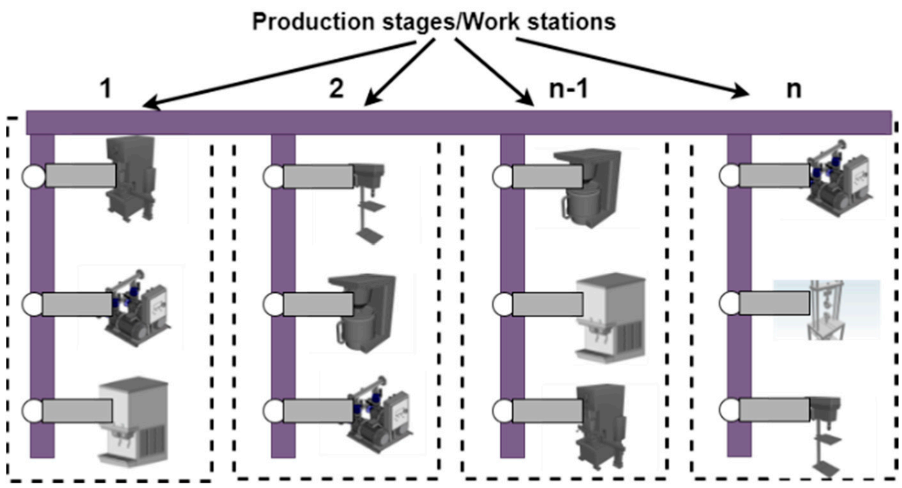

Figure 1. An illustration of the reconfigurable production line.

A mathematical model is proposed that includes the objectives of the Total Time (*TT*), the Line Efficiency Index (*LEI*), and the Customer Satisfaction Index (*CSI*) in a reconfigurable line balancing problem. Though we only focus on the assembling aspects during manufacturing, the disassembling aspects are implicit given the nature of reconfigurable manufacturing systems. We minimize the production time and maximize the line efficiency; thus, the line balancing problems Type 2 and Type E are combined in the form of the Simple Line Balancing Problem (SALB-2E). The considered line balancing problem is 'simple', as it is considered for the case of a single product; however, it can be extended for the case of multiple products. The proposed line balancing approach assigns configurations to workstations, positions the workstations, and schedules operations on configurations by ensuring that the customer preferred delivery times are respected.

The operations precedence graph is respected in the application phases of most RMS studies (for example, in [10]), which is one of the baseline principles of the line balancing problems [11,12]. This study proposes a line balancing approach and investigates the reconfigurable manufacturing line efficiency when the precedence constraint is respected and when the precedence of operations constraint is not intact. Two case studies are analyzed where case study 1 works in the presence of operation precedence constraint, while case study 2 is implemented without considering the precedence constraint of operations. The operation precedence can be shown by an acyclic directional graph moving from left (start) to right (end task). A discussion on the acyclic directional graph can be found in [11]. Case study 2 is more suitable for situations where the final product is the result of the assembly of all sub-components. Thus, each component/part can be independently processed to attain the final product.

To summarize, this study contributes to the reconfigurable manufacturing system literature in the following ways:

- A Simple Line Balancing Problem (SALB-2E) is proposed for a reconfigurable manufacturing system by combining the line balancing problems Type 2 and Type E. The results compare the findings of Type-2, Type-E, and Type-2E line balancing problems.
- The impact of assignment of configurations to workstations, the position of workstations, and scheduling operations on configurations is examined for a reconfigurable line balancing problem.
- A mathematical model including the objectives of the Total Time (*TT*), the Line Efficiency Index (*LEI*), and the Customer Satisfaction Index (*CSI*) is proposed in a reconfigurable manufacturing environment.
- The application of the model is conducted with and without the operation precedence through case study 1 and case study 2, respectively.
- A heuristic approach is designed to assess different solutions based on no repositioning, separate repositioning of workstations and configurations, and simultaneous repositioning of workstations and configurations. The performance of the proposed approach is compared with other evolutionary approaches.

The remaining study is organized as follows. Section 2 provides the literature review concerning the line balancing problems and their importance in analyzing RMSs and a review of the heuristic approaches applied to the line balancing problems and reconfigurable manufacturing systems. Section 3 details the research problem related to the line balancing problem. Section 4 details the mathematical model. Section 5 offers a heuristic solution approach to analyze the problem. Section 6 discusses the results and findings. Section 7 provides the conclusion and offers future research directions.

2. Literature Review

This section presents a review on the literature related to the line balancing problems and reconfigurable manufacturing system and the meta-heuristic approaches used for solving both problem types.

2.1. Line Balancing Problems and Reconfigurable Manufacturing Systems

Bryton [13] first coined the concept of line balancing. The simple line balancing problem assigns tasks to workstations by minimizing the idle time, cost, and the number of workstations while respecting the precedence constraints [12]. In the earlier line balancing problems, the common goal or objective was to optimize the sum of time delays at each workstation [14]. The assembly line is often used for the mass production of standardized products [6]. On the other hand, this study adopts a line balancing approach to the reconfigurable manufacturing system. The passages below review some of the recent publications related to the line balancing problems. A detailed review of the line balancing problems can be found in Battaia and Dolgui [15].

Gurevsky et al. (2013) [5] studied the stability of feasible and optimal solutions in an environment where parallel tasks are performed on an assembly line balancing problem. Pereira and Alvarez-Miranda (2018) [6] studied the uncertain task time issue in a line balancing problem. A robust formulation was used to examine the changes in operation lead time. Azizoglu and Imat (2018) [7] minimized the sum of squared deviations of the workload for optimal distribution of workload among workers. The workload was smoothed in a single model assembly line using a fixed number of workstations and a predetermined cycle time. The line balancing problem can also be conceived in the form of a tree wherein an arc corresponds to a workstation and a path refers to a feasible solution [16].

Dolgui and Gafarov (2017) [12] addressed the assembly line balancing problem Type 1 and minimized the number of workstations with a fixed cycle time. The modified graph of precedence and opposite optimality criteria were used as improvement strategies for addressing the line balancing problem. More recently, Liu et al. [17] considered the uncertainty in line balancing problems and used probability and fuzzy numbers to map the uncertain demand. A multi-objective model comprising the objectives of minimizing the workload difference, minimizing the station complexity, and maximizing the productivity was solved by using a genetic algorithm. Li et al. (2019) [11] studied a line balancing problem considering multiple workers. A two-stage approach combining the Simulated Annealing (SA) meta-heuristic and neighborhood generation approach was used to solve the problem.

Rich literature is available on the line balancing problem. However, it has not been adapted to the reconfigurable manufacturing systems. To the best of our knowledge, only two studies (Bejlegaard et al., 2017 [18] and Son et al., 2001 [19]) have quantitatively examined the line balancing problem in a reconfigurable manufacturing system. Son et al. 2001 [19] studied the RMS design for changing the demand for a product. The authors compared the parallel RMS design with a balanced transfer line and concluded that line balancing is not a requirement for a reconfigurable manufacturing system. Bejlegaard et al., 2017 [18], assessed the line balancing problem for a variety of part-family products.

The reconfigurable manufacturing system deserves more exploration considering the line balancing problem. There are many reasons that can strengthen this opinion. Firstly, a reconfigurable machine requires different modules and tools to be reconfigured before processing an operation. Few reconfigurable machines assigned to a workstation may require more tools and modules (and hence more time to reconfigure) compared to other configurations assigned to another workstation. This will ultimately result in a time imbalance between different workstations. Secondly, a reconfigurable machine may add or subtract tools, modules, etc., as per the requirement of an operation. The addition of modules can be regarded as assembling the system while the subtraction can be referred to as the disassembling. Thus, due to its reconfigurable nature, RMS is a case of the simultaneous analysis of assembling and disassembling. The studies of Zheng et al. (2018) [8] and Wang et al. (2019) [9] can be consulted for a detailed analysis of the disassembly line balancing problems.

Lastly, time optimization is one of the central themes in RMS literature [2]. The workstations can perform the tasks assigned to them, and each task can be performed by either a human or automated agents (robots, AGVs, etc.). A workstation with the maximum processing time/working time is the bottleneck workstation and can reduce the line efficiency [5]. Such workstations are the weakest link in the chain and require more effort for improving the overall efficiency of a production system. Eswaramoorthi et al. (2012) [20] highlighted that the unequal distribution of workload creates imbalance and enhances the risk of ergonomics. The unequal distribution of workload reduces the lifetime of machines and increases the chances of a breakdown. As a reconfigurable system is an expensive manufacturing paradigm, it is imperative to ensure the equal distribution of workload for the prolonged life of this manufacturing system.

In a line balancing problem, workstations are used successively to process the unfinished products, where each workstation performs certain tasks up until the product is completed and leaves the production line. The simple line balancing problem can be categorized into three diverse types [21,22]. The first one is concerned with minimizing the number of workstations against a fixed cycle time (Type 1). The second type minimizes the working time of the most loaded workstation for a fixed (apriori known) number of workstations (Type-2). The last type is concerned with maximizing the line efficiency of the production system (Type-E). This study combines the latter two types of line balancing problems and minimizes the total time and maximizes the efficiency of a reconfigurable manufacturing line. The manufacturing line is designed for a single product; however, it can be extended for the case of multiple product types.

2.2. Meta-Heuristics Adapted to RMS Problems

The RMS problems are computationally hard and small-sized problems are predominantly solved using exact approaches, whereas practical-sized problems are solved using non-exact approaches in the form of heuristics. As per [2], almost 60% of the studies in RMS literature have applied the non-exact solution approaches. This sub-section briefly reviews the use of heuristic approaches in solving the problems related to reconfigurable manufacturing systems.

Among the heuristic approaches, genetic algorithms have more often been applied to the relevant problems. For example, the scalability planning under multiple constraints was studied in [3], using the evolutionary approach of genetic algorithm. In [23], a genetic algorithm-based approach was presented to align the scalable capacities and functionalities with the market requirements. A multi-objective model was presented in [24] to assess the performance of process planning in RMS subject to quality decay. Exact approach and a hybrid heuristic combining the strengths of non-sorting genetic algorithm and multi-objective particle swarm optimization were applied to solve the problem. In [25], the authors adapted the concept of bio-inspired approaches to enhance the multi-agent systems for solving complex problems related to manufacturing systems. In another study [26], a mixed integer linear programming approach was applied to identify a feasible configuration for the realization of scalability and changes in a planning process.

The objectives of throughput and buffer capacity were analyzed in [27] to examine the performance of a reconfigurable manufacturing system. A simulation-based optimization approach was applied to RMS lines subject to scalable resources. The diagnostics of a reconfigurable manufacturing system was studied in [28]. A mathematical model was applied in deterministic and dynamic settings. The deterministic problem was solved by using a set of problem-specific heuristic approaches, whereas the dynamic settings were examined by applying a simulation-based optimization approach. In [29], a novel heuristic was proposed to identify the modules during the preliminary design of RMS. The approach assisted in facilitating/optimizing the performance of the manufacturing system.

2.3. Meta-Heuristic Approaches Adapted to Line Balancing Problems

The line balancing problems are also a computationally hard set of problems and are more often solved by using evolutionary approaches. There are several extensions of such problems such as U-shape assembly line balancing problems, human–robot collaborative line balancing problems, partial disassembly problems, etc. In [30], the authors optimized a multi-objective line balancing model by using an improved multi-functional algorithm. The native operators were reformulated to extend the knowledge sharing among allocation plans. In addition, a matrix reduction approach was formulated for reducing the decoding effort in generating the sequence of operations.

The role of robots in line balancing problems was examined in [31]. Ant colony-based heuristic was used to examine the efficiency of large-size line balancing problems. The efficiency of the proposed heuristic was assessed by comparing its performance with other heuristics. An analysis of the risks and cycle time was performed in a U-shaped assembly work assignment and line balancing environment in [32]. A problem specific heuristic initialization was embedded in the restarted pareto greedy algorithm to solve the problem. A stochastic single-model and parallel stations line balancing problem was studied in [33]. A solution algorithm based on simulated annealing was presented using diversification, repair, tabu list, and probability mass function.

In [34], a multi-objective, multi-constraint two-sided partial disassembly line balancing problem was analyzed. A discrete flower pollination algorithm based on pareto dominance was proposed to solve the problem. Four heuristic rules were proposed to strengthen the algorithm. An ant colony algorithm was proposed in [35] to solve a single model U-type line balancing problem. A mixed-model assembly line balancing problem considering collaboration between robots and workers was proposed in [36]. A bee algorithm and artificial bee colony algorithm with novel aspects were proposed to solve practical-sized problems.

An evolutionary simulated annealing algorithm was proposed in [37] to solve a mixed-model assembly line balancing problem. The results demonstrated that the proposed approach outperformed other heuristics according to the criteria of several performance assessment metrics. In another study [38], an improved imperial competition algorithm was proposed to solve the two-sided assembly line balancing problem under multiple constraints. An assembly line balancing problem from the perspective of cost was analyzed in [39] to examine the objectives of cycle time and robot purchasing cost. A migrating bird optimization algorithm was developed to acquire non-dominated solutions. The proposed solution approach was based on the fast non-dominated sorting to update the population and provide a restart mechanism.

Although there is enough emphasis on both reconfigurable manufacturing system and line balancing problems, there is a dearth of studies and meta-heuristic approaches that integrate both problem types. To this end, this study designs a tailored solution approach by integrating the reconfigurable manufacturing system and line balancing problems. A heuristic approach is designed to assess different solutions based on no repositioning, separate repositioning of workstations and configurations, and simultaneous repositioning of workstations and configurations.

3. Research Problem

RMS can co-exist in different forms and capabilities due to its reconfigurable nature. Thus, it can be reconfigured from one configuration to another by changing tools, modules, etc. We consider the case where reconfigurable machines $j = \{1, 2, \ldots, J\}$ are assigned to different workstations $w = \{1, 2, \ldots, W\}$, as shown in Figure 2. Each workstation $\{1, 2, \ldots, W\}$ is placed at a distinctive position $p = \{1, 2, \ldots, P\}$. A product which comprises a set of operations $o = \{1, 2, \ldots, O\}$ may enter the first workstation where different machines are available to operate on it. Following this, the product passes through the remaining workstations and the resultant product is handed over to the customer. The red line shows that a product first passes through the 1st configuration of machine 1 (mc_1^1), followed by the 3rd configuration of machine 1 (mc_1^3), 1st configuration of machine 4 (mc_4^1), and 4th configuration of machine 3 (mc_3^4). The blue and green lines show the production routes $mc_2^3 \rightarrow mc_1^2 \rightarrow mc_2^1 \rightarrow mc_4^2$ and $mc_3^4 \rightarrow mc_4^2 \rightarrow mc_4^3 \rightarrow mc_4^2$ to process the same product, respectively. Each reconfigurable machine in a workstation requires modules $m = \{1, 2, \ldots, M\}$ to process o. We assume that the worker attributes in different workstations are different. This will result in different processing time values of operations in different workstations. The assignment of configurations to workstations and the scheduling of operations on them will affect the line balancing efficiency. For example, in Figure 2, there will be a concern of overloading/excessive work on the forthcoming stations (workstation 2 and onwards) if workstation 1 takes less time in operating the product. On the other hand, if workstation 1 takes more time in processing the respective operations, there will be idle time on the forthcoming workstations. The red, blue, and green lines in Figure 2 refer to the possible routes/process plans for producing the product.

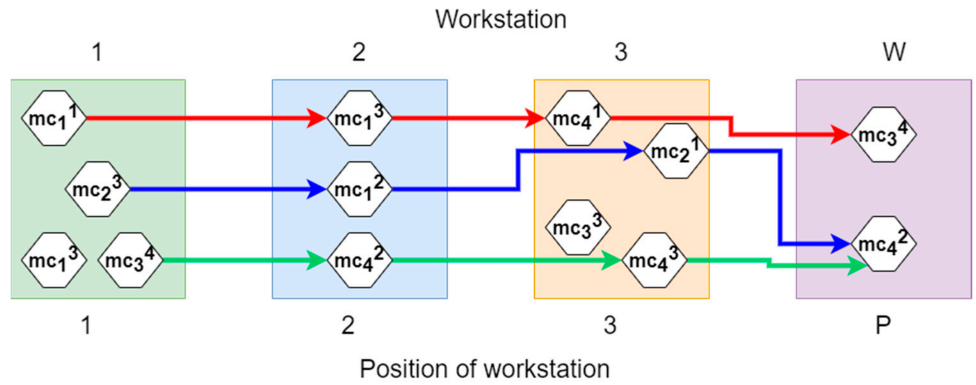

Figure 2. An illustration of the assignment of configurations to workstations.

The time spent by a product in the workstations can be divided into productive time and non-productive time. The productive time refers to the processing time of an operation. The non-productive time accumulates the reconfiguration time, module adjustment time, and idle time between workstations. In other words, the productive time adds value to the product while the non-productive time components are the non-value-added tasks. Reconfiguration of a machine (modules, tools, etc.) will impact the line balancing efficiency of the manufacturing system. The analysis of productive time and non-productive time of workstations design (Figure 2) is presented in Figure 3. It can be observed that workstation 1 has the least value of productive time whereas workstation 3 exhibits the least value of non-productive time. The total time of workstation 1 (productive time + non-productive time) is less than the total time of workstation 2. This means that there will be an overloading concern in workstation 2. Operation $o + 1$ coming from workstation w will wait for operation o to be completely processed in workstation $w + 1$.

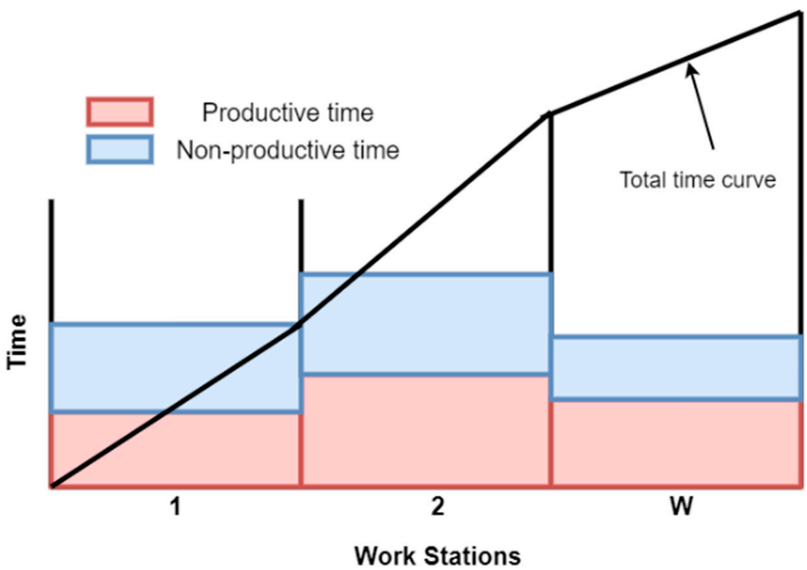

Figure 3. Representation of time components of different workstations.

There are two adjustments to avoid the overloading/idle time concerns:

(1) Firstly, by changing the position of workstations, it can be made possible to reduce the time gap between different workstations. For example, workstation 2 can be re-positioned to position $p = 1$ if it takes more time in processing the operations as compared to workstation 1. The re-positioning of workstations will also affect the material handling/movement between successive workstations. Ideally, a balanced production line calls for less movement of material during production.

(2) Secondly, the production line can be balanced by re-assigning configurations from one workstation to another. For example, a few machines requiring more reconfiguration and module adjustment time can be shifted from one workstation to another workstation. This will help in distributing the work equally among different workstations. Of course, both adjustments will respect the constraint of operation precedence in the case of case study 1.

The assumptions considered for the problem are presented below. Few assumptions are changed and adapted from the studies of Fathi et al. (2018) [40] and Zheng et al. (2018) [8].

- The manufacturing line is designed to produce product specific product; however, it can be adapted for producing a variety of products as it is reconfigurable.
- The assembly tasks are connected by precedence constraint for case study 1, while case study 2 is implemented without the influence of precedence constraint.
- The product includes different operations, and each operation is considered a task. Therein, a set of candidate configurations exists to perform each task. These configurations are assigned to different workstations.
- Each workstation has a minimum of one configuration. A task can be performed in any workstation if the candidate configuration to perform the task is present in that workstation.
- A workstation can process no task at all, or it may process one or more than one task.
- The time to perform a task depends on the assignment of configuration to a workstation where it is performed. This is because each workstation is run by a worker with differential attributes, skills, experience, etc., which can affect the completion time of a task.
- The processing time of each task on a configuration assigned to a workstation is known and deterministic.
- Since tasks are independent in case study 2, their processing times are also independent of the tasks.

4. Mathematical Formulation

A product comprising a set of operations o (where o = {1, 2, ..., O}) is to be produced on a set of reconfigurable machines J assigned to workstations W. The processing time of operation o in each workstation is different due to the differential attribute of workers assigned to each workstation. The configurations are to be assigned to workstations, operations are to be scheduled on these configurations and the positioning of workstations is to be done by optimizing the objective function values. For case study 1 based on precedence relationship, the operations are scheduled according to the acyclic directed graph of operations. The definition of acyclic directed graph and fulfillment of precedence relationships, as given by [12] is: if $o_1 \rightarrow o_2$, $o_1 \in O_{k1}$ and $o_2 \in O_{k2}$, then $k1 \leq k2$.

A multi-objective model is presented to analyze this problem. It includes the objectives of the Total Time (TT), the Line Efficiency Index (LEI), and the Customer Satisfaction Index (CSI). The mathematical model is applied in two segments, i.e., with and without the constraint of operation precedence, respectively.

Parameters and Decision Variables

$Prt_o^{j,w}$	$Processing\ time\ of\ operation\ o\ on\ conf.\ j$
γ_w	$factor\ of\ module\ adjustment\ in\ w.s\ w$
$Ta_m^{j,w}$	$adjustment\ time\ for\ module\ m\ on\ conf.\ j\ in\ w.station\ w$
a	$average\ time\ to\ reconfigure\ a\ machine$
x_w^p	$1,\ if\ w.s\ w\ is\ located\ at\ position\ p,\ otherwise\ 0$
$y_o^{j,w}$	$1,\ if\ op.\ o\ is\ scheduled\ on\ conf.\ j\ assigned\ to\ w.s\ w,\ otherwise\ 0$
S_o^m	$set\ and\ type\ of\ modules\ m\ needed\ for\ op.\ o$
ET	$expected\ time\ of\ receipt\ of\ a\ product\ by\ customer$
$mht_{pp'}^{ww'}$	$material\ handling\ time\ between\ w\ and\ w'\ placed\ at\ p\ and\ p'$

4.1. Total Time (TT)

The total time expression comprises the productive time and the non-productive time. Its expression is provided in Equation (1). The productive time is the time when value is added to the product, and it is the Operation Processing Time (*OPT*), as shown in Equation (2). The expression for *OPT* is provided in Equation (3).

$$Total\ Time\ (TT) = Productive\ Time\ (PT) + Non\ productive\ Time\ (NT) \tag{1}$$

$$PT = Operation\ Processing\ Time\ (OPT) \tag{2}$$

$$OPT = \sum_{w \in W} \sum_{o \in O} \sum_{j \in J} y_o^{j,w} \times Prt_o^{j,w} \tag{3}$$

The Non-productive Time (*NT*) is the sum of the Reconfiguration Time (*RT*), the Module Adjustment Time (*MAT*), and the Idle Time (*IT*), as given in Equation (4). The relationship for *RT* is provided in Equation (5) and it considers the product of the average time to reconfigure a machine and the ratio of intersection and union of modules. The reconfiguration time will have a smaller value if there is more similarity between two successive machine configurations. The expression for *MAT* is provided in Equation (6) and it is the product of module adjustment effort in a particular workstation, the number and type of modules needed, and the time to adjust one module. The expression for the Idle Time (*IT*) is given in Equation (7). It is based on the absolute value of waiting between workstations due to the different processing times.

$$\begin{aligned} NT = {} & Reconfiguration\ Time\ (RT) + Module\ Adjustment\ Time\ (MAT) \\ & + Idle\ Time\ (IT) \end{aligned} \tag{4}$$

$$RT = \sum_{m \in M} \sum_{w \in W} \sum_{o \in O} \sum_{j \in J} y_o^{j,w} \times \frac{S_o^m \cap S^{m'}}{S_o^m \cup S^{m'}} \times a \tag{5}$$

$$MAT = \sum_{m \in M} \sum_{w \in W} \sum_{o \in O} \sum_{j \in J} y_o^{j,w} \times \gamma_w \times S_o^m \times Ta_m^{j,w} \tag{6}$$

$$IT = \sum_{w=1}^{w=W-1} \left(\sum_{j \in J} \sum_{o \in O} |y_o^{j,w} \times Prt_o^{j,w} - y_o^{j,w+1} \times Prt_o^{j,w+1}| \right) \tag{7}$$

4.2. Line Efficiency Index (LEI)

The manufacturing line comprises a set of workstations that are used to process the product. Balanced manufacturing ensures that workload is equally distributed among different workstations. In other words, the time taken by a product in each workstation is equal. We define the Line Efficiency in terms of the Idle Time (*IT*) and the Material Handling Time (*MHT*) among workstations. This aspect is mapped with the help of the Line Efficiency Index (*LEI*) index. The expression for *LEI* is given in Equation (8) and it is the ratio of the Operation Time (productive time) and the sum of the *IT* and the *MHT*. It will have a maximum value if the *IT* and the *MHT* among workstations have minimum values. In other words, an efficient production line will need less material handling/movement and there will be less waiting among workstations. The expression for the *MHT* among workstations is provided in Equation (9).

$$Line\ Efficiency\ Index\ (LEI) = \frac{OPT}{IT + Material\ Handling\ Time\ (MHT)} \tag{8}$$

$$MHT = \sum_{pp' \in P} \sum_{ww' \in W} x_w^p \times mht_{pp'}^{ww'} \tag{9}$$

4.3. Customer Satisfaction Index (CSI)

The goal of every manufacturing system is to maximize customer satisfaction. One way of gauging and ensuring customer satisfaction is by offering the on-time delivery of products. An apriori information on product delivery time called the Expected Time of Receipt (*ETR*) is normally available with the manager. The Customer Satisfaction Index (*CSI*) is measured by using Equation (10) based on the ratio of the Expected Time of Receipt (*ETR*) and the Total Time (*TT*).

$$Customer\ Satisfaction\ Index\ (CSI) = \frac{Expected\ Time\ of\ Receipt\ (ETR)}{TT} \tag{10}$$

The satisfaction of a customer can be maximized by reducing the Total Time (*TT*) taken during production. Thus, higher customer satisfaction can be warranted if *ETR* > *TT*. On the other hand, it will be a Just-In-Time (*JIT*) strategy if *ETR* = *TT*, meaning that the production is completed at the exact time when the product is required by the customer. Lastly, customer dissatisfaction will be caused if *ETR* < *TT*. It means that the promised/expected time of product delivery is violated. To summarize, the positioning of workstations, assignment of configurations to workstations, and the scheduling of operations on these configurations will impact the Total Time (*TT*), the Line Efficiency (*LE*), and the Customer Satisfaction Index (*CSI*). The set of constraints required to execute the model is provided below.

Equation (11) ensures that each workstation will occupy only one position.

$$\sum_{w w' \in W} x_w^p = 1; \ \forall p \tag{11}$$

Equation (12) is used to ensure that an operation can be performed by only one configuration assigned to a particular workstation.

$$\sum_{o \in O} y_o^{j,w} = 1; \ \forall j, w \tag{12}$$

Equation (13) is the precedence constraint for case study 1 to ensure that the operations are performed keeping in view their order in the acyclic graph of precedence.

$$Prec.(y_o^{j,w}) > y_{o+1}^{j\prime,w\prime}\ for\ o < o+1 \tag{13}$$

Equation (14) specifies the compatibility between an operation and a configuration. A binary parameter z_o^j containing the information of operation-configuration compatibility is to be respected.

$$Prec.(y_o^{j,w}) > y_{o+1}^{j\prime,w\prime}\ for\ o < o+1 \tag{14}$$

Equation (15) is the boundary constraint, and it contains the information on the binary decision variables.

$$x_w^p,\ y_o^{j,w} \in \{0,1\} \tag{15}$$

5. Solution Method and Approach

Line balancing problems are combinatorial problems, and they involve the task assignment to workstations for the sake of optimizing the efficiency of the production line [11]. The simple line balancing problems are non-polynomial hard and are difficult to be solved in adequate time [41]. All types of line balancing problems are non-polynomial hard in nature [42]. Meta-heuristic approaches are more conducive to solving such problems [43]. The reconfigurable manufacturing system problems are also non-polynomial hard and are more often solved by administering meta-heuristic approaches [2]. Integrating the line balancing problem with a reconfigurable manufacturing system makes the considered problem strong NP-hard. Thus, a heuristic approach is designed in this study to analyze the line balancing problem in a reconfigurable manufacturing system. It assesses different solutions based on no readjustment, separate repositioning of workstations and configurations, and simultaneous repositioning of workstations and configurations. Four different assessments are performed to achieve optimality, i.e., the optimal values of *TT*, *LEI*, and *CSI*. These assessments are discussed below.

5.1. One: Base Model—No Repositioning

The base model solutions are attained by randomly assigning configurations to workstations and then scheduling operations on these configurations. These solutions are archived at the end of generations. The consolidated framework of all four assessments is given in Figure 4. The black arrows refer to the steps involved in executing the no repositioning strategy or the common steps among all four assessments. Separate color codes are used to designate the steps of the remaining assessments. The base model is based on the no-repositioning strategy as the position of workstations and configurations are not changed and they are considered as given by the initial solution. A workstation is mounted at each position of the manufacturing system, configurations are assigned to the workstation, and operations are scheduled on such configurations. The algorithmic steps of the no repositioning strategy are provided below:

```
1:   Input: positions, workstations, configurations, and operations
2:   Input: processing time, adjustment time, the module adjustment factor
3:   Set: time counter t = 0
4:           p' = 1
5:       Random selection of workstation w. s
6:       Assign n*j configurations to workstation w. s
7:       Schedule operations on n*j
8:       Compute the values concerning w. s
9:       p = p' + 1
10:      Increment the workstation to w. s + 1
11:      Assign m*j configurations to w. s + 1
12:      Repeat step 7
13:      Compute the OBV values
14:          While operations assigned < total operations
15:              p = p' + 2
16:              Increment the workstations to w. s + 2
17:              Repeat steps 11 to 13
18:          End While
19:  Stop
20:  Archive the solutions
```

5.2. Two: Repositioning of Workstations

In this strategy, an initial solution attained by the base model is compared with the revised solutions. The revised solutions are attained after changing the position of workstations. The positions of workstations are randomly changed for the same set of operations and the revised results are archived. The unique steps involved in the repositioning of the workstation's strategy are indicated through orange lines in Figure 4. The steps associated with the repositioning of workstations are provided below. For a defined number of generations, the position of workstations is randomly changed in each iteration to assess any improvement in the values of objective functions.

```
1:   Input: positions, workstations, configurations, and operations
2:   Input: processing time, adjustment time, the module adjustment factor
3:   Set: time counter t = 0
4:   For    g∈ g_max do
```

5: **For** $p = p'$ to P **do**
6: Random selection of workstation w. s
7: Assign n*j configurations to workstation w. s
8: Schedule operations on n*j
9: Compute the values concerning w. s
10: $p = p' + 1$
11: Increment the workstation to w. s + 1
12: Assign m*j configurations to w. s + 1
13: Repeat step 8
14: Compute the OBV values
15: **While** operations assigned < total operations
16: $p = p' + 2$
17: Increment the workstations to w. s + 2
18: Repeat steps 13 to 15
19: **End While**
20: **End For**
21: g = g + 1
22: **End For**
23: Stop
24: Archive the solutions

5.3. Three: Repositioning of Configurations

In this case, the workstations are placed at fixed positions and only the positions of configurations are swapped/changed across the different workstations. The unique steps of repositioning of configuration strategy are indicated by green lines in Figure 4. As can be seen, the position/order of configurations is swapped on two occasions, i.e., once when the number of operations is not completed, and secondly, in each iteration of the heuristic. All solutions are stored in an archive until the number of generations is exhausted. It is worth noticing that the results of all revised solutions are compared with the base model.

1: **Input:** positions, workstations, configurations, and operations
2: **Input:** processing time, adjustment time, the module adjustment factor
3: **Set:** time counter t = 0
4: **For** g$\in g_{max}$ **do**
5: **For** $j \in$ J **do**
6: Random selection of workstation w. s at p' =1
7: Assign n*j configurations to workstation w. s
8: Select a subset of J and schedule operations on n*j
9: Compute the values concerning w. s
10: $p = p' + 1$
11: Increment the workstation to w. s + 1
12: Assign another subset m*j configurations to w. s + 1
13: Schedule operations on m*j
14: Compute the OBV values
15: **While** operations assigned < total operations
16: $j = p * j$
17: Increment the workstations to w. s + 2
18: Repeat steps 13 to 15
19: **End While**
20: **End For**
21: g = g + 1
22: **End For**
23: Stop
24: Archive the solutions

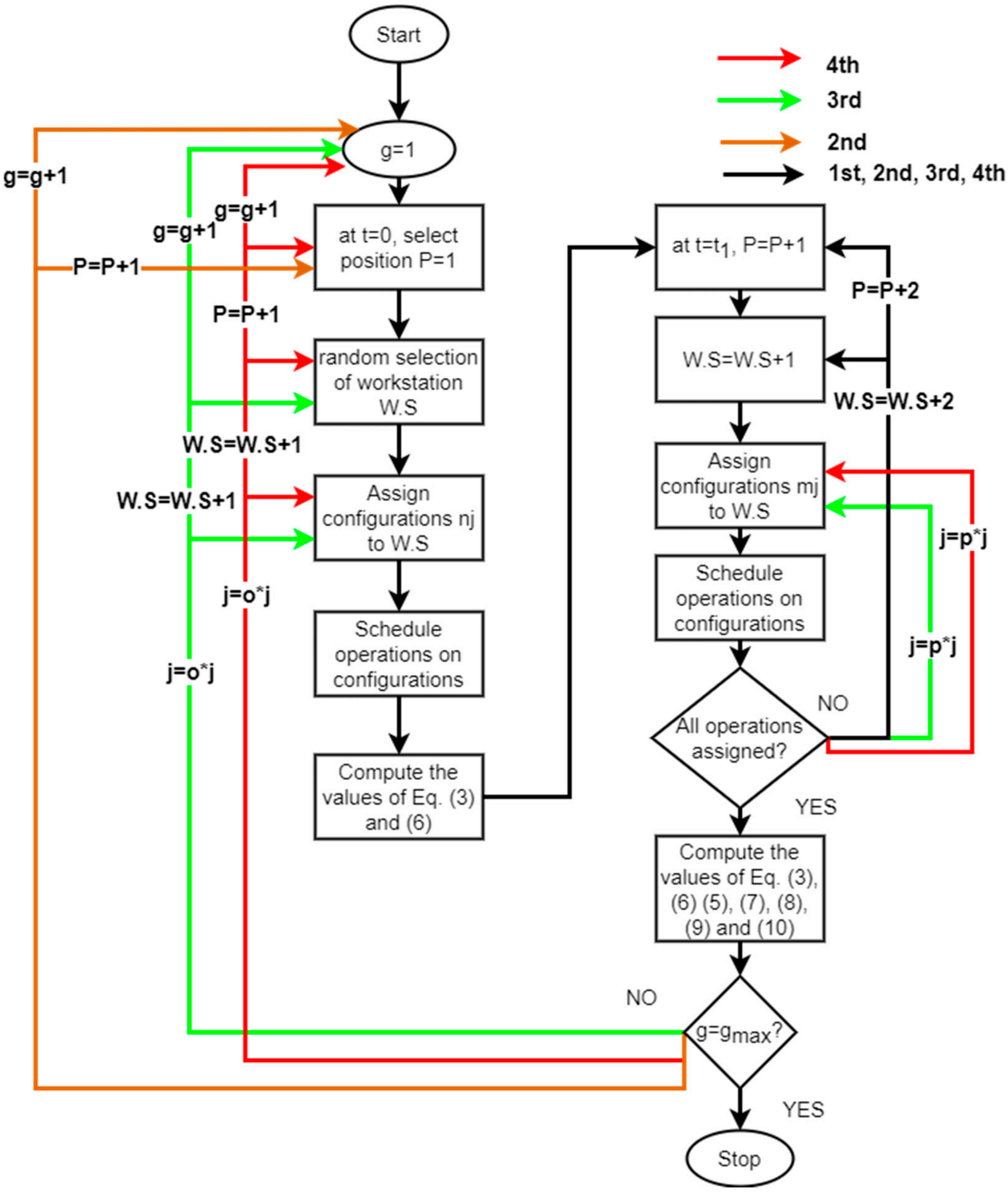

Figure 4. Consolidated framework for all strategies.

5.4. Four: Simultaneous Repositioning of Configurations and Workstations

The approaches adopted for the repositioning of workstations and configurations are combined here in this stage, i.e., the positions of workstations and the locations of configurations are simultaneously changed to seek any improvement in the objective function values. The unique steps of simultaneous repositioning of configurations and workstations are indicated by the red lines in Figure 4, and its detailed pseudocode is provided below:

Input: positions, workstations, configurations, and operations
Input: processing time, adjustment time, the module adjustment factor
Set: time counter t = 0
For $g \in g_{max}$ **do**
    For $p = p'$ to P **do**
        For $j \in$ J **do**

7:	Random selection of workstation w. s
8:	Assign n*j configurations to workstation w. s
9:	Select a subset of J and schedule operations on n*j
10:	Compute the values concerning w. s
11:	$p = p' + 1$
12:	Increment the workstation to w. s + 1
13:	Assign another subset m*j configurations to w. s + 1
14:	Repeat step 9
15:	Compute the OBV values
16:	**While** operations assigned < total operations
17:	$j = p * j$
18:	Increment the workstations to w. s + 2
19:	Repeat steps 14 to 16
20:	**End While**
21:	**End For**
22:	$p = p + 1$
23:	**End For**
24:	g = g + 1
25:	**End For**
26:	Stop
27:	Archive the solutions

To summarize, an optimal answer to the problem can be attained by:

— Assigning configurations to workstations, scheduling operations, and keeping the solutions as is,

— Repositioning the workstations and configurations separately or simultaneously to improve the RMS design and reduce the distances/configuration efforts.

5.5. Solution Representation

Solution representation is an integral aspect of any algorithm. It translates the information of decision variables and mathematical models into the coding structure/software. There are four layers involved in the execution of the considered problem, i.e., the position of a workstation, the number assigned to a workstation, the configuration allocated to a workstation, and the operation scheduled on the assigned configuration. The representation of a sample solution will contain this set of information, as shown in Figure 5. Accordingly, workstation 1, at position 1, comprises configurations 2, 3, and 3 to process operations 1, 3, and 4, respectively.

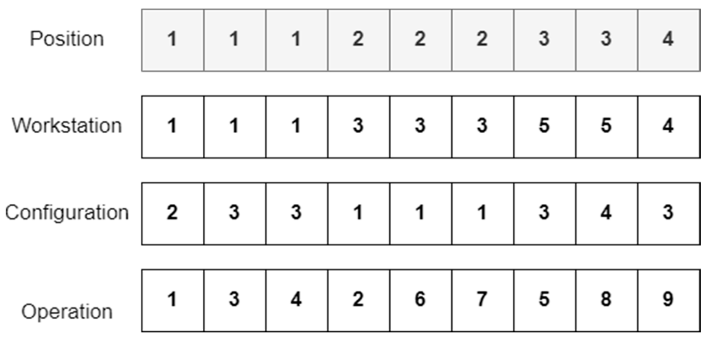

Figure 5. Structure of solution representation.

5.6. Comparison with Other Approaches

The performance of the proposed heuristic approach is compared with several heuristic approaches presented in literature. To serve this purpose, three heuristic approaches, i.e., Artificial Electric Field Algorithm (AEFA) [44], Co-evolutionary Particle Swarm Optimization (C-PSO) [45], and Variable Neighborhood Search (VNS) [46] approaches, were selected. These approaches have earlier been applied to solve the line balancing problems. The AEFA heuristic is proposed by Anita and Yadav [47]. It takes inspiration from the laws of motion and Coulomb's first law. The Particle Swarm Optimization (PSO), proposed by Keneddy and Eberhart [48], is based on the movement of particles. PSO has a downside of getting trapped into local optima. To address this concern, a Co-evolutionary Particle Swarm Optimization (C-PSO) was proposed in [45]. VNS works based on neighborhood structures and considers an initial solution to improve its performance.

5.7. Performance Assessment Metrics

The performance of meta-heuristic approaches has traditionally been evaluated by using several performance assessment metrics. The performance assessment metrics can be divided into the dimensions of effectiveness and efficiency [49]. The effectiveness of a meta-heuristic refers to its ability of returning quality solutions, whereas the efficiency of a meta-heuristic is related to its speed of returning capable solutions. This study considers two assessment metrics related to efficiency and two assessment metrics related to effectiveness. The efficiency measurement metrics are CPU time and rate of convergence. On the other hand, the effectiveness related metrics are Inverted Gravitational Distance (IGD) and Hyper Volume (HV). The IGD improves the quality and uniformity of solutions. The HV calculates the curved space between the Pareto solution and a reference point. Except for the convergence rate, which is interpreted quite differently, smaller values of CPU, IGD are preferred and a higher value of HV is preferred.

6. Results

6.1. Performance Assessment

The considered problem of line balancing is novel, and it has not been examined in the case of a reconfigurable manufacturing system. Therefore, several test problems were generated, and they were divided into three groups, i.e., small-size problems, medium-size problems, and large-size problems. A description of these problems is provided in Table 1. The set of operations in small, medium, and large problem sizes ranged between (4, 7), (10, 20), and (25, 48), respectively, and so on.

Table 1. Classification of problems into small, medium, and large sizes.

Problem Size	Problem Instance	Operations	Configurations	Workstations
Small	1	4	2	2
	2	5	2	2
	3	5	3	2
	4	6	4	2
	5	7	4	2
Medium	6	10	5	3
	7	13	6	3
	8	15	7	3
	9	17	8	4
	10	20	10	5
Large	11	25	12	7
	12	32	14	9
	13	37	17	10
	14	43	19	10
	15	48	21	11

It is pertinent to select specific input parameter values of meta-heuristics as these parameters are sensitive to changes. A random selection of input values can potentially undermine the effectiveness as well as efficiency of a meta-heuristic. To this end, the parameters of meta-heuristics were calibrated by using the infamous Taguchi design of experiments [50] in Minitab V. 19.

Table 2 contains the parameters related to AEFA, C-PSO, and VNS, along with the set of values for calibration. The 4th column in Table CC provides the number of experiments needed for calibration. The orthogonal array L_{16} was used for AEFA as well as for C-PSO, while L_9 orthogonal array was used for VNS due to its small number of experiments. The last column contains the optimal values of each parameter to be used for assessment.

Table 2. Levels of meta-heuristics, array type, and optimal values using TDE.

Meta-Heuristic	Parameters	Set of Values	# Experiments	Array	Optimal Values
AEFA	N D-dimensional solutions	100, 200, 300			200
	Max. iterations	70, 90, 100			90
	K0 initial parameter	100, 200, 300	243	L_{16}	100
	β initial parameter	15, 25, 40			40
	Small positive value	0.003, 0.005, 0.02			0.005
C-PSO	Particles	30, 50, 70			50
	Number of swarms	5, 7, 9			7
	Acceleration co-efficient	0.3, 0.5, 0.7	243	L_{16}	0.7
	Iterations for modification	50, 100, 150			50
	Iteration for restart	30, 50, 70			50
VNS	ω iterations	100, 150, 200			150
	n_1 iterations	100, 150, 200	81	L_9	100
	n_2 iterations	100, 150, 200			100
	n_3 iterations	100, 150, 200			150

The performance of all four meta-heuristics (AEFA, C-PSO, VNS, and the proposed heuristic) was compared for all 15 problem instances. The Line Efficiency Index (*LEI*) values are provided in Table 3. A maximum value of *LEI* means that the reconfigurable assembly line is more productive and efficient. It can be observed that the proposed heuristic outperforms other heuristic approaches. The AEFA performed better than the C-PSO in test problem instances. The Total Time (*TT*) values are provided in Figure 6. The proposed heuristic offers the least values of *TT* as compared to other approaches.

Table 3. Line Efficiency Index (*LEI*) values of all heuristics against several problem instances.

Problem Instance	*LEI* Values of Meta-Heuristics			
	AEFA	C-PSO	VNS	Proposed Heuristic
1	3.21	3.25	2.67	3.48
2	3.43	3.67	2.89	4.45
3	4.57	4.31	3.16	5.06
4	4.16	3.85	3.22	4.51
5	3.48	3.97	3.14	4.32
6	5.69	5.15	4.13	5.86
7	5.34	5.03	3.88	5.93
8	3.85	3.61	3.25	4.21
9	3.97	3.49	3.15	4.78
10	4.65	4.51	4.07	4.91
11	4.12	4.37	4.08	4.83
12	3.70	4.21	3.25	4.47
13	5.96	5.36	4.63	6.18
14	6.32	6.01	5.02	6.82
15	6.89	5.75	4.83	5.87

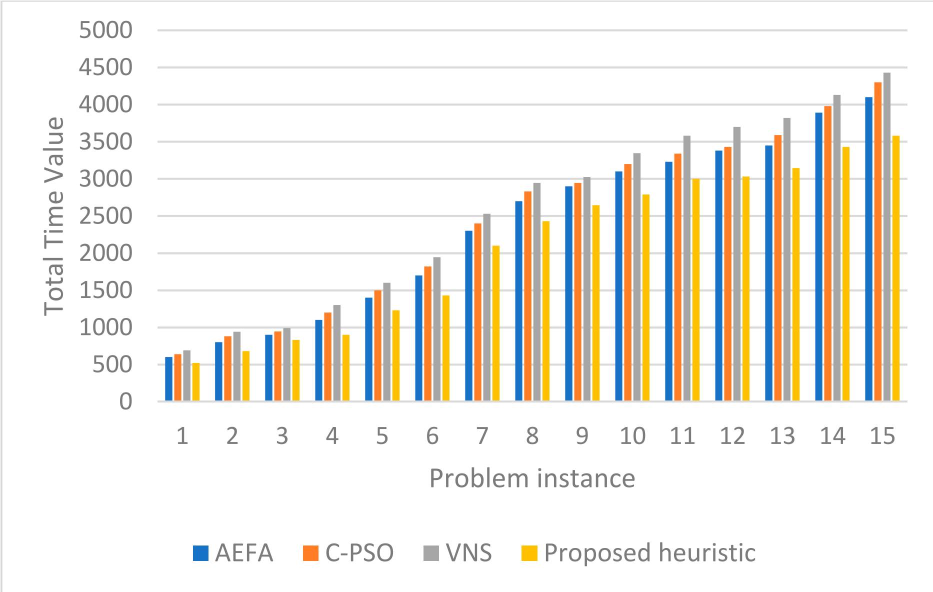

Figure 6. *TT* values of several meta-heuristics.

A statistical Tukey's test was conducted in IBM SPSS statistics V. 20 for pairwise comparison and to assess whether the difference in performance is significant or not. The relevant results are provided in Table 4. A significance level less than $p < 0.005$ means that the alternate hypothesis is approved, and the results are significant. It can be observed in the pairwise comparison that all results are statistically significant, and substantial support exists for the improved performance of the proposed heuristic approach.

Table 4. Tukey's pairwise comparison results.

Meta-Heuristic	AEFA	C-PSO	VNS	Proposed Heuristic
AEFA	—-	0.00	0.00	0.00
C-PSO	—-	—-	0.00	0.00
VNS	—-	—-	—-	0.00
Proposed heuristic	—-	—-	—-	—-

The performance results of efficiency metrics are provided in Figures 7 and 8. Figure 7 provides the CPU time taken by each heuristic. All heuristic behaved somewhat similarly for small problem sizes (1 and 2). However, the proposed heuristic approach outperformed other heuristics as the problem size increased. The Matlab R2016 based stair graph in Figure 8 shows that the proposed approach converges much faster to the optimal value of *LEI*. In fact, it takes almost 300 iterations in converging to the optimal objective function value.

The performance results of effectiveness metrics are provided in Figures 9 and 10. Combining the results of both figures, it can be argued that the proposed heuristic has maximum HV values and minimum IGD values for all problem instances. The improved performance of the proposed approach is primarily due to its simple and problem-specific nature. To summarize, the proposed heuristic offers optimal values of objective functions for all test cases, performs significantly better, and is both efficient as well as effective.

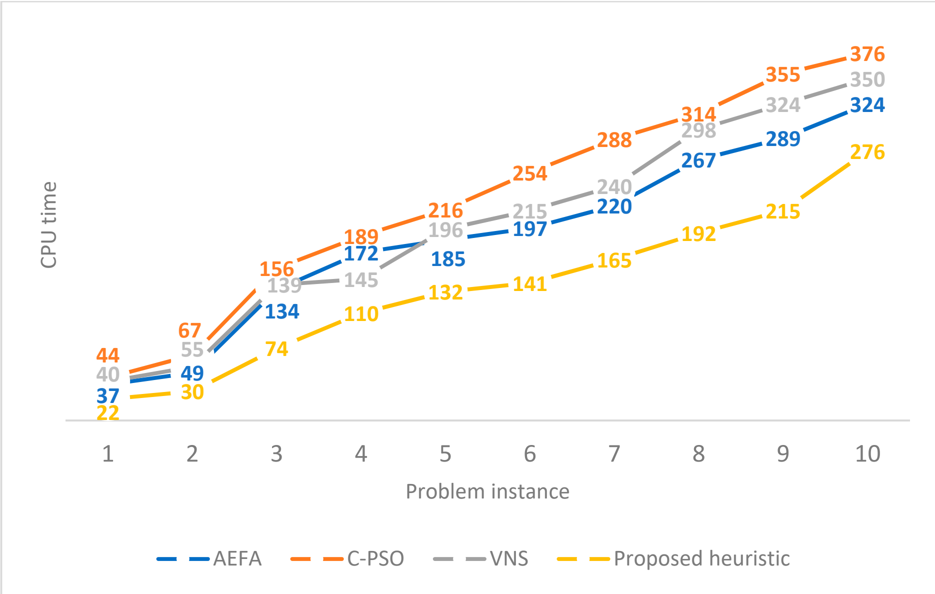

Figure 7. CPU time of meta-heuristics against several problem instances.

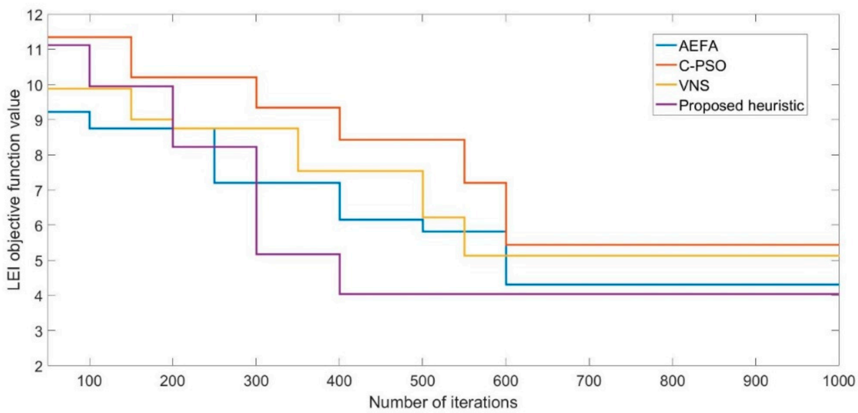

Figure 8. Stair graph of convergence of meta-heuristics.

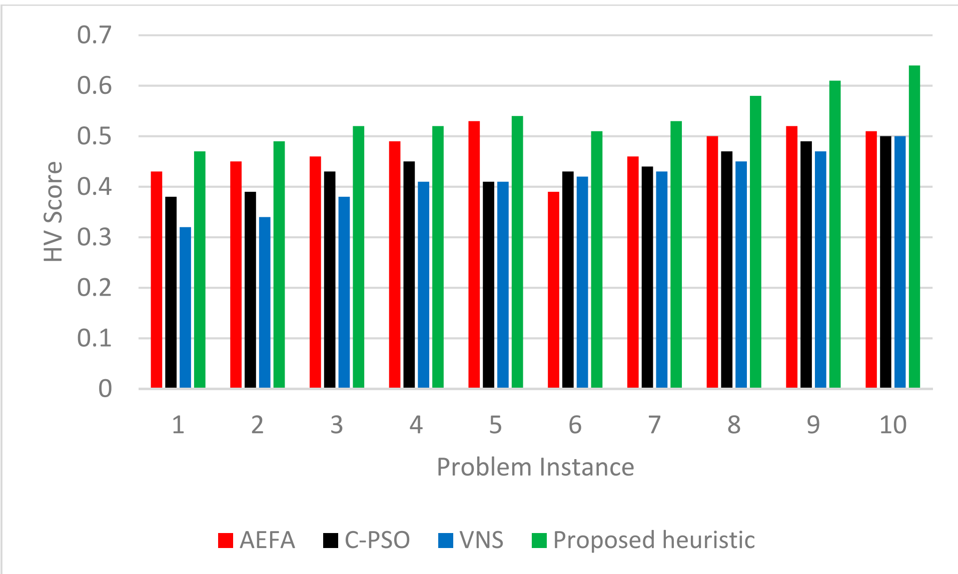

Figure 9. HV scores of meta-heuristics against several problem instances.

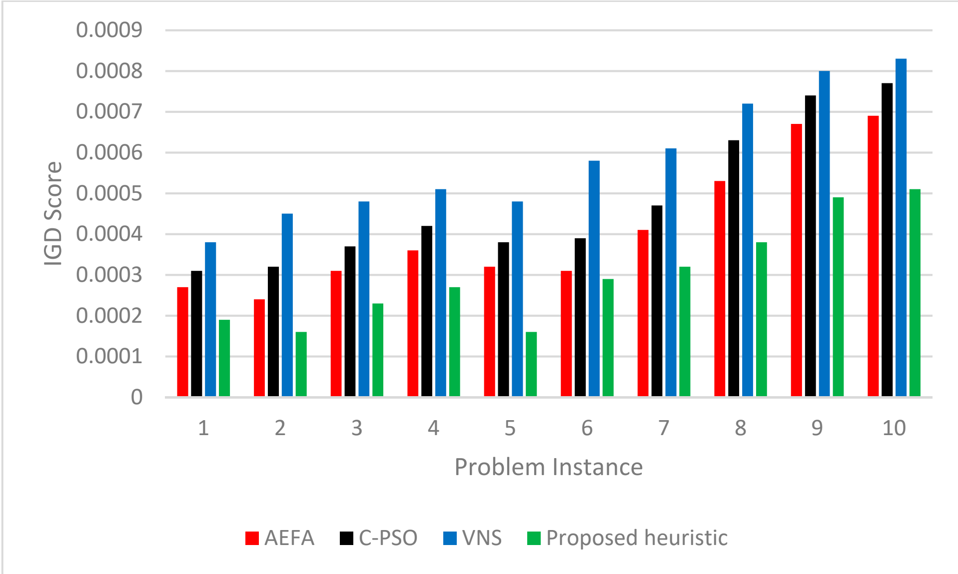

Figure 10. IGD scores of meta-heuristics against several problem instances.

6.2. Comparative Analysis of Case Studies

The heuristic approaches are applied to two case studies, i.e., case study 1 (based on precedence) and case study 2 (without the constraint of precedence). Case study 1 is adapted from [51], where a mechanical part is developed by processing five inter-connected operations. For easy reference, only the precedence relationship between operations is shown in Figure 11. It can be inferred that operations 2 (O_2) and 3 (O_3) can be independently processed; however, they cannot be started up until operation 1 (O_1) is completed. In this way, there is a precedence relationship among operations.

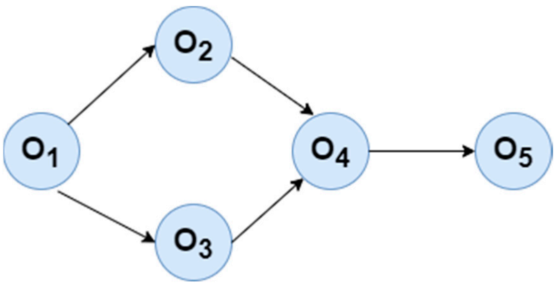

Figure 11. Precedence relationship for case study 1 adapted from [51].

Case study 2, where there is no precedence constraint, is related to the manufacturing of a hand light and its sub-assemblies. It is adapted from the studies of Tang et al. (2002) [8,52]. The schematic of a hand light is given in Figure 12, and it requires the completion of seven operations to get a final product. Each operation (sub-assembly) can be independently produced and then assembled at the end to get a hand light, hence, there is no need to follow a specific pattern of precedence.

Figure 13 provides an initial layout/design of reconfigurable machines assigned to 5 production stages. There are four configurations of machine 1, three configurations of machine 2, three configurations of machine 3, three configurations of machine 4, and two configurations of machine 5. Each reconfigurable machine is equipped with specific auxiliary modules which may be changed/re-adjusted as per the requirements of an operation. The adjustment time and factor of module adjustment effort in a workstation are provided in Table 5.

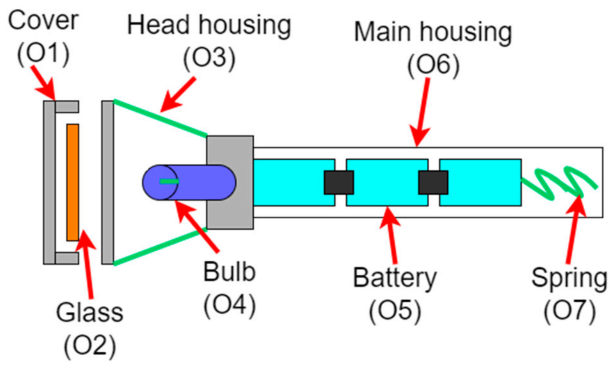

Figure 12. A hand light and its sub-assemblies adapted from [8,52] (case study 2).

Table 5. Module adjustment effort factor and module adjustment time in five workstations.

	Module Adjustment Effort				
	WS1	**WS2**	**WS3**	**WS4**	**WS5**
	1.3	1.6	1.8	0.9	1.75
Modules	**Adjustment Time**				
	WS1	**WS2**	**WS3**	**WS4**	**WS5**
	5.2	4.6	4.0	4.7	5.7
	5.6	5.2	6.1	5.8	4.9
	4.1	6.5	5.7	6.0	5.4
	3.8	5.4	5.5	4.7	4.4
	4.6	4.6	4.9	4.75	4.0
	5.7	4.1	5.0	5.4	4.8
	3.5	4.2	4.8	5.2	5.8
	5.3	5.8	5.5	4.8	5.0
	6.5	6.7	6.0	5.5	5.2
	3.8	5.5	4.9	4.7	6.6
	4.0	5.1	5.4	4.7	5.0
	4.6	3.7	4.1	4.4	5.3
	5.3	4.5	6.5	5.8	5.0
	3.8	4.4	4.7	4.2	5.7

The analysis of the assignment of configurations to workstations and position of workstations for case studies 1 and 2 is provided in Figures 14 and 15, respectively. The detailed process plans (which configurations are used to process which operations) and objective function values of five solutions (a–e) for case studies 1 and 2 are provided in Tables 6 and 7, respectively. The designs of only two solutions, i.e., a and b, are provided in Figures 14 and 15. It can be observed that although the solutions of case study 1 provide accommodating solutions by changing the position of configurations, there is no re-positioning of workstations (Figure 15).

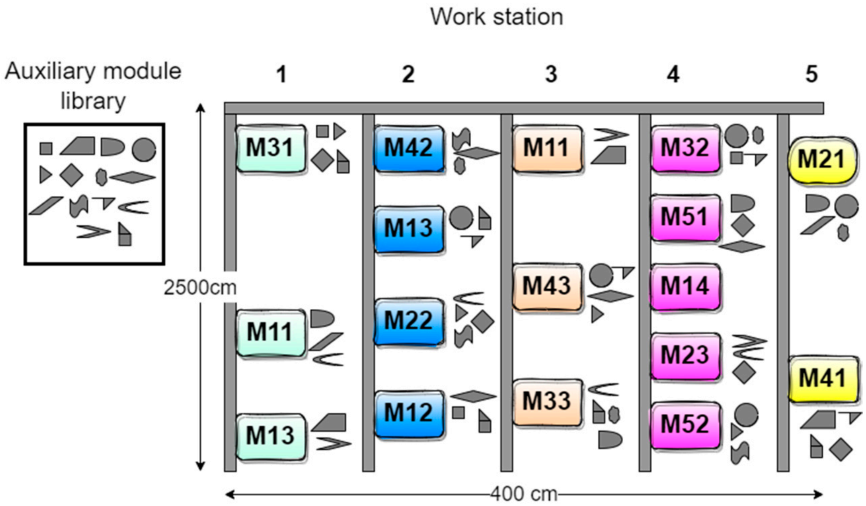

Figure 13. An initial scheme of configurations assignment to production stages.

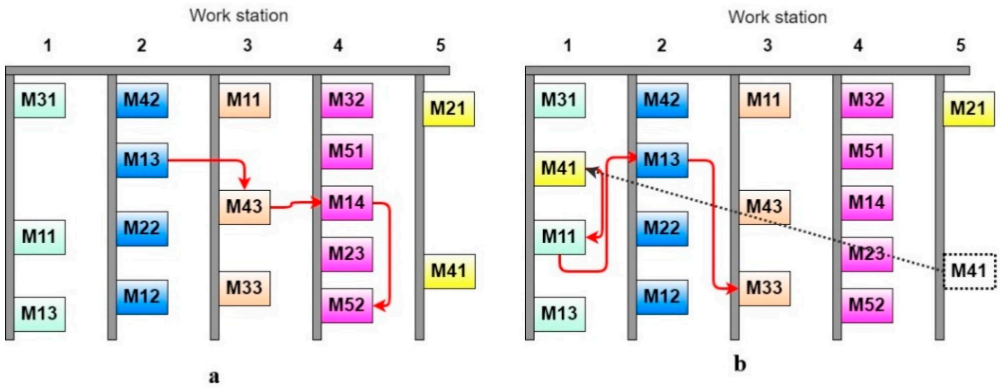

Figure 14. Production stage designs for the balancing problem of case study 1. (**a**) First configuration design, (**b**) second configuration design.

Comparatively, solution (a) in Figure 15 shows that not only is configuration M43 shifted to the 1st workstation, but workstations 4 and 5 are swapped to achieve better results. The reason behind no swapping of workstations in case study 1 is because of the ordering of operations in case study 1 which does not allow any repositioning if the precedence constraint is violated. Once the operational constraint is upheld, the system will look for all possible re-arrangements of configurations and workstations to achieve optimality.

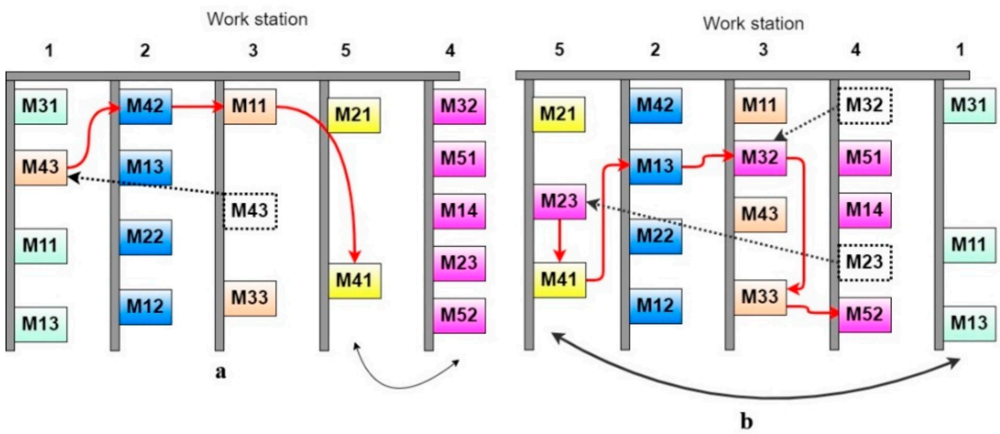

Figure 15. Production stage designs for the balancing problem of case study 2. (**a**) First configuration design, (**b**) second configuration design.

It can be inferred from Tables 6 and 7 that the Line Efficiency Index (*LEI*) values of case study 2 are higher than the *LEI* values of case study 1. This is a testimony to the effectiveness of a production line when the operations can be executed in any order. An enhanced level of configuration assignment and workstation positioning can be achieved with more flexibility. Configuration designs b (case study 1) and e (case study 2) offer the optimal values of the Total Time and the Customer Satisfaction Index. In addition, a different solution can be selected for an optimal value of *LEI*. In this sense, there is a conflict in the optimal objective function solutions. The detailed process plans are provided against each solution. The operations of case study 1 follow the same order regardless of the selected solution. On the other hand, different order patterns can be found in the process plans of case study 2. Thus, managers may not only assess the production stage positions, and assignment of configurations to workstations, as well as to the operations, but in addition to that, the ordering of operations can also be analyzed and changed for optimal values of the total cost, the line efficiency, and the customer satisfaction.

Table 6. Objective function values and plans for different configuration designs (Case study 1).

Configuration Design	Process Plan	Total Time (*TT*)	Line Efficiency Index (*LEI*)	Customer Satisfaction Index (*CSI*)
A	$O_1(M_{13})$, $O_2(M_{43})$, $O_3(M_{14})$, $O_4(M_{14})$, $O_5(M_{52})$	3635	2.95	0.88
B	$O_1(M_{41})$, $O_2(M_{11})$, $O_3(M_{11})$, $O_4(M_{13})$, $O_5(M_{33})$	***2865***	3.06	***1.12***
C	$O_1(M_{31})$, $O_2(M_{13})$, $O_3(M_{33})$, $O_4(M_{51})$, $O_5(M_{51})$	3365	3.02	0.95
D	$O_1(M_{42})$, $O_2(M_{22})$, $O_3(M_{11})$, $O_4(M_{51})$, $O_5(M_{52})$	3115	3.51	1.03
E	$O_1(M_{11})$, $O_2(M_{22})$, $O_3(M_{22})$, $O_4(M_{12})$, $O_5(M_{33})$	3340	***3.66***	0.96

Table 7. Objective function values and plans for different configuration designs (Case study 2).

Configuration Design	Process Plan	Total Time (*TT*)	Line Efficiency Index (*LEI*)	Customer Satisfaction Index (*CSI*)
A	$O_3(M_{43})$, $O_1(M_{43})$, $O_4(M_{42})$, $O_2(M_{42})$, $O_5(M_{11})$, $O_7(M_{41})$, $O_6(M_{41})$	3542	4.19	0.987
B	$O_1(M_{23})$, $O_3(M_{23})$, $O_7(M_{41})$, $O_2(M_{13})$, $O_4(M_{32})$, $O_6(M_{33})$, $O_5(M_{52})$	3576	***7.62***	0.980
C	$O_2(M_{31})$, $O_3(M_{31})$, $O_4(M_{22})$, $O_1(M_{12})$, $O_6(M_{11})$, $O_5(M_{21})$, $O_7(M_{51})$	3993	5.00	0.876
D	$O_7(M_{11})$, $O_1(M_{13})$, $O_2(M_{13})$, $O_4(M_{33})$, $O_3(M_{21})$, $O_5(M_{32})$, $O_6(M_{23})$	3945	4.71	0.887
E	$O_3(M_{13})$, $O_2(M_{11})$, $O_5(M_{11})$, $O_4(M_{33})$, $O_6(M_{33})$, $O_1(M_{21})$, $O_7(M_{41})$	***3485***	4.75	***1.004***

The breakdown of time components into Production Time (*PT*), Reconfiguration Time (*RT*), Module Adjustment Time (*MAT*), and Idle Time (*IT*) is provided in Figure 16 (case study 1) and Figure 17 (case study 2). For an *ETR* value of 3200 min (50 units required), only one solution (b) of case study 1 can respect the customer's preferred time of delivery. On the other hand, for an *ETR* value of 3500 min, one solution (e) satisfies the customer preferred delivery time, and two other solutions (a and b) fall on the borderline.

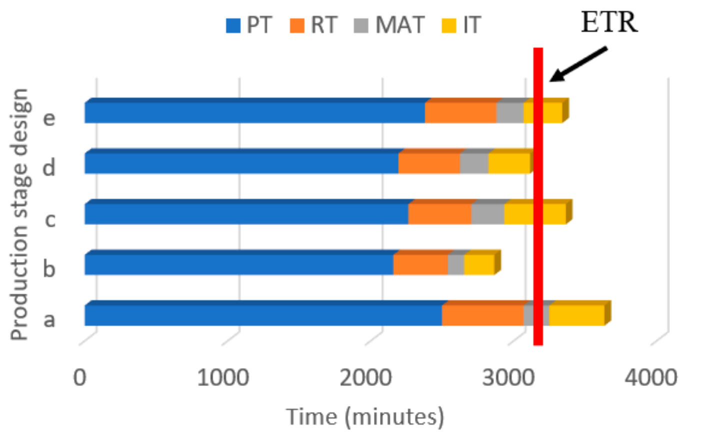

Figure 16. Time-based analysis of production stage designs (case study 1).

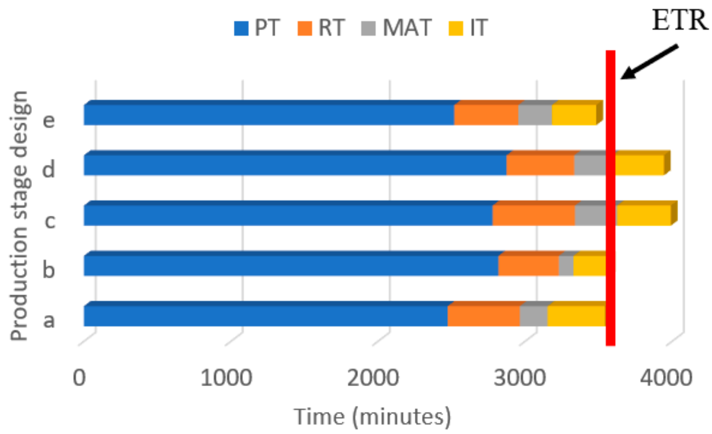

Figure 17. Time-based analysis of production stage designs (case study 2).

6.3. Comparison of Four Assessments

The four variants/assessments of the heuristic were separately implemented to understand their effectiveness in case study 1 and case study 2. The Total Time (*TT*) values for both case studies using different assessments are provided in Figure 18. Case study 2 findings show a substantial reduction in the total time value, as the assessment is changed from no-repositioning to the simultaneous repositioning of workstations and configurations. The *TT* value of case study 1 shows the only improvement in the simultaneous repositioning strategy. Thus, the precedence order (case study 1) puts a constraint/limit on the possible reconfiguration/arrangement of configurations and workstations.

The objective function values of the line efficiency index for both case studies in different assessment strategies are provided in Figure 19. A similar trend can be observed in these results, i.e., case study 2 findings provide a substantial increase in the line efficiency index. On the other hand, a static behavior is shown by case study 1 results, where only marginal improvement in the line efficiency index value is observed with both configurations, and workstations are simultaneously repositioned.

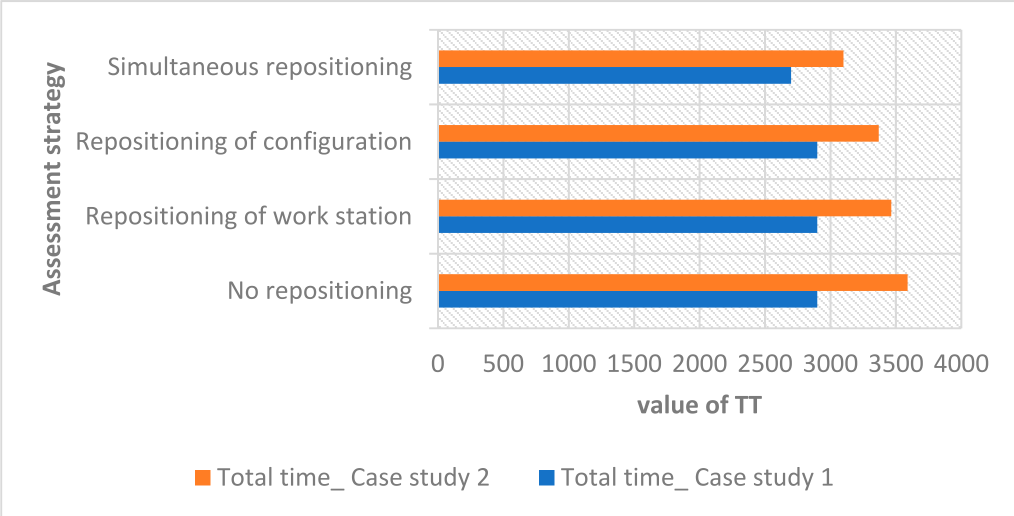

Figure 18. Total time values of different assessments.

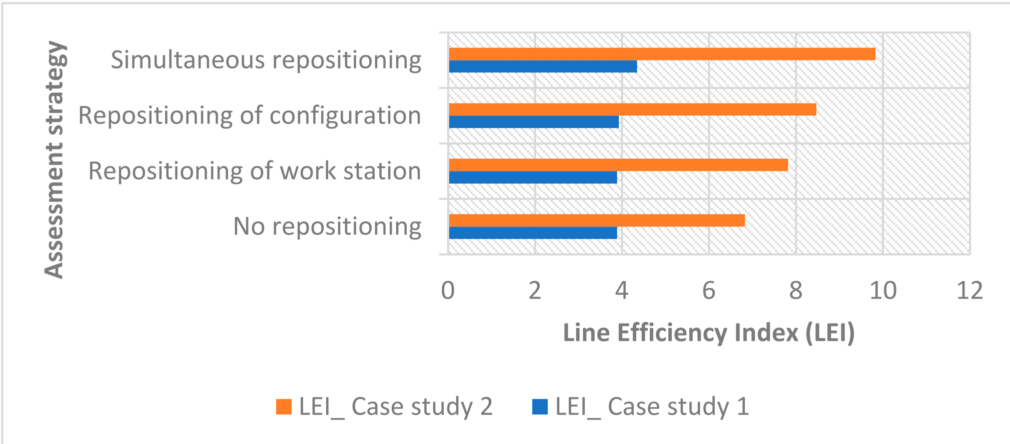

Figure 19. Line Efficiency Index (*LEI*) values of different assessments.

6.4. Comparison of Type 2 and Type E solutions

The earlier presented model was based on multiple objectives i.e., it considered the objectives of the Total Time (*TT*), the Line Efficiency Index (*LEI*), and the Customer Satisfaction Index (*CSI*). The *TT* value referred to the Type 2 problem, whereas the *LEI* value referred to the Type E problem. In this sub-section, the mono-objective functions of the *TT* and the *LEI* are considered, leading to the separate analysis of Type 2 and Type E problems, respectively. The configuration selection for the operations of case study 1 for both problem types is provided in Figure 20. Configurations M12 and M14 can be used for processing the first operation (O1) for the optimal values of Type 2 and Type E problems, respectively. These results can help to avoid the conflict of choosing a solution in a multi-objective environment.

The productive time (*PT*) and the non-productive time (*NT*) values of both problem types are provided in Figure 21. The *PT*, as well as the *NT* values of all operations, are less in the case of Type 2 problems. Thus, the summation of *PT* and *NT* leads to a smaller total time value and optimal solution to the Type 2 problem.

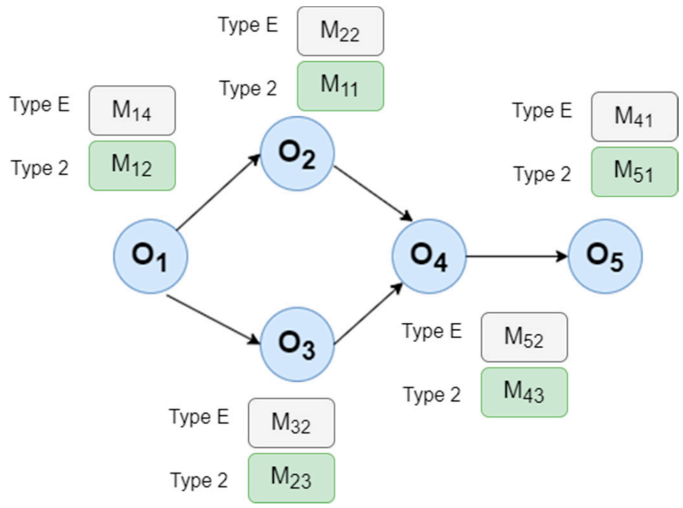

Figure 20. Configuration selection for different operations in Type 2 and E solutions (Case study 1).

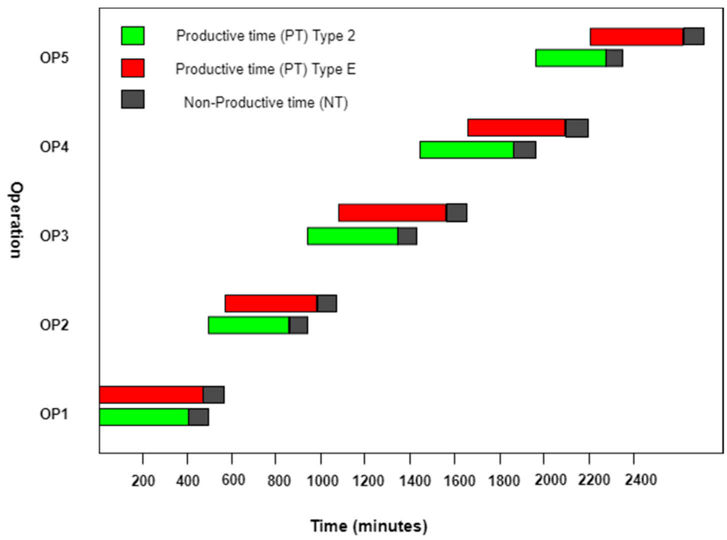

Figure 21. Productive and non-productive time assessment of Type 2 and E problems.

The summary of results and implications for practitioners are provided below:

- The earlier studies show that line balancing may not be an issue in a reconfigurable manufacturing system [19]. On the contrary, the current findings show that it is a pertinent issue in RMS, and different arrangements of reconfigurable machines can potentially affect the efficiency of line balancing in a reconfigurable manufacturing system.
- RMS is a sensitive manufacturing system, and its performance is affected both at macro and micro levels. It was observed that the efficiency of RMS is affected by macro level changes (repositioning of workstations) and micro level changes (repositioning of configurations and modular reconfigurations).
- The results show that there is a close connection between the Total Time (*TT*) of manufacturing and customer satisfaction. A minimum *TT*-based solution offered the maximum value of the Customer Satisfaction Index (*CSI*). Thus, the choice of specific configurations is pertinent in a reconfigurable environment to reduce time and enhance customer satisfaction.
- The line efficiency of RMS designed for case study 2 is always greater than the line efficiency of case study 1. Thus, when given an option, managers should always design a reconfigurable system for products which does not follow any specific precedence

order. This would provide a tremendous opportunity for the managers to exhaust all combinations choice of positions, configurations, and workstations to achieve optimality.

- The time window of delivery is an important aspect of the Supply Chain Network Design (SCND). This aspect was mapped with the help of the Expected Time of Receipt (*ETR*). The results show that more solutions of case study 2 can fulfil the requirements of *ETR*.
- The applications of all four assessment strategies show that the simultaneous repositioning of workstations and configurations helps in achieving improved results. The existing literature does not study the combinatorial impact of repositioning the workstations, as well as configurations on the line efficiency of a reconfigurable manufacturing system.
- A different process plan is available for optimizing the value of the Type 2 problem (Total Time) and/or Type E problem (line efficiency). These process plans and configurations will serve as a rubric for practitioners. They may switch the configuration if they want to move from one problem type to another.

7. Conclusions and Recommendations

In this study, a model for line balancing problems Type 2 and Type E was developed for a reconfigurable manufacturing system. A multi-objective model was proposed to optimize the Total Time (*TT*), the Line Efficiency Index (*LEI*), and the Customer Satisfaction Index (*CSI*). The model was applied in the presence and absence of precedence constraints using two separate case studies. A novel heuristic was used for implementing the model. The results suggest that the position of workstations and configurations affect the line efficiency of RMS. In addition, the efficiency is much higher when RMS is designed for a product without any precedence requirements. The simultaneous repositioning of workstations and configurations elevates efficiency and customer satisfaction.

The following constitutes the recommendations for extending this work. This study combined the line balancing problems Type 2 and Type E, while future research can also integrate the line balancing problem Type 1 into the model. As a result, the number of workstations can be minimized for a reconfigurable manufacturing system, along with optimizing the time and line efficiency. A new lower bound can be used for relaxing the precedence constraint of case study 1, which is quite popular in the line balancing literature. A time window constraint can be used for product delivery instead of using an apriori known expected time to hand over the product to the customer. The objective functions of cost and responsiveness can be used in the model, in addition to the considered objectives of time, efficiency, and satisfaction. We considered the case of a single product manufacturing while future research may extend the analysis by considering the production of a variety of products. This will help in justifying the investment in a reconfigurable manufacturing system. Lastly, the findings can be replicated by using other contemporary meta-heuristic approaches.

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