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ORIGINAL ARTICLE

Optimum machine capabilities for reconfigurable manufacturing systems

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Abstract

Reconfigurable manufacturing systems constitute a new manufacturing paradigm and are considered as the future of manufacturing because of their changeable and flexible nature. In a reconfigurable manufacturing environment, basic modules can be rearranged, interchanged, or modified, to adjust the production capacity according to production requirements. Reconfigurable machine tools have modular structure comprising of basic and auxiliary modules that aid in modifying the functionality of a manufacturing system. As the product's design and its manufacturing capabilities are closely related, the manufacturing system is desired to be customizable to cater for all the design changes. Moreover, the performance of a manufacturing system lies in a set of planning and scheduling data incorporated with the machining capabilities keeping in view the market demands. This research work is based on the co-evolution of process planning and machine configurations in which optimal machine capabilities are generated through the application of multi-objective genetic algorithms. Furthermore, based on these capabilities, the system is tested for reconfiguration in case of production changeovers. Since, in a reconfigurable environment, the same machine can be used to perform different tasks depending on the required configuration, the subject research work assigns optimum number of machines by minimizing the machining capabilities to carry out different operations in order to streamline production responses. An algorithm has also been developed and verified on a part family. As a result of the proposed methodology, an optimized reconfigurable framework can be achieved to realize optimal production of a part family. Finally, the proposed methodology was applied on a case study and respective conclusions were drawn.

Keywords Alternative process plans · Multi-objective genetic algorithm · Reconfigurable manufacturing systems · Reconfigurable process plans

1 Introduction

Reconfigurable manufacturing systems (RMS) have been recommended for the turbulent market conditions because of their flexible and changeable nature. Due to the rapid change in product's design and market demands, there is a need of a system that can adapt the varying requirements more efficiently [1, 2]. RMS is by default designed around a part family wherein customized flexibility is provided to manufacture all parts within that family. In RMS, each part within a family requires specific configurations which are adjusted by suitably reconfiguring the machine tool's configuration [3]. RMS allows flexibility not only by inducing variety in part design but also by modifying the system itself. Modularity, integrability, convertibility, diagnosability, and customization are the key characters of RMS that provide exact functionality and capacity needed for manufacturing a given product [2]. Since

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manufacturing system is an adaptive system that allows its components to tolerate the design changes up to a certain extent, the changing design of products requires a mechanism that can cater the changes accordingly. ElMaraghy [4] highlighted the evolution of manufacturing systems over the years and focused on the various challenges. In response to these challenges, key drivers such as optimality, quality, waste reduction, agility, and lean manufacturing were identified for survival [5].

Scalability is one of the significant features for a manufacturing system that can facilitate adding, removing, or modifying different workstations or machines, and enable the reconfigurability of the manufacturing system. The main purpose of a scalable production system is to adjust the performance measurement metrics such as throughput and waiting time. Using modeling techniques for capacity planning such as system dynamics simulation and mathematical programming is beneficial for finding a cost-effective solution to handle the changes associated from different customer demands. In the current literature related to capacity and scalability planning for RMS, there is no specific way to find the number of required machines with a single simulation model run during different time periods [6]. Moreover, scalability is a systematic approach which adds or subtracts from the system's capacity to fulfill the market demand [7]. When production time is low, parallelization of tasks leads to more machining cost. The need of the industry today is to have a more reliable and effective system that can offer optimum machining in terms of cost and time. This could only happen when the concept of co-evolution in the production system gets promoted. Co-evolution of product design and production system is basically a design for the production of product families and its reconfiguration over several product generations [8]. Reduction in product cost and responsiveness can be observed by customizing first the machining capabilities at product design stage and then the subsequent reuse of these capabilities at reconfiguration stage. It is also necessary to identify the maximum and minimum production capacity values among all configurations [9].

In reconfiguration, both hardware and software modules are involved which allow quick changeovers in functionality and capacity of the production system. It is modified physically and logically, i.e., either by changing machine configurations, machine layout, and material handling devices or through suitable routing, scheduling, and planning [10]. Throughout the past years, organizations have been in search of the best reconfiguration among a number of presented options to generate economical and distinctive configurations. The use of intelligent algorithms has proved their application handy in such situations [11]. Active research has been in progress in RMS field for the development of changeability enablers to adjust and rebalance the system configuration depending upon the market requirements. The concept of changeability allows the change enablers to sustain the life cycle of a manufacturing system at different levels of any industry. Changeability is considered as an umbrella that manages the necessary foresighted adjustments on various levels to respond to the change economically. It aids the manufacturers to have long-term competitiveness of companies. Both flexible manufacturing systems (FMS) and RMS accommodate changeability to some extent. The main difference lies in certain characteristics such as FMS gives generalized flexibility to switch between product variants unlike dedicated manufacturing systems (DMS). Since DMS is concerned with the production of specific parts, if specified part design is not available, then manufacturing of part is not possible. On the contrary, RMS is responsible for customizing flexibility and evaluating exact capacity [12].

Responsiveness, in RMS, is required at different levels in a manufacturing system in terms of changeability and scalability [13]. The first level is the "factory level" wherein due to the production variations, there is a need to modify the factory layout to accommodate the changing demands. "Assembly level" is the second area where process lines are transformable with the change in product design and demand. Next is the "process planning level" which is the major concern for companies to manufacture products in a part family. One of the major challenges for designers is to accommodate variations in product design level and manufacturing level to have a quick response in reaction to market fluctuations. Last is the "manufacturing level" where to be competitive in a global market, a manufacturing company must opt for a responsive system that fulfills the present production demands and reconfigures for the uncertain future demands. RMS has the ability to reconfigure quickly with low reconfiguration effort and at the same time having low cost. A modified reconfigurable layout can contribute in achieving the desired configuration by employing it on the assembly line and product scheduling [14].

RMS consists of different elements that contribute toward its sustainability including material handling, machinery, and organizational staff. All these factors are the change enablers having the tendency to reconfigure the system logically or physically depending upon its constraints. This research work is mainly concerned with machinery in which machine tools, assembly, and factory facilities are to be taken care of. The essential element is to identify the exact degree of changeability needed so that the exact system configuration could fulfill the desired performance. As a result, production planning becomes complex, quick, and reliable. The performance and flexibility depends upon the suitable data for scheduling and process planning. In order to achieve this performance, different approaches have been discussed in literature. One of the major solutions for increasing the changeability of a manufacturing system is reconfigurable process planning and control [15]. The emerging scope of RMS is due to the responsiveness at process planning level. Process planning and control is actually an interface between the customer needs and the manufacturing system. The desired performance and efficiency of a manufacturing setup truly depends upon the high-quality production data for both system and product level. Planning data also incorporates the resources, functionality, and scalability of a production system. It characterizes the imperative changeability enablers for products and manufacturing system evolution. Moreover, it cost-effectively manages the change in product and modifies the system accordingly. Since manufacturing process planning aids in bridging the gap between design and manufacturing, process planning plays a critical role in determining the manufacturing cost, time, and system responsiveness [16]. Various process planning techniques lend themselves to RMS, and like FMS, RMS is usually designed for a certain part family but with wider scope. However, generative process planning systems are better able to handle unplanned product variations. Therefore, a hybrid reconfigurable process planning (RPP) system that is variant in nature yet capable of generating process plans for parts with machining features beyond those present in the current part family's composite part can best meet the current challenges [17]. In this approach, product family is identified closest to the new part and the corresponding process plan is retrieved. Mathematical programming has been carried out for the generation of process plans that accounts for design and manufacturing changes in different features of part [18]. To determine the best location for the new added feature of a part family, precedence graph is reconfigured by adding/removing features iteratively to optimize the cost obtained. RPP helps in reconfiguring the system during production changeovers due to the dynamic nature and flexibility of RMS with minimal effort to meet the changes in production requirements.

Consequently, keeping in view the global trends and shorter manufacturing life cycles, the requirement of this era is to map different change enablers and sustainability paradigms of manufacturing systems. This has been taken as an ultimate goal in the work presented here. The proposed methodology is based on co-evolution model with two main objectives: first, to analyze the need of reconfigurability, and second, to exemplify how the reconfigurability can be carried out by generating minimum machining capabilities. More specifically, the goal is to present a generic approach for modifying the system according to desired capabilities to manufacture different features of the same part family. It has been carried out by reconfiguring manufacturing system in which optimized reconfigurable framework has been presented to modify the system according to production demands timely with minimum production capabilities. Considering a master part, applying multi-objective genetic algorithm (MOGA) on its generated process plans and configurations (co-evolution model) gives the global best individual. Moreover, the proposed approach is generic since it generates optimal process plans and machine configurations on co-evolution paradigm. It also has the ability to cost-effectively reconfigure the system. The presented algorithm can further manufacture the part family with minimum production changeover time and optimal machine capabilities. For systematic study, the remainder of the paper has been arranged as follows: Section 2 presents the concerned literature review; Section 3 shows the mathematical formulation; Section 4 presents the proposed methodology along with the application on a case study; Section 5 consists of results and analysis of the case study; and finally, Section 6 discusses the conclusions drawn and future work prospects.

2 Literature review

The globalization in the 1990s created intense competition in manufacturing industries leading to variations in product design and shorter product life cycles. This makes the prediction of future demands for any product difficult. To respond efficiently to achieve required design changes, there is no need to replace the entire system as the existing manufacturing capabilities are shared across products and production generations. Materials and technologies are here renewed frequently to create required and new product features [19]. RMS has been acknowledged as receptive toward capabilities and functionalities due to its ability to accommodate the variations at product design and manufacturing [2, 10]. This is achieved when the design is based on two principles which in turn reduce the cost and increase responsiveness. One is the design of a manufacturing system for adjustable structures which allows the system scalability to vary according to the production demands and machine's adaptability to manufacture products in a part family. Second is the structure adjustment which incorporates adding machines and changing machine's hardware and software control. Manufacturing system is designed around a part family having the customized flexibility desired for the production of different features of the same part family [20]. Hence, the core characteristics of RMS must be incorporated in developing an adjustable and flexible setup for production over part families.

RMS is an active research for more than a decade now. It was first proposed by Koren et al. [21] and was claimed as the only solution for the manufacturing industry to respond timely and efficiently. Most of the research is also done on reconfigurable layout considering performance measures to achieve high responsiveness, selection of reconfigurable machines, and formation of part family. Co-evolution of product families and assembly systems are introduced as a new product development methodology for the joint design and reconfiguration of assembly systems within and across product generations. The co-evolution methodology can also enable manufacturers to remain competitive as it maximizes the reuse of product modules and reconfigurable systems to ensure that manufacturing systems are effective for as many product generations as possible [22]. Moreover, process planning identifies how a product is to be manufactured according to the design specifications satisfying different constraints and available resources. Process planning is a multi-decision activity that determines both operation selection and operation sequencing. The former aspect is based on technological requirements while the latter is related to machine selection for producing a part satisfying the feature's technological constraints [23]. It is basically a bridge between the design and manufacturing. Changeability metric captures cost of changes in the process plan and can be used for choosing one process plan among alternate process plans. The plan having the least changes is then finally selected [18]. The explained methodology here is appropriate for macro process planning in which the optimum plan is explored while satisfying the precedence constraints.

Furthermore, different approaches have been discussed in literature in which scalability has been carried out through process planning and machine configurations. Since optimization techniques have gained significant interest by researchers in order to search the best performance value, a brief literature survey related to MOGA is also included in this section. RPP represents important changeability enabler for products and manufacturing systems. In RPP, two basic criteria are considered. In the first criterion, part's handling and re-fixturing time is minimized to get the optimum process plan having the minimum value of reconfigurability index. For the second criterion, changeability metric is introduced to evaluate reconfigured process plans. Also, the changeability metric captures cost of changes in the process plan. In addition, macro process planning has all the information regarding product's manufacturing steps and its logical sequences provide greater product variety and reduction in cost. Frequent and unpredictable market variations trigger the changes in the product manufacturing because the manufacturers keep on evolving the innovative products to sustain in the global market and stay competitive. These uncertain innovations can be catered effectively by developing a reconfigurable system at process planning level. An RMS approach was proposed by Renna and Ambrico [24] on the performance of classical cellular manufacturing. Different performance measures including work in progress, manufacturing utilization, and processing time were analyzed keeping in view the production mix changes, demand ratio, fluctuations, and machine processing time. Reconfigurable cellular manufacturing and flexible cellular manufacturing are best alternatives to cellular manufacturing. Cellular manufacturing systems are best when demand and product mix are at medium level.

In the literature, few methodologies have been presented for part family formation. Kashkoush and ElMaraghy [25] suggested a hierarchical clustering method to generate various groups of product families that have similarity coefficient. Group technology is a manufacturing philosophy in which similar parts are identified and grouped together into groups and families. Parts are grouped into families based on the similarity of their processing requirements. Each family gets a dedicated production facility, known as a production cell. Typically, cells operate as switching flowlines, with switching taking place between the productions of batches of different part types. Frequent switching can then involve substantial effort and time, known as setup time. RMS has advantage over cellular manufacturing and group technology due to its flexible and customizable nature. In cellular manufacturing, the rapid changes of markets force the manufacturing systems to be able to react to demand changes. In scientific literature, the periodic reconfiguration or robust design methodologies for the cellular manufacturing systems that maintains a high performance level when market changes occur is proposed. Reconfigurable assembly system (RAS) is basically RMS for assembly process. Another approach was proposed by Goyal et al. [26] in which a similarity coefficient was proposed on the basis of operation sequence. Considering alternative process plans, Rakesh et al. [27] proposed a modified average linkage clustering algorithm.

Azab and ElMaraghy [17] presented a mathematical model for reconfiguring macro-level process plans. To add validity in the previous technique, Azab and ElMaraghy [28] applied genetic algorithm (GA) to obtain an optimized process plan. Most of the process planning issues in literature have been solved using non-polynomial (NP)-hard approach since calculus techniques are limited in assuring optimality. Shabaka and ElMaraghy [29] developed a methodology to ensure the generation of feasible process plans using real coded GA for the first time in process planning as it has a large search domain compared to traditional GA. Chaube et al. [30] proposed a technique of non-sorted GA (NSGA)-II in which non-dominated solutions were sorted and plotted to generate optimal machine configuration and optimal process plan. This integrated approach also required the study of structural configurations of different machining operations. One of the major contributions in configuration selection was carried out by Youssef and ElMaraghy [31]. Since reconfigurability is the main factor on which the industrial future depends, the significance of reconfigurable machine tool (RMT) is undeniable. RMT is a modular type of machine tool having core characteristics like convertibility, integrability, and modularity [32]. These characteristics of RMS allow mass customization and rapid response to the product design change. Moreover, machine kinematic configurations are generated from the set of functional requirements and process plans in order to design RMTs as stated by Moon and Kota [33]. Another approach, involving the machine configurations to generate the minimum machine capabilities considering the concept of co-evolution, was proposed by Shabaka and ElMaraghy [34]. This approach is generic and can be used to generate machine configurations in any manufacturing system since it can be extended in generating the reconfigurable machine structure for part family rather than a single part. The co-evolution theory further reveals that the product, process, and production system are interlinked and have a direct impact on each other [8]. In addition, co-evolution of product design and production system is basically a design for the production of product families (having design or feature similarities) and its reconfiguration over several product generations [35]. Reduction in product cost and responsiveness can be observed by customizing the machining capabilities at product design stage and then reusing these capabilities at reconfiguration stage. Kumar and Deb [36] carried out an analysis by minimizing weighted function in case of a simultaneous setup and tool change. The results not only gave the optimal solution for each parameter but also optimized the overall effect. Elitist GA methodology was also applied to generate optimal operation sequences in setup planning.

Goyal et al. [37] proposed an approach for optimal assignment of machines in parallel setups through NSGA-II and TOPSIS ranking theory. This approach led to the machine tool reconfiguration by adding or subtracting machine modules going through different performance measures. A quantitative model was also developed for RMS scalability by Wang et al. [9] who calculated the number of reconfigurations based on adjustment gradient. NSGA-II technique has also been used by Bensmaine et al. [38] in the selection of optimal machines from the set of candidate machine configurations. In this research, work multi-product case with a high degree of freedom can be considered as future work, and with the idea of co-evolution, the machine configurations can be used for different product designs over and over again, preserving the feasibility of the system for a long period of time. Baqai [39] also proposed a methodology to generate reconfigurable process plans and its structural configurations simultaneously considering the precedence and topological and logical constraints. As setup planning plays a vital role in the integration of scheduling and process planning, it is closely related to process plan generation and machine selection. Mohapatra et al. [40] proposed the method to bridge the gap between scheduling and setup planning by grouping the machining features on the basis of tool approach directions (TAD), adopted NSGA-II, and fuzzy set theory to get the Pareto optimal solution. In extension to this work, the integration of process planning and scheduling was achieved through an improved version of NSGA-II [41]. Three objective functions, makespan, cost, and idle time, were considered on minimizing criteria to obtain the Pareto fronts. A comparative study was also done between NSGA-II, controlled elitist NSGA-II, and improved controlled elitist NSGA-II. Further, it was observed that the proposed algorithm-improved controlled elitist NSGA-II outperformed the other two when efficacy and efficiency were used as comparison parameters. A new methodology was introduced by Azab et al. [12] based on control loop for effective scheduling and planning for system reconfiguration. In this methodology, the inherent characteristics of RMS are analyzed to implement desired changes at system or machine level. Bensmaine et al. [42] proposed a new approach to integrate the process planning and scheduling simultaneously rather than as two separate functions. Considering the multi-configuration nature of RMTs, a selection index determined the candidate machine which was capable enough to perform certain operations. Recently, Azab and Naderi [43] proposed a methodology in modeling of large problems which included subfamily sequencing and parts in each subfamily to minimize the maximum completion time using mathematical programming software. Benderbal et al. [44] addressed the problem of machine selection in a reconfigurable environment and developed an approach for the selection of best performance process plan using NSGA. The responsiveness is increased based on flexibility of the designed system and generated process plan which also caters the situation of unavailability of particular machine. Two objectives, maximization of flexibility index and minimization of completion time, are considered. The main objective of this work was to evaluate the flexibility of reconfigurable process plan for a part family. Different machines were identified and allocated on the basis of optimality criteria considering the available tools and their configuration. A methodology was also presented for modularity assessment by Benderbal et al. [45] in which three main objectives were targeted: maximization of system, modularity, and minimization of system cost.

RMS are built to effectively respond to market changes. Although plenty of literature exists on the issues of RMS, a wide scope of study is still required in all fields of RMS. In order to have a reliable and efficient system, non-monetary product performance measures can also be integrated for balancing production line [46]. To balance the workload and minimize production cost, a methodology combining the capacity control and production planning methods was proposed by Gyulai et al. [47]. This approach gave the feasible process plans by considering the requirements for capacity in terms of multivariate linear function which is an integral part of a mathematical model. Moreover, Zhang et al. [48] presented a simulation-based approach related to remanufacturing through scheduling and process planning to give optimized framework. Considering process routes, the detailed process scheduling was generated through computational experiments using NSGA. Furthermore, Hees and Reinhart [49] discussed scalability planning through modeling simulation technique. The required capacity in terms of machining was attained using integrated model of discrete event simulation and resources' pool functions. One of the drawbacks of this approach was that it required more computational efforts and expertise to get the optimum solution to meet the exact number of machines. Another mathematical approach was proposed by Koren et al. [18] to minimize the total number of machines and maximize system throughput by concurrently reconfiguring and rebalancing the system to match new market demand. This approach offered a set of principles for system design for scalability and was validated for an industrial case. The scalability process planning required simultaneous changing of the system configuration and rebalancing of the related reconfigured system. An optimal scalability-planning problem, which is subject to realistic constraints, was then formulated and solved using GA. This paper also extended the work done by Wang and Koren [6] by applying the mathematical analysis to systems with buffers.

The concept of learning factories was proposed by ElMaraghy et al. [50] wherein the methodology for product family development was introduced to an existing learning factory characterized by changeability factors. When a new product was to be manufactured, the intelligent manufacturing system initially assembled family desk with variants. The learning factories vary based on required education and research domain objective catering for the weights and volumes of product variants. Navei and ElMaraghy [51] also proposed an approach for determining the similarities between the product families by analyzing the aim of increasing the efficiency and speed of production. Master operation sequence was retrieved for new variants. The variant approach has advantage over generative approach as there is no need to retrieve the process plan at every stage and the generated master sequence has a similar operation within variants of part family. This results in improving the planning efficiency and variety of product design. The proposed MIP algorithm further relies on available information of existing variants. It does not consider new features/components that may be present in new variants. This is basically a potential approach for multiple alternative process plans. In addition, Hassan et al. [52] proposed the methodology for the determination of optimal configuration of multiple part family orders. Machine configuration was selected through NP-hard problem, but optimization techniques can also be used to reduce computational efforts and ultimately to obtain improved results. One of the improved algorithms of machine configuration was proposed by Hassan et al. [53] in which machine adaptive retainability approach was proposed to select process plan by comparing the previously employed process plan with the proposed process plan considering kinematic configurations. A model was proposed for the synthesis of manufacturing systems by Abbas and ElMaraghy [54] to reduce the cost of product variants by optimization of co-platforming model. Total investment and testing of machines into manufacturing systems were minimized as part of the objective function. Goyal et al. [55] also suggested an approach that focused on creating a responsive index to measure the responsiveness of RMTs. The responsiveness of a RMT is proposed to be the average of operational capability and machine reconfigurability normalized values because it is quite apparent that both metrics, i.e., operational capability and machine reconfigurability, directly influence the rapidity with which capacity and functionality requirements can be handled on the machine level.

Mostly optimization of engineering designs are carried out through evolutionary algorithms (EAs) which are characterized as stochastic global search methods inspired by natural evolution. These algorithms do not need any gradient information unlike other optimization methods. They make use of design points to search an optimum solution rather than any gradient information. Moreover, they are inspired from different natural phenomena and make use of the best character of that phenomenon. The EAs search for the global optimum solution and possess extreme robustness which increase the probability of getting the minimum global solution. For this purpose, EAs are best suited for discrete optimization problems. These algorithms require high computational cost and have poor constraint handling abilities [56]. Among all EAs, GAs are most popular. Moreover, the natural evolution for selecting the best solutions can be implemented only in the presence of a certain measure. This measure could be an objective function which is a mathematical model of the fitness evaluation criteria. The recombination operator exchanges the characters of chromosomes among two parents, and random mutation exchanges the genes at some location, rearranging the order of genes in a chromosome. Recombination and mutation are the two GA operators that extract the best and dominating character of the parent chromosome to form the child chromosome [57].

Conclusively, based on the expansive literature review conducted and the over-arching aim of the research, it was deduced that the application of MOGAs will make the approach more reliable for co-evolution of process planning and machine configurations to generate optimal machine capabilities since they preserve best solutions over the generations. Also, MOGAs give the best solution in process planning problems. The purpose of this research work is to propose a generic methodology for producing a variety of parts through changeable and RMS. Scheduling issues and the selection of optimal process plan have been discussed many times in literature, but there is a lack of an optimized framework to counter the changeability extent for production changeovers in a part family while taking the machine's kinematic configurations under consideration. The proposed methodology will fill this gap through the application of MOGA on a set of alternative process plans and integrating machine configurations depending upon the machine's accessibility, simultaneously. The flexibility in the system is attained due to the parameters selected for process planning such as tool changeovers, configuration changeover, and part rotation. These parameters are directly linked with the production cost and run time. The presented approach can be further modified according to the demand and production environment on the basis of considered optimization parameters. Currently, all these parameters have been assigned equal weights, but preference can be given to any one depending upon the production scenarios. Finally, the proposed approach can give the information of all the machining requirements including tools and its configuration by having the information related to features and the associated technological and precedence constraints.

3 Mathematical formulation

To carry out production in a part family or when a new part arises and production is to be shifted from one part to another, some major issues faced by decision makers are as follows: Which new machines are required? Are the available machines sufficient for production? Does the setup require reconfiguration? Is the available or proposed layout cost-effective?, etc. Since the study is about RMS, the production is to be carried out around a part family having operational similarities. The nomenclature involved is given below:

OP = operation
NOP = number of operations
N = number of features to be added
i, j, k = indices for OP number of particular part [$i, j, k, \ldots$, NOP]
x, y = indices for OP number [$x, y, \ldots$, NOP]
Op_x = operation at ith position, and Op_y = operation at jth position in a particular sequence
TAD = tool approach direction for each operation

Designing a manufacturing system consists of two different tasks. The first task consists of determining the set of machines to be involved in the production process, while the second task concerns the definition of the selected machine's layout. Considering a multi-product case, each machining feature of a given part is assigned a serial number and a suitable machining operation is identified on the basis of machining and geometrical requirements and the TAD matrix capable of producing each operation depending on the machine's visibility. The design variables involved which have a direct impact on the objective function [described later in Section 4 (see Eq. 4) in detail] are given as follows:

3.1 Design variables

A. Operation sequence (OS):

$$OS = \left\{Op_1, \mathrm{O}p_2, \mathrm{O}p_3 \ldots \mathrm{O}p_{nop}\right\},$$

where $\mathrm{O}p_i$is the operation taking the ith position in the sequence.

B. Tool approach directions (TADs)

$$TADs = \left\{tad_{1,} tad_{2,} tad_{3,} \ldots\ldots . tad_{NOP}\right\},$$

where tad_i is the TAD assigned to operation Op_i.

C. Precedence group matrix (PGMS):

Operations are grouped based on precedence and technological constraints.

Op (x, y) is the precedence between Op_x and Op_y.

Tool change, setup change, and part rotation matrices are used as input to find the optimal process plan and to select a set of machines that are able to achieve all the necessary operations to accomplish the desired product while minimizing time and costs in terms of tool and configuration changeovers incurred during the production. Suppose Op_x and Op_y are the randomly generated sequence of operations, they will go through tool change, setup change, and part rotation check. For this, the data in matrix form is required. If the corresponding value against the operations in matrix is 1, it means there is change in tool, setup, and part rotation between operations, and 0 means otherwise. Each machine comprises various modules performing as different tools and providing different operations of parts. Configuration changeover depends upon the machine's visibility for that particular operation. Depending on the required product design, these modules can be added or removed. The mathematical formulation for the inputs and the constraints involved are given below:

3.2 Inputs

$Mtool \left[Op_{i,j}^N\right] \left[Op_{i,j}^N\right]$ = Matrix showing the tool change between operations.

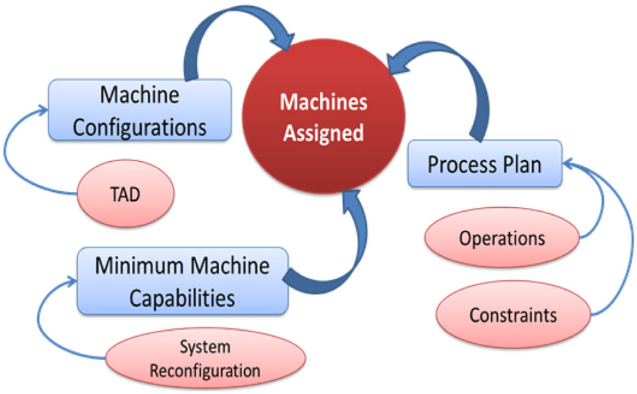

Fig. 1 Reconfigurable framework

$Msetup\left[Op_{i,j}^{N}\right]\left[Op_{i,j}^{N}\right]$ = Matrix showing the post/setup change between operations.

$Mrot\left[Op_{i,j}^{N}\right]\left[Op_{i,j}^{N}\right]$ = Matrix showing the part rotation between operations

A. Tool change:

$$TOC = \sum_{i=1}^{NOP-1}[1-(1-Mtool(Op(i),\ \ Op(i+1))]$$
$$Mtool(x,y) = \begin{cases} 1, & |x\neq y \\ 0, & |x = y \end{cases} \tag{1}$$

B. Post/setup change:

$$Setup_i = \sum_{i=1}^{NOP-1}[1-(1-Msetup(Op(i),\ \ Op(i+1))]$$
$$Msetup(x,y) = \begin{cases} 1, & |x\neq y \\ 0, & |x = y \end{cases} \tag{2}$$

C. Part rotation:

$$Rot_i = \sum_{i=1}^{NOP-1}[1-(1-Mrot(Op(i),\ \ Op(i+1))]$$
$$Mrot(x,y) = \begin{cases} 1, & |x\neq y \\ 0, & |x = y \end{cases} \tag{3}$$

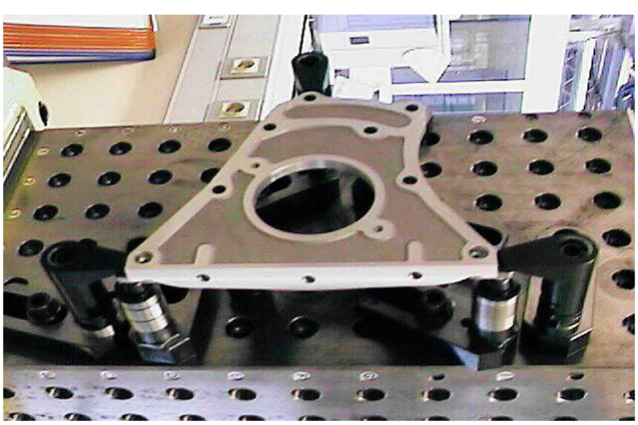

Fig. 2 Part A: Couvercle De Vileberequin (CDV)

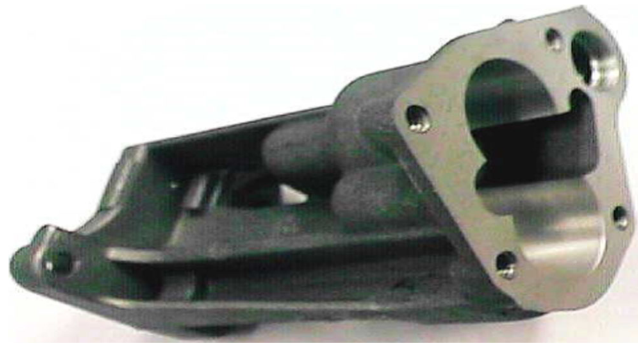

Fig. 3 Part B: Corps de Pompe a Huile moteur (CPHC)

3.3 Constraints

A. Precedence constraints for operations:

$$\text{If } Op_x \text{ is performed before } Op_y, Prced\left(Op_x, Op_y\right) = 1.$$
$$\text{If } Op_y \text{ is performed before } Op_x, Prced\left(Op_x, Op_y\right) = -1$$
$$\text{If } Op_x = Op_y, Prced\left(Op_x, Op_y\right) = 0$$

B. Operations assigned only once:

$$Op_{i,j} \neq Op_{i,k} \qquad \forall j\neq k \qquad \text{where } j,k \in NOP$$

4 Proposed methodology and case study

The proposed solution to the identified problem is based on co-evolution model. Figure 1 demonstrates the output and the

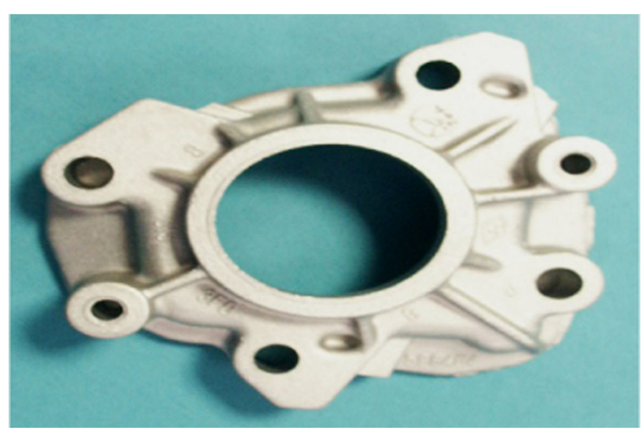

Fig. 4 Part C: Couvericle d'Abrdre (CAI)

inputs of the proposed methodology. Already generated part families have been used in this work. Operational data, precedence constraints, and technological constraints are the inputs required to produce alternative process plans (APPs). Machine configurations are obtained from the combinations of TADs and applying algorithm of system reconfiguration gives minimum machine capabilities. To achieve better performance and better combinations, properly designed crossover mechanism for GA is required. Many crossover mechanisms have been developed such as uniform crossover, cycle crossover, order-based crossover, partially matched crossover, etc. [57]. Position-wise crossover has been used in the proposed methodology. The idea of selection is to prefer the best-fit individuals and discard the weak ones. The minimization criteria are set for the current problem to converge the system toward minimum changes in tool and configuration changeovers using real coded MOGA. The major difference of GAs from other search techniques is its initialization of random solutions called population and each individual in a population is a chromosome representing the solution to the problem. These chromosomes are evolved iteratively and are called generations. In each generation, the chromosomes having the best fitness are selected and the weak individuals are discarded from the population.

As a result of this framework, optimum machines are obtained for a part family considering reconfigurable setup. Furthermore, the proposed methodology has been categorized into two stages. In the first stage, the algorithm for generating and optimizing APPs and machine configurations is presented while in the second stage, best-fit solutions obtained for master part from GA are compared with the APPs and configurations of other

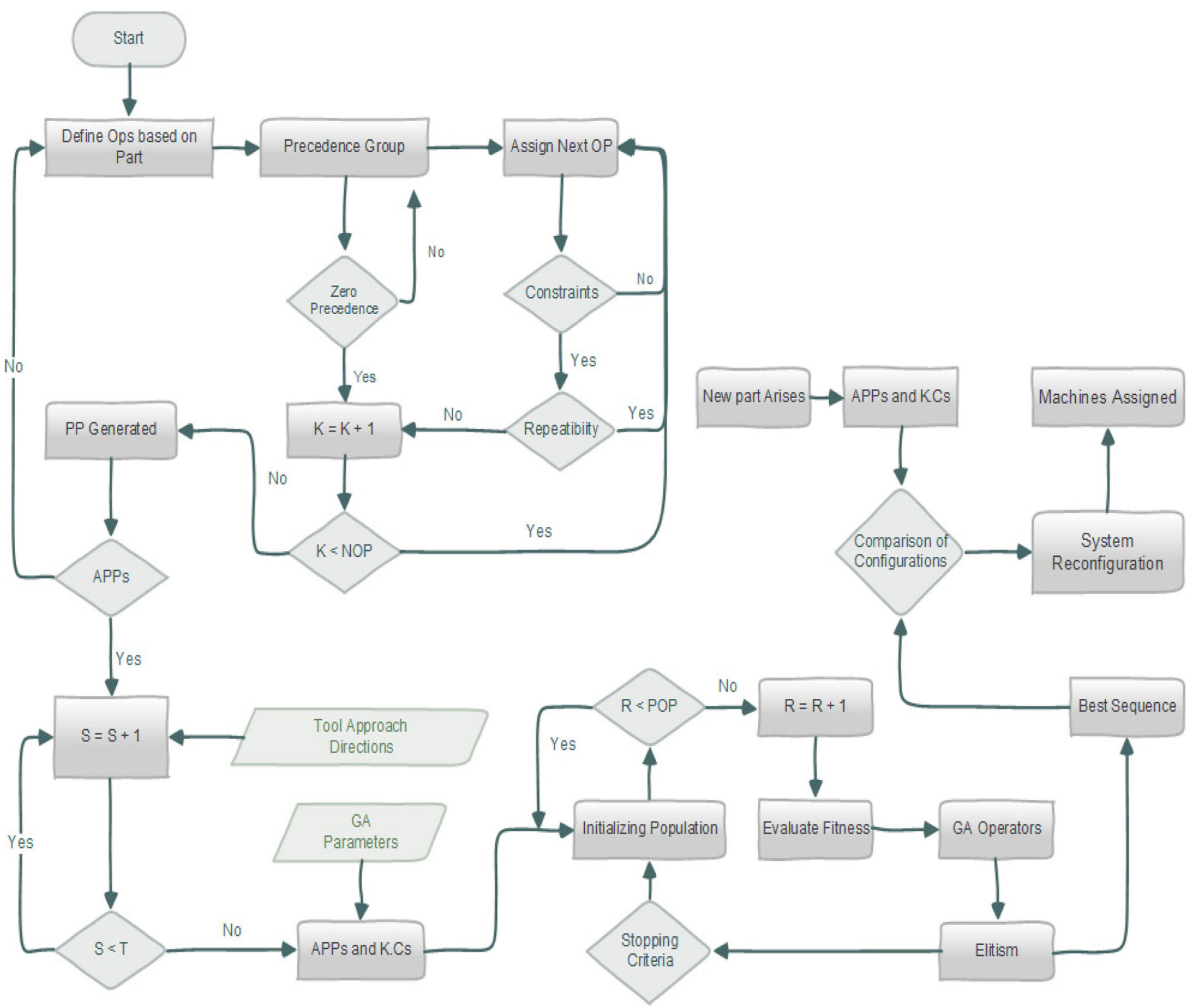

Fig. 5 Proposed methodology

Table 1 Ranking-based groups for Part A (CDV)

Number of operations	Pre-operations	Post-operations
OP1	[]	[2,7,8,9,10,11]
OP2	[1]	[7,8,9,10,11]
OP3	[]	[4,12,13,14]
OP4	3	[12,13,14]
OP5	[]	6
OP6	5	[]
OP7	[]	8
OP8	[1,2]	[]
OP9	[1,2,7]	10
OP10	[1,2]	[]
OP11	[1,2,9]	[]
OP12	[1,2]	[]
OP13	[3,4]	[]
OP14	[3,4]	[]

parts to get the minimum machining requirements. The proposed approach is hybrid variant approach having few characteristics of variant and generative to carry out production in a part family.

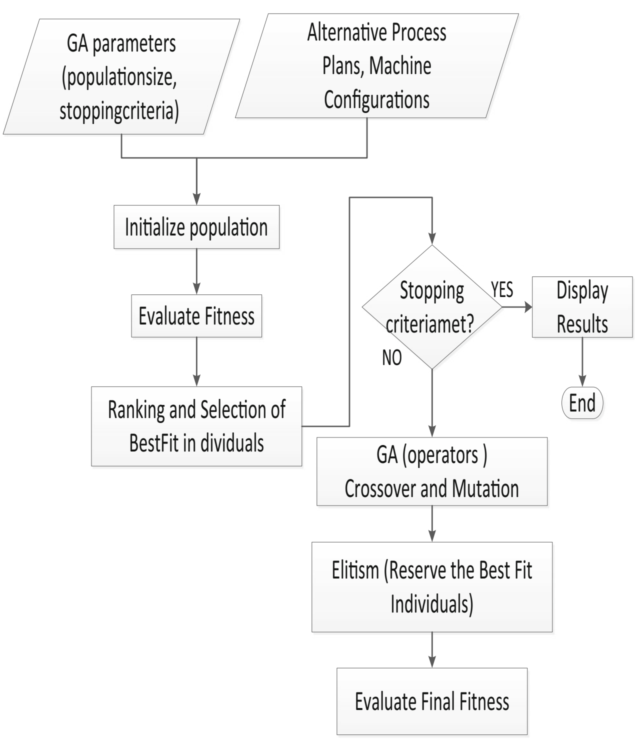

Fig. 6 Algorithm for multi-objective genetic algorithm

Best possible machines are assigned to all the parts belonging to the same part family on the basis of minimum machine capabilities obtained by reconfiguring the setup. The comparison is carried out on the basis of the minimum difference between the machine configurations of the new part and the optimized configurations of master part available. Moreover, machine configurations are generated corresponding to the generated process plans considering tool orientation for a particular operation. Three parts are considered for the validation of proposed methodology since they belong to the same part family and are similar on the basis of operational similarity: Part A—Couvercle De Vileberequin (CDV—shaft cover), Part B—Corps de Pompe a Huile moteur (CPHC—engine oil pump), and Part C—Couvericle d'Abrdre (CAI—intermediate shaft cover). The specifications for these parts are shown in the Appendix. Part A is considered as the master part as shown in Fig. 2. Parts B and C are shown in Figs. 3 and 4, respectively.

Table 2 Tool approach directions

Precedence groups (PG)	Operation (Op)	Possible TADs					
		X	$-X$	Y	$-Y$	Z	$-Z$
PG1	1	1	0	0	0	0	0
		0	0	1	0	0	0
		0	0	0	0	0	1
	2	1	0	0	0	0	0
		0	0	1	0	0	0
		0	0	0	0	0	1
	7	0	0	0	0	1	0
		0	0	0	0	0	1
	8	0	0	0	0	1	0
		0	0	0	0	0	1
	9	0	0	0	0	1	0
		0	0	0	0	0	1
	10	0	0	0	0	0	1
	11	0	0	0	0	0	1
PG2	3	0	0	1	0	0	0
		0	0	0	0	0	1
	4	0	0	1	0	0	0
		0	0	0	0	0	1
	12	0	0	0	0	0	1
	13	0	0	0	0	0	1
	14	0	0	0	0	0	1
PG3	5	0	0	0	0	1	0
		0	0	0	0	0	1
	6	0	0	0	0	1	0
		0	0	0	0	0	1

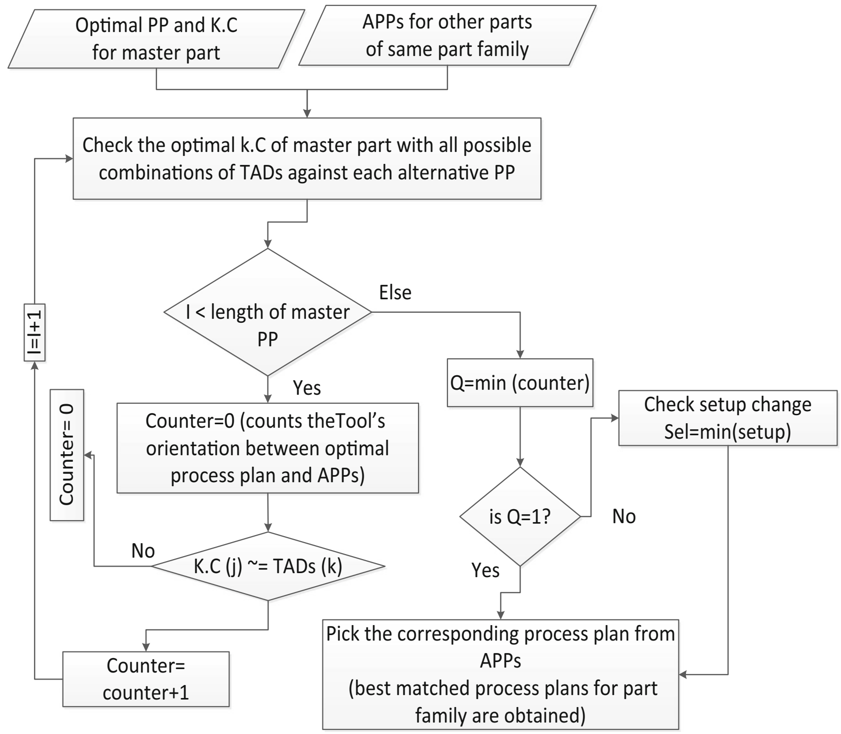

Fig. 7 Algorithm for system reconfiguration

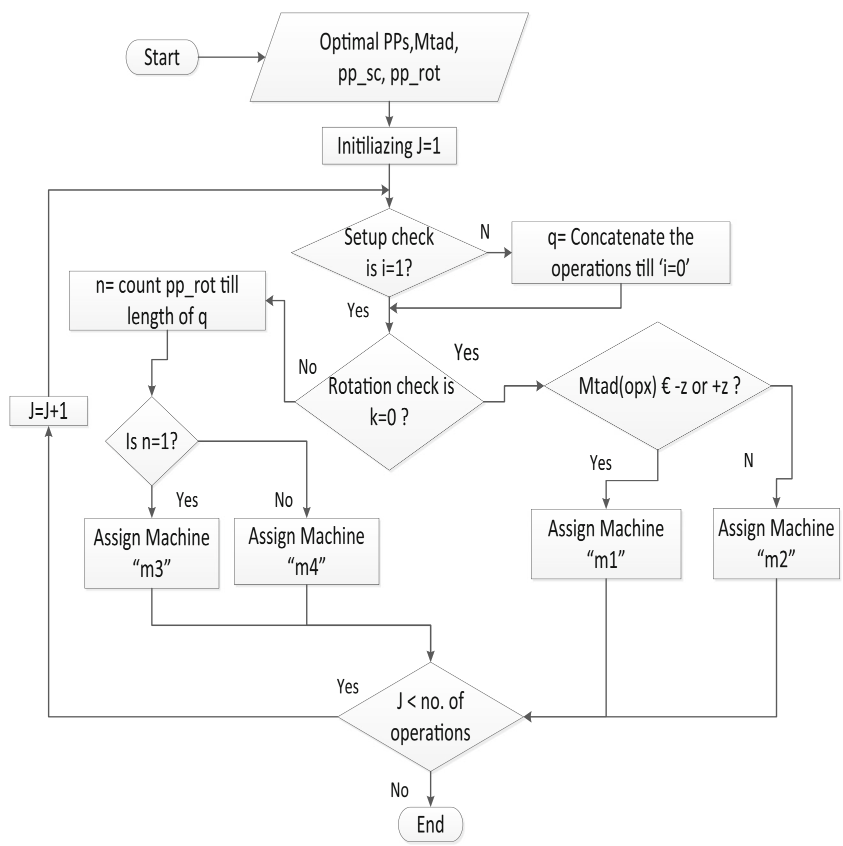

Fig. 8 Algorithm for machine assignment

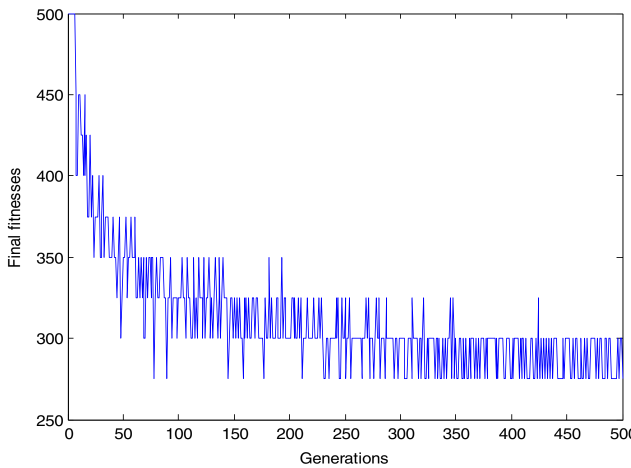

Fig. 9 Fitness graph

The proposed reconfiguration framework is shown in Fig. 5 which is explained in the following subsections. The implementation of the framework starts from process planning algorithm which has been applied on all of the three parts.

4.1 Co-evolution of process planning and machine configuration

The inputs of the algorithm are the set of operations, precedence relationship(s), constraints, tool change(s), setup change(s), part rotation(s), and TAD matrix. The tool change, setup change, and part rotation matrix for Part A are shown in the Appendix for more insight. APPs are generated from the proposed algorithm considering specific constraints such as precedence, datum, geometrical, and technological constraints [33]. Precedence constraints are taken into account to get feasible process plans since they determine which operation needs to be performed before the other one to assist the planner in taking the scheduling decision. Datum constraints account for those operations which can be performed on the same machine with the same setup. Geometrical constraints are used for reference purposes, while technological constraints are incorporated where any particular operation is inevitable to be performed after a specific machining operation. These constraints are to be satisfied while manufacturing any product. In the proposed algorithm of process planning, the precedence check is added to verify the precedence and technological constraints. The major step is the grouping of operations on the basis of ranking. It gives pre- and post-operations of a particular part as shown in Table 1.

As the optimal process plan and its corresponding configuration is required for the master part (Part A), the application of MOGA gave the optimal solution from local solutions. The optimal search was further carried out by applying the classical MOGA which is referred to as the weighted GA (WGA) in literature. In WGA, optimal

Table 3 Machine configuration for Part A: CDV

Features	Operations	Ops ID	Machine configuration						Tool change	Setup change	Part rotation
			Tool direction			Spindle degree of freedom					
			X	Y	Z	α	β	Υ			
PL 101	Rough milling	Op3	0	1	0	−90	0	0			
PL 100	Rough milling	Op1	0	0	−1	0	0	0	×	×	
FL 108	Drilling	Op12	0	0	−1	0	0	0			
CY 103	Drilling	Op7	0	0	−1	0	0	0		×	
CY 102	Drilling	Op5	0	1	0	0	180	0		×	×
CY 102	Reaming	Op6	0	1	0	0	180	0		×	×
CY 103	Reaming	Op8	0	1	0	0	180	0		×	×
PL 101	Finish milling	Op4	0	0	−1	0	0	0			
PL 100	Finish milling	Op2	0	1	0	−90	0	0	×	×	
CY 104	Drilling	Op9	0	0	1	0	180	0			×
CY 104	Reaming	Op10	0	0	−1	0	0	0		×	×
FL 106	Drilling	Op11	0	0	−1	0	0	0		×	
FL 109	Drilling	Op13	0	0	−1	0	0	0			
FL 110	Drilling	Op14	0	0	−1	0	0	0			

solutions can be controlled and the preference to any objective can be given by increasing its weight. However, it is worthy to note that the solutions having equal weights of the objectives offer least conflict. The advantage of this technique is that it controls the dominance of one objective over the other and converges the system toward Pareto optimum solution. Real coded GA has also been used to obtain an optimized process plan and to ensure that the generated process plan conforms to the subjected precedence constraints. A comparison between two optimization approaches, i.e., WGA and NSGA-II, was carried out in a previous work [58]. The flow chart for the WGA is shown in Fig. 6.

A machine's structural configuration is generated on the basis of a machine's visibility to generate any particular feature of the part family. Different combinations of TADs help in finding out the appropriate combination for a particular process plan to carry out production with minimum capabilities. In Table 2, different combinations of TAD for Part A are shown against each operation along with precedence groups. For example, Operation 1 (Op1) can be performed from X, Y, and $-Z$ directions, but the objective is to find the optimum direction. If *Op1* is performed from $+ve\ X$ direction of tool, *Op2* with $+ve\ Y$ direction and *Op7* from $-ve\ Z$ direction, a five-axis machine will be required to carry out these operations.

Table 4 Machine configuration for Part B: CPHC

Features	Operations	Ops ID	Machine configuration						Tool change	Setup change	Part rotation
			Tool direction			Spindle degree of freedom					
			X	Y	Z	α	β	Υ			
Pl 100	Rough milling	Op1	0	1	0	−90	0	0			
Pl 109	Rough milling	Op5	0	0	− 1	0	0	0	×		×
Pl 109	Finish milling	Op6	0	0	− 1	0	0	0		×	×
Cy 110	Drilling	Op13	0	0	− 1	0	0	0		×	×
Pl 100	Finish milling	Op2	0	1	0	−90	0	0			×
Cy 107	Drilling	Op7	0	0	− 1	0	0	0		×	×
Cy 110	Boring	Op14	0	0	− 1	0	0	0			×
Pl 101	Rough milling	Op3	0	0	− 1	0	0	0			×
Pl 101	Finish milling	Op4	0	0	− 1	0	0	0		×	×
Cy 102	Drilling	Op20	0	0	− 1	0	0	0		×	×
Cy 110	Reaming	Op15	0	0	− 1	0	0	0			×
Cy 102	Boring	Op21	0	0	− 1	0	0	0			×
Cy107	Boring	Op8	0	0	− 1	0	0	0		×	×
Cy 102	Reaming	Op22	0	0	− 1	0	0	0		×	×
Cy 103	Drilling	Op23	0	0	− 1	0	0	0		×	×
Cy 107	Reaming	Op9	0	0	− 1	0	0	0		×	×
Cy 103	Reaming	Op24	0	0	− 1	0	0	0		×	×
Cy 108	Drilling	Op10	0	0	− 1	0	0	0		×	×
Cy 108	Boring	Op11	0	0	− 1	0	0	0		×	×
Cy 108	Reaming	Op12	0	0	− 1	0	0	0		×	×
Cy 117	Drilling	Op16	0	0	− 1	0	0	0		×	×
Cy 117	Boring	Op17	0	0	− 1	0	0	0		×	×
Cy 118	Drilling	Op18	0	0	− 1	0	0	0		×	×
Cy 118	Reaming	Op19	0	0	− 1	0	0	0		×	×
Cy 112	Drilling	Op25	0	0	− 1	0	0	0		×	×
Cy 113	Drilling	Op26	0	0	− 1	0	0	0			
Cy 114	Drilling	Op27	0	0	− 1	0	0	0			
Cy 115	Drilling	Op28	0	0	− 1	0	0	0			

Table 5 Machine configuration for Part C: CAI

Features	Operations	Ops ID	Machine configuration						Tool change	Setup change	Part rotation
			Tool direction			Spindle degree of freedom					
			X	Y	Z	α	β	Υ			
Pl 100	Rough milling	Op1	0	0	1	0	0	0			
Cy 108	Drilling	Op10	0	0	1	0	0	0			×
Cy 107	Reaming	Op9	0	0	1	0	0	0	×	×	×
Cy 105	Drilling	Op7	0	0	0	0	− 90	0		×	×
Cy105	Boring	Op8	0	0	1	0	0	0		×	×
Pl 100	Rough milling	Op2	0	0	1	0	0	0			×
Cy 103	Drilling	Op3	0	0	1	0	0	0			×
Cy 103	Boring	Op4	0	0	1	0	0	0			×
Cy 104	Drilling	Op5	0	0	1	0	0	0		×	×
Cy 104	Boring	Op6	0	0	1	0	0	0			

On the other hand, a single three-axis machine will be required if all of the three operations are performed from $-ve\ Z$ TAD. Therefore, different combinations of TADs help in finding out which combination is best suited for a particular process plan to carry out production with minimum capabilities. And for the same reason, all combinations are considered in analysis of the case study parts.

Fitness evaluation of the whole population generated was based on the minimization of the fitness criteria (objective function) as shown in Eq. 4:

$$f = \min\left[\sum_{i=1}^{n} T_i\, w1 + \sum_{i=1}^{n} S_i\, w2 + \sum_{i=1}^{n} R_i\, w3 + \sum_{i=1}^{n} dof_i\, w4\right] \tag{4}$$

where T_i = tool change array, S_i = setup change array, R_i = part rotation array, dof_i = spindle degree of freedom, n = total

Table 6 Machine assignment to Parts A, B, and C

Part	Machine ID	Machine type	Operations
A (CDV)	M3	4-axis	[OP3,OP1]
	M4	5-axis	[OP12,OP7,OP5,OP6,OP8]
	M4	5-axis	[OP4,OP2]
	M3	4-axis	[OP9,OP10,OP11,OP13,OP1]
B (CPHC)	M2	3-axis horizontal	[OP1]
	M1	3-axis vertical	[OP5,OP6,OP13]
	M1	3-axis vertical	[OP2,OP7]
	M1	3-axis vertical	[OP14]
	M1	3-axis vertical	[OP3,OP4,OP20]
	M1	3-axis vertical	[OP15]
	M1	3-axis vertical	[OP21,OP8,OP22,OP23,OP9,OP24,OP10,OP11,OP12,OP16, OP17,OP18,OP19,OP25,OP26,OP27,OP28]
C (CAI)	M2	3-axis horizontal	[OP1]
	M1	3-axis vertical	[OP10,OP9,OP7,OP8]
	M2	3-axis horizontal	[OP2]
	M1	3-axis vertical	[OP3]
	M1	3-axis vertical	[OP4]
	M1	3-axis vertical	[OP5,OP6]

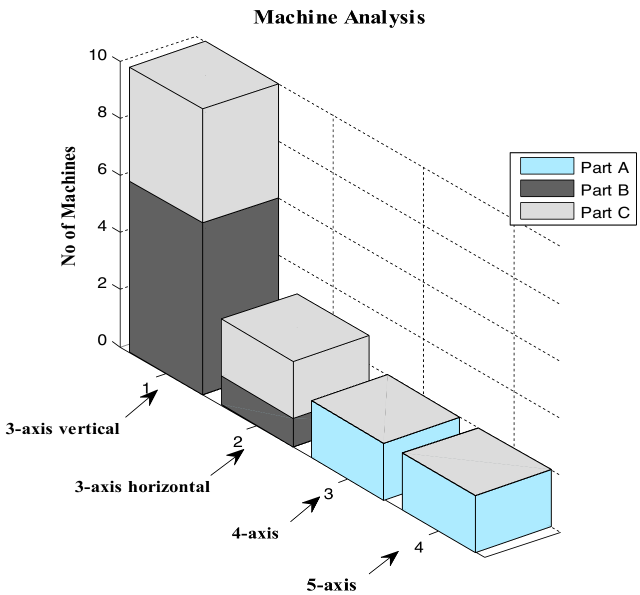

Fig. 10 Analysis of machine chosen

number of alternative process plans, and *w1–4* = weightages of each parameter considered. The process gave best-fit process plans along with their corresponding kinematic configurations. Machine configurations are considered in the next stage of the methodology.

4.2 System reconfiguration

To produce parts within the same part family, there is a need of certain criteria based on which the production could be switched from one part to another. The proposed algorithm shown in Fig. 7 is used to reconfigure the setup according to the production requirements. For Part A, optimal plan and its optimal machine configuration are obtained and then compared with all possible APPs and configurations of other parts belonging to the same family. "Counter" saves the minimum difference in configurations of both parts. If the minimum values in "counter" are more than 1, minimum setup is checked for; otherwise, the optimized process plan having minimum change in configuration is extracted. Modification

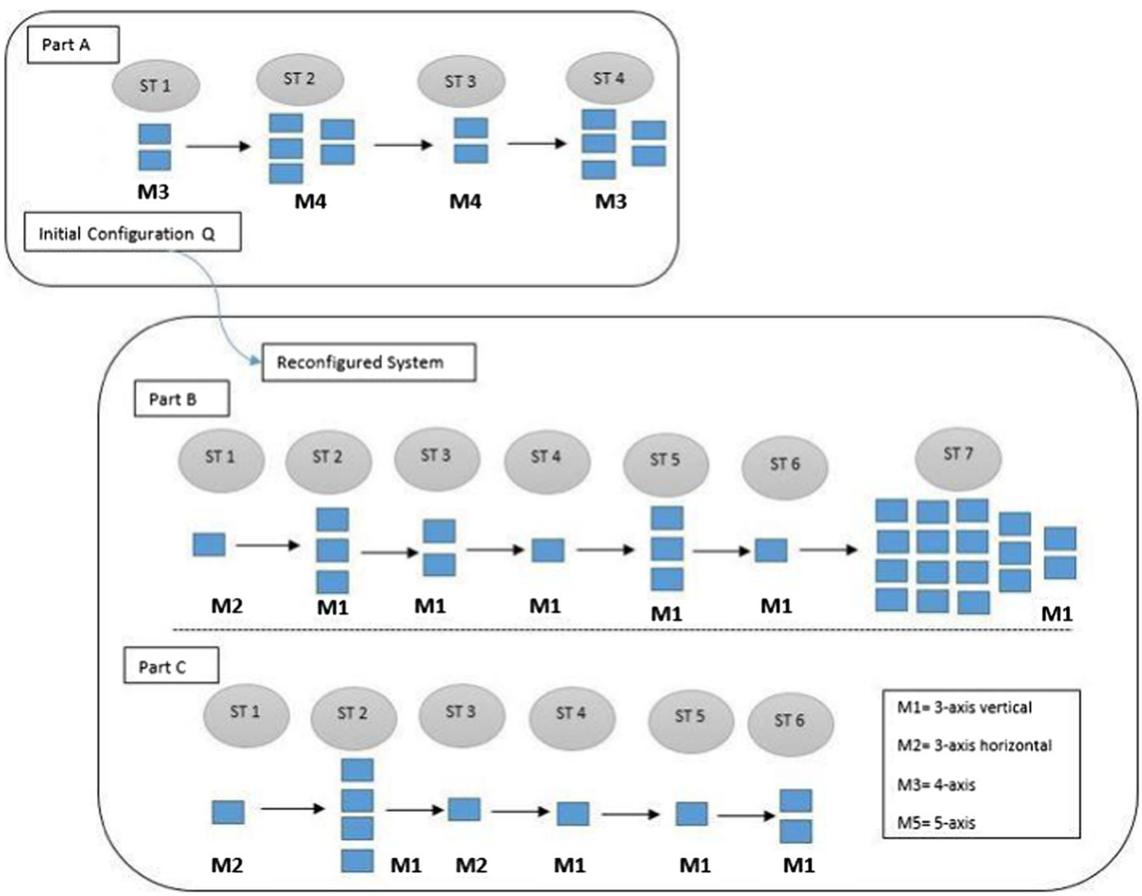

Fig. 11 Reconfigurable machining setup

of setup is carried out based on the information obtained by applying this algorithm. The results of this algorithm are illustrated later in the next section.

The assignment of operations on machines is carried out in three steps. First, TAD and the type of tool required to carry out the operation is identified which is the machine kinematic configuration. In the second step, among the available machines, the set of machines capable of performing that particular operation are identified. This is done by identifying the TAD offered by the machine and the available tools. Finally, the machines and the appropriate configuration are assigned to the particular operation of the sub-part.

Machines are assigned to manufacture different parts belonging to the same part family on the basis of information obtained from the system reconfiguration algorithm (see Fig. 8). Three-axis, four-axis, and five-axis machines are assigned considering machine configuration required to produce a particular feature.

The developed methodology was applied on Parts A, B, and C. As described earlier, Part A was taken as master part and by the application of above stated algorithm, the system was reconfigured to produce Parts B and C with optimum capabilities.

5 Results and analysis

This section presents the optimized assignment of machines to the operations using optimum machine capabilities. The optimized process plan and kinematic configuration of Part A was obtained using Eq. 4. The individuals, i.e., process plans, after evaluating the fitness were ranked. The ones having better fitness were preferred for the next generation to produce children, i.e., to make new combinations. The recombination operator exchanged the characters of chromosomes among two parents, and mutation randomly exchanged the genes at some location rearranging the order of genes in a chromosome. Recombination and mutation are the two GA operators that extract the best and dominating character of the parent chromosome to form the child chromosome. The generation versus fitness graph (see Fig. 9) shows the convergence of system toward minimum fitness. Over the generations of 500, fitness converges up to 275 for a population size of 50. Small population size may result in premature convergence and large population size takes unnecessary computational time. This feature is set carefully and updated to increase randomness and search region which guarantees the convergence of GA. In the proposed approach, the objective of using MOGA has been achieved by its application on process plans and machine configuration considering a master part.

The optimized process plan and its machine configuration (spindle rotates clockwise from its default position at an angle of 90° about X-axis) for Part A are obtained through MOGA and shown in Table 3. The application of reconfiguration algorithm gave the optimal machining capabilities for Parts B and C. The optimal process plans for Part B and Part C are given in Tables 4 and 5. The purpose of RMS also satisfies here which is to provide the exact capacity required. As the optimum machine configurations are obtained for each operation, the machines can be assigned according to these capabilities and process planning parameters. The machines assigned to Parts A, B, and C are mentioned in Table 6.

Graphical representation of machine assignment is given in Fig. 10. The reconfigurable setup as shown in Fig. 11 gives the minimum machine capabilities required for manufacturing parts within the part family.

6 Conclusions and future suggestions

The concept of reconfigurability in manufacturing system has gained significant importance. To respond to the high-frequency variations and to stay competitive, an industrial requirement is to adapt the production system efficiently. The concept of co-evolution was taken into consideration in this paper. The machine configurations were generated for different features of a part family corresponding to that of generated process plans. This research work is concerned with the development of an integrated approach for modifying the setup according to the variations in product design. By the application of WGA on co-evolution model, the system yielded global optimal. Furthermore, the framework included optimum process plans, optimum machines' kinematic configurations, and reconfiguration changeability extent. Reconfigurable process planning represents important changeability enablers for product and manufacturing system evolution. It cost-effectively manages the change in product and modifies the system accordingly. In the proposed approach, the extent of reconfiguration was measured which formed the basis for defining the process plans and machine configurations of other parts. This approach also helped in carrying out production with optimized capabilities. In case of random market demands and design variations, the proposed approach is reliable as it determines the minimum and optimal required capabilities to the corresponding operations of a part. Moreover, the presented algorithm can manufacture the part family with minimum production changeover time and optimal machine capabilities. This work can be extended for multiple and parallel setups. Extension of the same algorithm by increasing the number of parts will add versatility in the system. Different manufacturing costs, time and machining specifications like spindle speed, depth of cut, etc., can also be considered as part of the future work.

Appendix

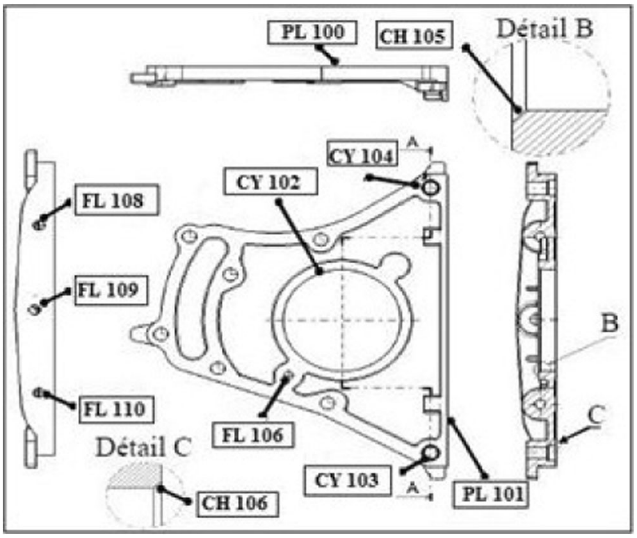

Fig. 12 Part A: CDV

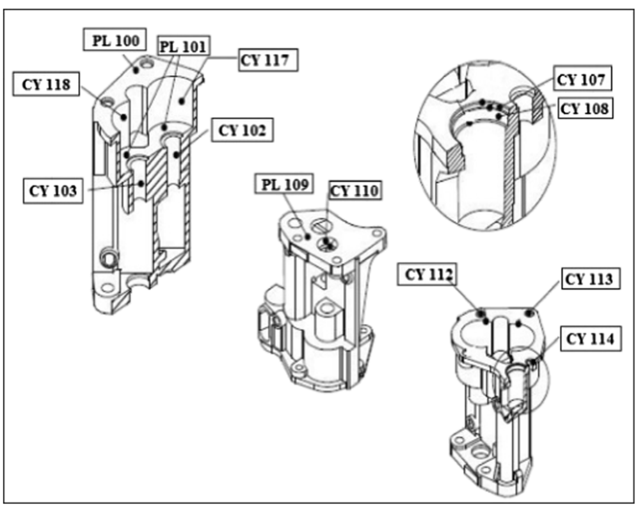

Fig. 13 Part B: CPHC

Fig. 14 Part C: CAI

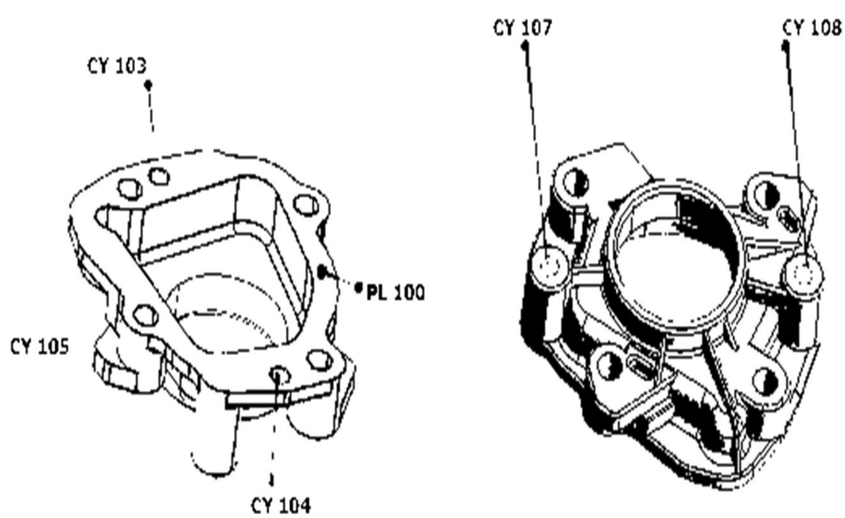

Table 7 Operation Data for Part A: CDV

Features	Operations	Op ID	TAD
PL 100	Rough milling	1	$+x, +y, -z$
PL 100	Finish milling	2	$+x, +y, -z$
PL 101	Rough milling	3	$+z, +y$
PL101	Finish milling	4	$+z, +y$
CY 102	Drilling	5	$+z, -z$
CY 102	Reaming	6	$+z, -z$
CY 103	Drilling	7	$+z, -z$
CY 103	Reaming	8	$+z, -z$
CY 104	Drilling	9	$+z, -z$
CY 104	Reaming	10	$+z, -z$
FL 106	Drill	11	$-z$
FL 108	Drill	12	$-z$
FL 109	Drill	13	$-z$
FL 110	Drill	14	$-z$

Table 8 Operation Data for Part B: CPHC

Features	Operations	OP ID	TAD
PL 100	Rough milling	1	$+x, +y, -z$
PL 100	Finish milling	2	$+x, +y, -z$
PL 101	Rough milling	3	$-z$
PL 101	Finish milling	4	$-z$
PL 109	Rough milling	5	$+x, +y$
PL 109	Finish milling	6	$+x, +y$
CY 107	Drilling	7	$-z$
CY 107	Boring	8	$-z$
CY 107	Reaming	9	$-z$
CY 108	Drilling	10	$-z$
CY 108	Boring	11	$-z$
CY 108	Reaming	12	$-z$
CY 110	Drilling	13	$-z$
CY 110	Boring	14	$-z$
CY 110	Reaming	15	$-z$
CY 117	Drilling	16	$-z$
CY 117	Boring	17	$-z$
CY 118	Drilling	18	$-z$
CY 118	Reaming	19	$-z$
CY 102	Drilling	20	$-z$
CY 102	Boring	21	$-z$
CY 102	Reaming	22	$-z$
CY 103	Drilling	23	$-z$
CY 103	Reaming	24	$-z$
CY 112	Drilling	25	$-z$
CY 113	Drilling	26	$-z$
CY 114	Drilling	27	$-z$
CY 115	Drilling	28	$-z$

Table 9 Operation data for Part C: CAI

Features	Operations	OP ID	TAD
PL 100	Rough milling	1	$+x, +y, -z$
PL 100	Finish milling	2	$+x, +y, -z$
CY 103	Drilling	3	$-z$
CY 103	Boring	4	$-z$
CY 104	Drilling	5	$-z$
CY 104	Boring	6	$-z$
CY 105	Drilling	7	$-z$
CY105	Boring	8	$-z$
CY 107	Reaming	9	$-z$
CY 108	Drilling	10	$-z$

Table 10 Tool change matrix for Part A

		PL 100	PL 100	PL 101	PL 101	CY 102	CY 102	CY 103	CY 103	CY 104	CY 104	FL 106	FL 108	FL 109	FL 110
Operations	ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14
PL100	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1
PL100	2	1	0	1	0	1	1	1	1	1	1	1	1	1	1
PL101	3	0	1	0	1	1	1	1	1	1	1	1	1	1	1
PL101	4	1	0	1	0	1	1	1	1	1	1	1	1	1	1
CY 102	5	1	1	1	1	0	1	1	1	1	1	1	1	1	1
CY 102	6	1	1	1	1	1	0	1	1	1	1	1	1	1	1
CY 103	7	1	1	1	1	1	1	0	1	0	1	1	1	1	1
CY 103	8	1	1	1	1	1	1	1	0	1	0	1	1	1	1
CY 104	9	1	1	1	1	1	1	0	1	0	1	1	1	1	1
CY 104	10	1	1	1	1	1	1	1	0	1	0	1	1	1	1
FL 106	11	1	1	1	1	1	1	1	1	1	1	0	0	0	0
FL 108	12	1	1	1	1	1	1	1	1	1	1	0	0	0	0
FL 109	13	1	1	1	1	1	1	1	1	1	1	0	0	0	0
FL 110	14	1	1	1	1	1	1	1	1	1	1	0	0	0	0

Table 11 Setup change matrix for Part A

		PL 100	PL 100	PL 101	PL 101	CY 102	CY 102	CY 103	CY 103	CY 104	CY 104	FL 106	FL 108	FL 109	FL 110
Operations	ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14
PL100	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1
PL100	2	1	0	1	0	1	1	1	1	1	1	1	1	1	1
PL101	3	0	1	0	1	1	1	1	1	1	1	1	1	1	1
PL101	4	1	0	1	0	1	1	1	1	1	1	1	1	1	1
CY 102	5	1	1	1	1	0	0	0	0	0	0	0	0	0	0
CY 102	6	1	1	1	1	0	0	0	0	0	0	0	0	0	0
CY 103	7	1	1	1	1	0	0	0	0	0	0	0	0	0	0
CY 103	8	1	1	1	1	0	0	0	0	0	0	0	0	0	0
CY 104	9	1	1	1	1	0	0	0	0	0	0	0	0	0	0
CY 104	10	1	1	1	1	0	0	0	0	0	0	0	0	0	0
FL 106	11	1	1	1	1	0	0	0	0	0	0	0	0	0	0
FL 108	12	1	1	1	1	0	0	0	0	0	0	0	0	0	0
FL 109	13	1	1	1	1	0	0	0	0	0	0	0	0	0	0
FL 110	14	1	1	1	1	0	0	0	0	0	0	0	0	0	0

Table 12 Part rotation matrix for Part A

		PL 100	PL 100	PL 101	PL 101	CY 102	CY 102	CY 103	CY 103	CY 104	CY 104	FL 106	FL 108	FL 109	FL 110
Operations	ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14
PL100	1	0	0	1	1	0	0	0	0	0	0	1	1	1	1
PL100	2	0	0	1	1	0	0	0	0	0	0	1	1	1	1
PL101	3	1	1	0	0	1	1	1	1	1	1	0	0	0	0
PL101	4	1	1	0	0	1	1	1	1	1	1	0	0	0	0
CY 102	5	0	0	1	1	0	0	0	0	0	0	1	1	1	1
CY 102	6	0	0	1	1	0	0	0	0	0	0	1	1	1	1
CY 103	7	0	0	1	1	0	0	0	0	0	0	1	1	1	1
CY 103	8	0	0	1	1	0	0	0	0	0	0	1	1	1	1
CY 104	9	0	0	1	1	0	0	0	0	0	0	1	1	1	1
CY 104	10	0	0	1	1	0	0	0	0	0	0	1	1	1	1
FL 106	11	1	1	0	0	1	1	1	1	1	1	0	0	0	0
FL 108	12	1	1	0	0	1	1	1	1	1	1	0	0	0	0
FL 109	13	1	1	0	0	1	1	1	1	1	1	0	0	0	0
FL 110	14	1	1	0	0	1	1	1	1	1	1	0	0	0	0

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