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Manufacturing process planning optimisation in reconfigurable multiple parts flow lines

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ABSTRACT

Purpose: This paper explores the capabilities of genetic algorithms in handling optimization of the critical issues mentioned above for the purpose of manufacturing process planning in reconfigurable manufacturing activities. Two modified genetic algorithms are devised and employed to provide the best approximate process planning solution. Modifications included adapting genetic operators to the problem specific knowledge and implementing application specific heuristics to enhance the search efficiency.

Design/methodology/approach: The genetic algorithm methodology implements a genetic algorithm that is augmented by application specific heuristics in order to guide the search for an optimal solution. The case study is based on the manufacturing system. Raw materials enter the system through an input stage and exit the system through an output stage. The system is composed of sixteen (16) processing modules that are arranged in four processing stages.

Findings: The results indicate that the two genetic algorithms are able to converge to optimal solutions in reasonable time. A computational study shows that improved solutions can be obtained by implementing a genetic algorithm with an extended diversity control mechanism.

Research limitations/implications: This paper has examined the issues of MPP optimization in a reconfigurable manufacturing framework with the help of a reconfigurable multiparts manufacturing flow line.

Originality/value: The results of the case illustration have demonstrated the practical use of diversity control implemented in the MGATO technique. In comparison to MGAWTO, the implemented MGATO improves the population diversity through a customized threshold operator. It was clear that the MGATO can obtain better solution quality by foiling the tendency towards premature convergence.

Keywords: Reconfigurable manufacturing; Manufacturing process planning optimisation; Process selection; Process sequencing; Parts loading scheduling

1. Introduction

The importance and significance of reconfigurable manufacturing in the 21st century and beyond has been thoroughly discussed in the literature for reconfigurable manufacturing systems. A reconfigurable manufacturing system (RMS) is a system that is designed for cost-effective response to changes in production requirements. The goal in implementing an RMS is to be able to cope with random changes in production requirements through reconfiguration [2]. Reconfiguration is an iterative process that entails selection of a manufacturing configuration that is optimally fit for purpose. Due to the operational complexity in running an RMS, the tasks involved in identifying an optimally fit manufacturing configuration include matching of activities and resources. A manufacturing function that can be employed to handle such tasks is manufacturing process planning (MPP). This work focuses on a study of an optimization approach that can be used to address issues that are critical in providing an optimal match of activities and resources in a multiresource manufacturing line that produces multiple parts with reconfigurable flows. Such issues include: process selection, process sequencing and part load scheduling, i.e. the order of processing multiple parts.

2. Literature review

Central to the need to reconfigure a manufacturing system in order to cope with changes in production requirements is the issue of selecting an optimal manufacturing process plan suitable for a given production scenario. Traditionally, MPP has been tackled using two approaches: the Variant Approach and the Generative Approach [1]. The variant approach groups and assigns codes to families of components that require similar manufacturing set-ups. In the event of a new production scenario, mostly in the form of a new component for manufacture, the code for the new component is mapped onto existing component families and the appropriate process plan is retrieved. Traditional techniques for retrieving the appropriate process plan included simple searches of existing data bases with the hope of finding an existing family with a similar code to that of the new component. Other more advanced techniques that have been used are based on applications of artificial intelligence [4]. However, the major drawbacks of using the variant approach include: (i) the approach assumes that the existing database contains a family whose attributes are similar to those of the new component and (ii) the retrieved process plan almost always has to be modified to suit the specific needs of the new component.

Although implementation of artificial intelligence, as was the case-based reasoning technique suggested in [4], may enable more efficient retrieval and enhancement of the process plan modification activities, the previously cited drawbacks still outweigh the advantages when such an approach is implemented in dynamic manufacturing environments where changes to products, product configurations and production mix are random. Consequently, the probability of invalid mappings may be high since new components may not be represented in an existing database. Moreover, the time frames for the necessary modifications may be inadequate and existing component family databases risk obsolescence.

On the other hand the generative approach selects a new process plan by using manufacturing heuristics and process knowledge. Although systematic and computer-based techniques have been used to improve this approach, as discussed in [6], the resulting plan is only feasible hence its implementation may result in suboptimal processing in the manufacturing system. Moreover, due to complexity in design and operation of new and innovative manufacturing systems like RMSs, implementing an only feasible plan may result in localized optimization that may down grade the overall manufacturing system performance. There is, therefore, a need to focus not only at implementing optimal manufacturing process plans but developing globally optimal ones.

In the literature, considerations of optimal process plans have been proposed through applications of meta-heuristics like genetic algorithms [7] and simulated annealing [3]. The advantages of using such meta-heuristics lies in that unlike the random search or gradient descent methods, carefully designed meta-heuristic algorithms have the capability to find a near optimal solution in reasonable time and can escape from local optima. Hence; they provide better alternatives for the solution of complex optimization problems.

A wide variety of process planning issues exists in the public literature. Due to the complexity in analyzing process planning and related issues, process planning research has tended to focus on analyzing one aspect of process planning issues. For example process selection as in (Ro et al, 1990; Lan et al, 2005) or process sequencing as in (Guo, Mileham, Owen and Li, 2006). In either case, the authors acknowledge that such process planning issues are intractable problems that require an optimization approach. The work presented in this paper discusses MPP optimization in reconfigurable multiparts flow lines from a macroscopic process planning optimization perspective. Although this work, like those cited above, generally takes the generative approach to process planning, the difference lies in (i) modelling reconfigurable multiparts flows rather than single part flows and (ii) capturing three aspects of process planning in a single optimization framework.

3. Manufacturing process planning optimization

The goal of an optimization strategy for MPP is to help manufacturing engineers in identifying optimal manufacturing process plans in complex manufacturing activities. Implementation of optimal manufacturing process plans is crucial in dynamic manufacturing environments since it ensures that optimal operating levels are attained. In seeking an optimal solution, it is necessary to employ an appropriate optimization solution technique. From public literature on process planning, genetic algorithms have been identified as one option for solving complex process planning problems in an optimization perspective.

The problem under study considers applications of the genetic algorithms in handling MPP optimization for multiple parts flowing in a reconfigurable manufacturing line. Thus, given a production scenario (composed of many parts to be manufactured) and manufacturing resources (an array of processing modules that make up the reconfigurable manufacturing line), the problem is to select an optimal manufacturing process plan. Figure 1 depicts an illustrative reconfigurable multiparts flow line.

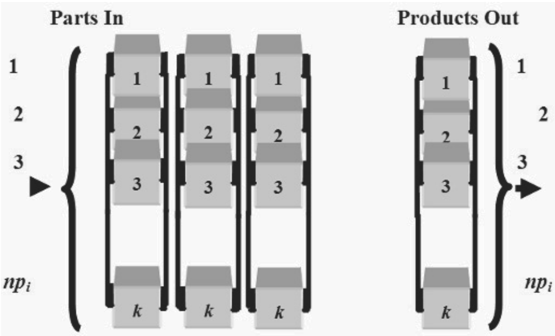

Fig. 1. Reconfigurable multiple parts flow line

The system is composed of a number of Processing Stages, PS=(ps_i), where i=1,2,3,…PS, and M=(m_i), serial lines, where i=1,2,3…m. Each processing stage is composed of a number of Processing Modules, PM=(pm_i), where i=1,2,3,…PM. Multi-purpose processing machines, K = (k_i), are also available in the manufacturing line, where k=0, 1, 2, 3….k. Such multiple purpose machines take the form of productive reserve capacity. The manufacturing system is designed to manufacture a product family of total parts NP = (np_i), where i=1, 2, 3…np, under the following conditions:

(i) Parts are not necessarily processed at all stages
(ii) Processing modules in the same stage do not necessarily perform identical tasks
(iii) Flexible routing exists in the multi stage processing line

In such a manufacturing line, alternative processing routes are key issues that enhance the operations of a multiple parts line since they provide; routing flexibility, sequencing flexibility and processing flexibility, which can be used for logical reconfiguration issues. In analyzing such a manufacturing line, two issues may arise depending on the available information. In certain circumstances, alternative process plans may be available but due the numerous possible combinations of the alternative process plans, the goal in computing a solution methodology is to answer the question: which of the alternative combination of process plans results in the best operational level in addressing a given production scenario? On the other hand, the goal in computing the solution methodology may be to answer the question: for each of the individual parts of a given production scenario, what process plans are more flexible with respect to the available resources and which plans result in the best operating levels? The problem under study addresses the later.

At each stage, a number of processes exist. The advantage of operating such a system is that it allows repeat processing and rearrangement of processes and, therefore, parts flowing in the system can be conveniently rerouted to alternative paths in response to changes in production capacity and manufacturing functionality. In operating such a line, it is always necessary to assess the routing of parts and sequencing of processing modules in terms of manufacturing system performance-based criteria. The selection problem considered in this work is based on a decision making process that matches activities and resources in an effective and efficient manner while simultaneously maximizing throughput and minimizing direct operating costs. Solving such a problem requires a comprehensive analysis of interrelated decision making activities that aim at selecting an optimal manufacturing process plan.

4. Manufacturing process planning optimization model

The modelling approach starts with a description of the domain over which the solution is required. This step requires domain specific knowledge, which for this work includes: part types to be processed, the processes to be used, the type of processing machine primitives available to the manufacturing system and the way the manufacturing system is designed and operated. The solution space is given by the number of processing types (PSTs) required for each part, the available processing modules (PMs) for each processing type (PST), and the possible sequencing of the PMs for each part with respect to processing constraints.

The next step in the solution is to represent the problem knowledge in a state depended design vector from which neighbourhood searches can generate new trial points through iterative perturbation. An objective function is then required to weigh out the design variables for goodness of fit for each trial point.

(a) Inputs

Key inputs to the model include: a set of parts that make up a given production scenario, relevant product and production information and available processing module data that includes technological processing capabilities of the manufacturing system.

Product information-The manufacturing system is to manufacture parts that belong to a range of part families. Let the number of part families be *NPF=(npf_i)*, where i=1,2,3,…npf, and let the number of parts in a family be *NP=(np)*, where i=1,2,3…np. Vector matrices can be defined from such product information as follows:

Part Array **(PA)** is defined as an array of parts in a given production scenario to be manufactured in the system i.e. PA=[p_i], where p_i is a unique identity of the i^{th} part in the production scenario.

Production Volume Array (**PVA**) is defined as an array of production volume demands for parts in the production scenario i.e. PVA=[pv_i], where pv_i is the volume of the i^{th} part.

Production Cost Array **(PCA)** is defined as an array of estimated manufacturing costs for parts in the production scenario i.e. PCA=[pc_i], where pc_i is the production cost of the i^{th} part

Manufacturing system information-The parts are to be manufactured by an array of processing modules (PMs), defined by the processing module type and arranged in processing stages, *n*. Let the number of stages be $N=(n_i)$, where i=1,2,3…n, let the number of processing modules be $NPM=(npm_i)$, where i=1,2,3…npm., let the part similarity coefficient between parts i and j be $PS=(ps_{i,j})$, where i and j are an ordered pair of parts, and let the processing module similarity coefficient between modules i and j be $PMS=(pms_{i,j})$, where i and j are an ordered pair of processing modules in the manufacturing system. Vector matrices for the manufacturing system can be defined as follows:

Process Module Array **(PMA)** is defined as an array of available process modules from which alternative process modules can be specified for each part i.e. PMA=[PM_i], where PM_i is a unique identity of the i^{th} process module. The part similarity (PS) coefficient matrix can be written as PS=[$PS_{i,j}$], where $PS_{i,j}$ is the similarity coefficient between parts i and j. The processing module similarity coefficient matrix can be written as PMS=[$PMS_{i,j}$], where $PMS_{i,j}$ is the processing module similarity coefficient between process modules i and j.

(b) Evaluation criterion

An optimal manufacturing plan that gives maximum throughput and minimum processing cost under dynamic changes in production requirements is bound to result in optimal operating levels. Most research efforts in the literature consider an evaluation based on one criterion [6]. However, as discussed in [5], combining criteria can result in a more revealing and comprehensive analysis of the system performance. Tang, Yip-Hoi, Wang and Koren [5] suggested an implicit model that combines investment costs and throughput analysis. Investment cost was appropriate for their analysis since the problem they were dealing with focussed more on optimal line design. In this work, the emphasis is on operating characteristics; hence processing costs, rather than investment costs, are more appropriate for the analysis presented in this work. The evaluation criterion used in this work is, therefore, based on an implicit function that combines processing costs and throughput. The mathematical model can be represented as follows:

$$Min\ \ F(y) = \frac{total\ processing\ costs}{throughput} = \frac{\sum_{n=1}^{nf}\sum_{k=1}^{pfn}\sum_{i=1}^{K}\left[\left(v_{i,j} * F_{TOC}\right)\right]}{\sum_{n=1}^{nf}\sum_{k=1}^{pfn}\sum_{i=1}^{K}\left(F_{TH}\right)}$$

where

v - $1/ps_{i,j}$ and:

F_{TOC} - total operating cost function, defined as the sum of the cost components

F_{TH} - throughput function,

K - the operations required to produce the respective part(s)

5. Genetic algorithm methodology

The genetic algorithm methodology implements a genetic algorithm that is augmented by application specific heuristics in order to guide the search for an optimal solution. In order to foil the tendency of the algorithm to get stuck in local optima the usual approach in a simple genetic algorithm (SGA) is to foil premature population convergence by means of a mutation operator. Such a strategy works well depending on the specifics of the problem domain as well as the complexity of the search space [6].

For the multiresource manufacturing environment defined for the MPPO problem, there are alternative processing modules for a given process type. Since multiple parts are considered, there is a high chance of having many similar processing requirements that need similar alternative processing modules. This results in an increment in the number of similar chromosomes in the population. Such an increment spoils the ability of the mutation operator to maintain high population diversity.

To solve the above mentioned problem, a customized threshold operator was developed to improve population diversity. Due to the complexity of the MPPO problem, the SGA was modified by inclusion of: (a) application specific heuristics to support the simple genetic algorithm, and (b) adapting genetic operators to the problem specific knowledge. In the actual implementation, two versions of modified genetic algorithms (MGAs) were experimented with: (1) modified genetic algorithms without a customized threshold operator (MGAWTO) and (2) a modified genetic algorithm with a customized threshold operator (MGATO) for foiling the tendency towards premature convergence.

5.1. Application of the genetic algorithm technique

The case study is based on the manufacturing system shown schematically in Figure 2. Raw materials enter the system through an input stage and exit the system through an output stage. The system is composed of sixteen (16) processing modules that are arranged in four processing stages.

In Figure 2, the first digit represents the stage at which the processing module is located while the second digit uniquely identifies a specific processing module in a particular stage. The system in Figure 2 consists of a mixture of dedicated processing modules and two multi-purpose processing modules (2_7 and 2_8). A total of twenty (20) parts are to be manufactured in the manufacturing system. Relevant Production information include: production volume demands, estimated production costs, processing and handling times for the respective parts, process module similarity coefficients, part similarity coefficients as well as the linear distances between the processing modules.

The algorithmic parameters used in running the MGA algorithms are displayed in the user interface window of the simulation. The same algorithmic parameters were used for the two modified versions of the genetic algorithm. However, in running the MGAWTO the check box for the threshold operator was unchecked thereby excluding the threshold operator.

6. Discussion of results

In order to generalize the behaviours of the two modified genetic algorithms when solving the MPPO problem, averages values of the evaluation metrics were computed. Table 1 shows a

Table 1.
Comparison of the results of fifty (50) runs of two genetic algorithms

Algorithm	Best (fitness)	Solution time (min)	Mean (fitness)	Standard deviation	Median	Mean time (min)
MGATO	0.012037	21.80	0.012475	0.000298	0.012503	22.39
MGAWTO	0.012223	21.66	0.013068	0.000591	0.013108	22.42

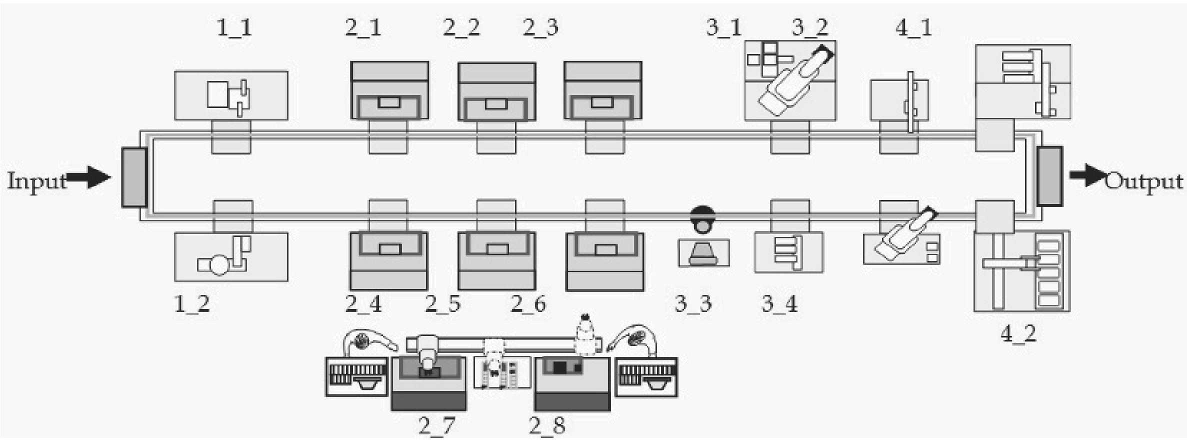

Fig. 2. Schematic representation of the manufacturing system for the case study

comparison of the mean cost function values and mean computation times required to reach an optimal solution.

A comparison of columns 2 and 4 shows that the trends in the cost function values does not change i.e. the values for MGATO are lower in both cases. The same trend is observed for the median values in column 6. However, comparison of columns 3 and 7 shows that on average, the computation time performance of MGATO is better than that of MGAWTO. This case illustrates one of the pitfalls of concluding based on single statistic performance values. A t-test analysis for a 95% confidence level revealed that the *p-values* for the mean fitness was less than 0.05 while that for the mean times was greater than 0.05. Therefore, it can be inferred that there is no significant difference, statistically, between the computation times of the two algorithms. On the other hand, there is a significant difference in the computed mean fitness values. Based on the standard deviation values in Table 1, it can be inferred that there is more variability in the fitness values obtained from MGAWTO than those obtained from MGATO.

The significant differences in the mean fitness values can be explained by considering the behaviour of the two algorithms. The two algorithms only differ in the sense that MGATO implements a threshold operator while MGAWTO does not. Therefore, the significant differences in the mean fitness values, which show superiority of MGATO over MGAWTO, can be attributed to the threshold operator. In this case, the threshold operator increases population diversity and hence allows a more extensive search for an optimal solution. Therefore, MGATO offers a better quality solution to the MPPO problem than MGAWTO.

The manufacturing process plans obtained from the MGAWTO and MGATO are shown in Tables 2 and 3 respectively. In these tables, P_i is the part identification number; P_L is part loading profile while the optimum processing route profile shows the sequences of the processing modules as selected by the GA algorithm. The tables also shows the respective number of changes for each part processing, (a to e), together with the percentage of the available processing modules seized, (f), for processing each part. The optimum processing route profiles also indicates that there is provision for repeat processing.

Comparison of the processing evaluations presented in Tables 2 and 3 shows that the total number of changes in the manufacturing processes recommended by each of the two modified genetic algorithms differs by nine (9), those for the MGATO being higher. In addition, the average percentage of available process modules seized during the manufacturing process is higher for the MGATO, 45.5%, than for the MGAWTO, 43.6%. This may be due to the increased diversity, and hence processing options, offered through more extensive search when the threshold operator is implemented.

The results reported in this section show that both MGA versions are able to converge to a feasible solution in real time. Therefore, they are suitable candidates for solving the MPPO model. However, MGATO demonstrated that it can find a better quality solution than MGAWTO. By comparing the processing evaluations in Table 2 and 3, it has been observed that; with the exception of the number of process module changes, difference of 10, the other changes in the manufacturing process are of similar magnitudes. However, a higher average percentage of PMs seized in the manufacturing process is apparent in the solution profile obtained from MGATO.

Table 2.
Optimal manufacturing process plan profiles obtained from the genetic algorithm without threshold operator (MGAWTO)

Pi	Optimum Processing Route Profiles	P_L	Processing Evaluation a	b	c	d	e	f (%)
1	1_2 2_6 2_6 2_5 2_2 2_2 3_3 4_2	8	5	7	0	3	0	38
2	1_2 2_13 2_13 2_4 2_4 2_1 2_1 3_3 4_2	2	5	8	2	6	2	38
3	1_1 2_5 2_5 2_2 2_14 2_14 3_3 4_2	4	5	7	3	5	2	38
4	1_2 2_5 2_14 3_3 4_2	13	4	4	2	3	1	31
5	1_2 2_14 2_13 2_13 2_6 2_4 2_2 3_2 3_3 4_1 4_2	16	9	10	4	5	3	56
6	1_2 2_5 2_14 2_14 2_4 3_3 4_2	10	5	6	3	4	2	38
7	1_1 2_14 2_1 2_5 2_3 2_2 3_2 3_3 4_1 4_2	9	9	9	2	3	1	63
8	1_2 2_5 2_13 2_2 2_14 2_4 3_3 3_4 4_1 4_2	5	9	9	4	5	2	63
9	1_2 2_14 2_14 2_4 2_4 2_2 3_3 4_2	18	5	7	3	5	2	38
10	1_2 2_13 2_5 2_5 2_2 2_6 3_3 4_2	7	6	7	2	4	1	44
11	1_2 2_5 2_5 2_5 3_2 3_3 4_1 4_2	1	5	7	0	3	0	38
12	1_2 2_13 2_13 2_2 3_3 4_2	6	4	5	3	4	2	31
13	1_2 2_5 3_3 3_4 4_1 4_2	11	5	5	0	1	0	38
14	1_2 2_6 2_6 2_6 2_4 2_4 3_3 4_2	14	4	7	0	4	0	31
15	1_2 2_13 2_1 2_2 2_13 2_4 3_3 4_2	17	7	7	4	5	2	44
16	1_2 2_14 2_5 2_1 2_2 2_14 2_4 2_5 2_5 3_3 4_1 4_2	12	10	11	4	6	2	56
17	1_2 2_5 2_5 2_6 2_4 2_14 3_3 4_2	3	6	7	2	4	1	44
18	1_2 2_14 2_4 2_4 2_13 3_3 4_1 4_2	15	6	7	4	6	2	44
19	1_2 2_14 2_14 2_2 3_2 3_3 3_4 4_1 4_2	19	7	8	3	4	2	50
20	1_2 2_6 2_13 2_13 2_13 2_2 2_14 2_4 2_4 3_3 4_2	20	7	10	6	8	4	50
	Total Changes in system = 440		123	148	51	88	30	A=43.6

Key to Table: a-number of process module changes; b-number of setup changes; c-number of tool changes; d-number of reconfiguration changes; e-number of Productive Reserve Capacity Used; f-percentage of available process module seized and A-average % of process modules seized.

Table 3.
Optimal manufacturing process plan profiles obtained from the genetic algorithm with threshold operator (MGATO)

Pi	Optimum Processing Route Profiles	P_L	Processing Evaluation a	b	c	d	e	f (%)
1	1_2 2_13 2_13 2_14 2_2 2_2 3_3 4_2	15	5	7	4	6	3	38
2	1_2 2_14 2_14 2_5 2_4 2_1 2_1 3_3 4_2	19	6	8	3	5	2	44
3	1_1 2_14 2_6 2_2 2_3 2_13 3_3 4_2	18	7	7	4	5	2	50
4	1_2 2_5 2_13 3_3 4_2	16	4	4	2	3	1	31
5	1_2 2_14 2_13 2_1 2_4 2_2 2_13 3_2 3_3 4_1 4_2	8	10	10	5	6	3	63
6	1_2 2_13 2_14 2_14 2_4 3_3 4_2	10	5	6	4	5	3	38
7	1_1 2_14 2_5 2_6 2_5 2_2 3_2 3_3 4_1 4_2	6	9	9	2	3	1	56
8	1_2 2_14 2_14 2_4 2_1 2_2 3_3 3_4 4_1 4_2	20	8	9	3	4	2	56
9	1_2 2_5 2_4 2_4 2_6 2_2 3_3 4_2	5	6	7	0	2	0	44
10	1_2 2_13 2_6 2_6 2_5 2_2 3_3 4_2	3	6	7	2	4	1	44
11	1_2 2_5 2_6 2_13 3_2 3_3 4_1 4_2	13	7	7	2	3	1	50
12	1_2 2_6 2_6 2_2 3_3 4_2	4	4	5	0	2	0	31
13	1_2 2_5 3_3 3_4 4_1 4_2	11	5	5	0	1	0	38
14	1_2 2_6 2_6 2_14 2_14 2_4 3_3 4_2	2	5	7	3	5	2	38
15	1_2 2_5 2_14 2_4 2_2 2_4 3_3 4_2	12	7	7	2	3	1	44
16	1_2 2_13 2_5 2_13 2_4 2_13 2_14 2_2 2_5 3_3 4_1 4_2	17	11	11	7	8	4	56
17	1_2 2_3 2_5 2_4 2_3 2_14 3_3 4_2	14	7	7	2	3	1	44
18	1_2 2_5 2_5 2_5 2_4 3_3 4_1 4_2	9	5	7	0	3	0	38
19	1_2 2_13 2_14 2_2 3_2 3_3 3_4 4_1 4_2	7	9	9	3	4	2	56
20	1_2 2_14 2_14 2_14 2_14 2_2 2_3 2_5 2_4 3_3 4_2	1	7	10	5	6	4	50
	Total Changes in system = 449		133	149	53	81	33	A=45.5

Key to Table: a-number of process module changes; b-number of setup changes; c-number of tool changes; d-number of reconfiguration changes; e-number of Productive Reserve Capacity Used; f-percentage of available process module seized and A-average % of process modules seized.

7. Conclusions

This paper has examined the issues of MPP optimization in a reconfigurable manufacturing framework with the help of a reconfigurable multiparts manufacturing flow line. The manufacturing line under investigation has been depicted as a multiresource and multistage line that manufactures multiparts.

Decisions for optimal selection of processes, optimal sequencing of the selected processes and optimal order of processing parts have been found to be interrelated thereby requiring a stochastic technique like genetic algorithms to search for an optimal solution.

Modelling the decision making process in an optimization perspective has been found to be a feasible approach for a reconfigurable manufacturing framework. The genetic algorithm method has been found to be effective in modelling MPP optimization with sufficient convergence characteristics and the capability to find an optimal solution. Since the time taken to find the solutions is comparatively reasonable, the genetic algorithm method can be used for generating feasible and globally optimal manufacturing process plans for RMSs.

The results of the case illustration have demonstrated the practical use of diversity control implemented in the MGATO technique. In comparison to MGAWTO, the implemented MGATO improves the population diversity through a customized threshold operator. It was clear that the MGATO can obtain better solution quality by foiling the tendency towards premature convergence. Moreover, processing evaluation indicate more flexibility in the manufacturing process plan selected through implementation of MGATO.

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