A METAHEURISTIC APPROACH TO MANUFACTURING PROCESS PLANNING IN RECONFIGURABLE MANUFACTURING SYSTEMS

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Abstract. Manufacturing process planning (MPP) is concerned with decisions regarding selection of an optimal configuration for processing parts. For multiparts reconfigurable manufacturing lines, such decisions are strongly influenced by the types of processes available, the relationships for sequencing the processes and the order of processing parts. Decisions may conflict, hence the decision making tasks must be carried out in a concurrent manner. This paper outlines an optimization solution technique for the MPP problem in reconfigurable manufacturing systems (RMSs). MPP is modelled in an optimization perspective and the solution methodology is provided through a metaheuristic technique known as simulated annealing. Analytical functions for modelling MPP are based on knowledge of processes available to the manufacturing system as well as processing constraints. Application of this approach is illustrated through a multistage parallel-serial reconfigurable manufacturing line. The results show that significant improvements to the solution of this type of problem can be gained through the use of simulated annealing. Moreover, the metaheuristic technique is able to identify an optimal manufacturing process plan for a given production scenario.

Keywords: Metaheuristics, simulated annealing, manufacturing process planning, reconfigurable manufacturing systems, production scenarios

Abstrak. Proses perancangan pembuatan adalah berkaitan dengan keputusan berdasarkan pemilihan tatarajah yang optimum daripada modul proses untuk pemprosesan bahagian kerja. Untuk pembentukan semula barisan pembuatan bagi pelbagai bahagian kerja, keputusannya dipengaruhi jenis proses yang sedia ada, hubungkait jujukan pemprosesan dan juga aturan pemprosesan bahagian kerja tersebut. Keputusan proses perancangan pembuatan mungkin bercanggah, oleh itu tugasan membuat keputusan perlu mengambil kira cara setemu. Kertas kerja ini membentangkan teknik optima untuk masalah berkaitan proses perancangan pembuatan dalam rangka kerja pembuatan pembentukan semula. Proses MPP dimodelkan sebagai masalah pengoptimuman dan keadah penyelesaian yang diperolehi daripada teknik metahuristik dikenali sebagai simulasi penyepuhlindapan. Fungsi analisis bagi memodel proses perancangan pembuatan adalah berdasarkan pengetahuan mengenai proses dan sistem pembuatan serta kekangan proses. Applikasi bagi pendekatan ini ditunjukkan melalui barisan pembuatan pembentukan semula berbilang tahap siri selari. Keputusan menunjukkan penambahbaik yang signifikasi diperolehi dalam penyelesaian untuk masalah jenis ini dengan menggunakan simulasi penyepuhlindapan.

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Tambahan pula, teknik metaheuristik berkebolehan untuk mengenal pasti kaedah proses pembuatan yang optima berdasarkan senario pengeluaran yang diberi.

1.0   INTRODUCTION

Manufacturing process planning (MPP) is a manufacturing function concerned with identifying the technological manufacturing capabilities for transforming raw materials into products. With rapid developments in process system technologies, a number of production systems is implementing heterogeneous collections of manufacturing modules. Specifying the manufacturing capabilities of such systems requires best selection and sequencing techniques that aim to select, based on some criteria, optimal manufacturing processing plans needed to accomplish a specified manufacturing mission.

In reconfigurable manufacturing, MPP is required for identifying basic courses of actions that form guidelines for manufacturing activities [1]. Since reconfigurable manufacturing is usually carried out in a multiresource environment, the task of selecting and sequencing processes is complex since "local" changes in the manufacturing system may affect performance in other dimensions of the system, thereby degrading overall manufacturing performance [2]. Therefore, a manufacturing planning function that aims at global optimization is required in order to minimize the probability of implementing a suboptimal manufacturing process plan.

Reconfigurable manufacturing systems (RMSs) have been developed to address the problems and challenges in dynamic manufacturing environments [3]. In such environments, there is no room for incompetence in MPP since changes to production requirements are random and companies are in turn expected to respond timely to changes. Moreover, scheduling flexibility is an important component for improving operating efficiencies. Consequently, process planning has a strong relation with route flexibility, since alternative routes may have to be used depending on the part flow intensities [4]. For RMSs that tailor changes in production requirements, intermingling a new product with current ones has an impact on the part loading rate among the available feasible route profiles. This consideration means that MPP function takes a new role that includes: optimal process selection, optimal process sequencing and optimal part loading in a manufacturing system with many possible combinations of processes and many possible permutations of sequences. Therefore, an effective MPP function for RMSs must be established if the RMS is to live up to its expectation.

Simultaneous consideration of the multi-dimensional issues discussed above

implies that the MPP problem in an RMS is essentially an optimization problem. In this paper, the optimization solution framework is provided through the use of a metaheuristic technique known as simulated annealing (SA). The remainder of the paper is organized as follows: in Section 2, a brief review of work related to SA is presented, in Section 3, the proposed optimization approach is outlined, in Section 4, applications of SA technique are described, the results and discussions are presented in Section 5 and finally, conclusions are given in Section 6.

2.0   LITERATURE REVIEW

Simulated annealing (SA) is a metaheuristic approach for solving optimization problems. The algorithm design technique for simulated annealing is based on heuristics. A heuristic is a robust technique for the design of randomized algorithms for optimization problems [5]. SA is analogous to physical annealing, which is a heat treatment process, but incorporates the concepts of statistical mechanics to describe the energy of the material as it is annealed. The physical annealing process finds low energy states of a solid material by melting the substance initially and then lowering the temperature slowly, spending a long time at temperatures close to freezing point. In the SA analogy, the different states of the substance correspond to the different feasible solutions of the optimization problem, and the energy of the system corresponds to the function to be minimized.

The SA algorithm has found numerous applications in optimization problems. In 1953, Metropolis proposed a Monte Carlo model for simulating the transition of a solid from a given state to a thermal equilibrium state for a fixed value of temperature [6]. Although the metropolis proposal marks the novel beginnings of the SA technique, the success of SA algorithm in optimizing functions of many variables was first reported by Kirkpatrick *et al.* [7]. This capability of the Metropolis algorithm to solve optimization problems was echoed by many researchers and later become a popular method for implementing the SA algorithm.

Although SA was invented a long time ago, it has emerged as a fundamental non-deterministic strategy for solving optimization problems that include: travel salesmen problems (TSPs); quadratic assignment problems (QAPs); scheduling problems of a wide variety and manufacturing process planning (MPP) problems at different scales.

In general, MPP tasks fall into two categories differentiated by task specifications: (i) process design and (ii) operation design. Operation design focuses more on the microscopic scale of MPP, i.e. decision making activities that detail the operations, operation sequencing and operating parameters required to produce a part as specified by an engineering drawing. On the other hand, process design focuses more on the macroscopic scale of MPP, i.e. decision making activities that determine the

overall processing routings for producing parts. This work focuses on applications of the simulated annealing technique to macroscopic MPP problems in RMSs.

In reviewing literature on applications of the SA technique, it is apparent that the most documented weakness of the SA algorithm is its slow speed in generating a solution [8]. This emanates from the sequential way in which the solution is deployed by the algorithm. The SA technique imitates the physical annealing process employed in the cooling of metals. The logic in applying the SA analogy lies in that if the energy function of a physical system is replaced by an objective function or cost function, J, that is dependent on a vector of design variables, then the slow progression towards an ordered ground state is representative of a progression to a global optimum. To achieve this, a control parameter, analogous to temperature in the physical annealing process, and a constant, analogous to the Boltzmann constant, must be specified for the optimization problem.

In light of the analogy described above, the temperature must be reduced very gradually and slowly for simulated annealing to produce an optimal solution. Hence the slow speed of the SA technique. Over the years, a number of improvements targeting the convergence rate have been made to the original SA algorithm. For example, Connolly suggested an improved annealing schedule, otherwise known as a cooling scheme, based on a sequential search rather than a random search [9]. Connolly observed that the sequential search was more effective than the random search. Of interest to this research work are the suggested variants of the SA algorithm such as the fast simulated annealing technique [10]. Fast simulated annealing uses local search and occasional long jumps coupled with a special cooling schedule. Such variations have also been reported to improve the implementation of the SA algorithm.

In seeking solutions to manufacturing problems, most work in the public literature focus on obtaining feasible, near optimal or optimal solutions [11]. However, the complexity in dynamic operations requires implementation of globally optimal solutions. In the literature, discussions of global optimization solutions in manufacturing have been proposed through applications of metaheuristics [11]. Such applications have found potential in manufacturing process planning problems. An example of applications of metaheuristics to process planning was discussed by Ma *et al.* [12] who implemented a SA algorithm to search for an optimal solution to the process planning problem of prismatic components in a job shop machining environment. Another example is in the work of Zhang *et al.* [13] who implemented a genetic algorithm (GA) to find an optimal solution to the process planning task of prismatic components. Conclusions from these works confirm that metaheuristic techniques based on SA and GA algorithms are able to find a near optimal solution in reasonable time and have the capability to escape from entrapment in local

optima. As such, metaheuristic algorithms have the potential to find globally optimal solutions for macroscopic MPP problems in RMSs.

The advantages of using such metaheuristic approaches lie in that unlike the random search or gradient descent methods, carefully designed heuristics that support the SA algorithm play an important role in arriving at a near optimal solution in reasonable time and in escaping from entrapment in local optima. Consequently, a heuristic-supported-implementation of the SA algorithm provides better alternatives for the solution of optimization problems. The proposed metaheuristic approach is described in the following section.
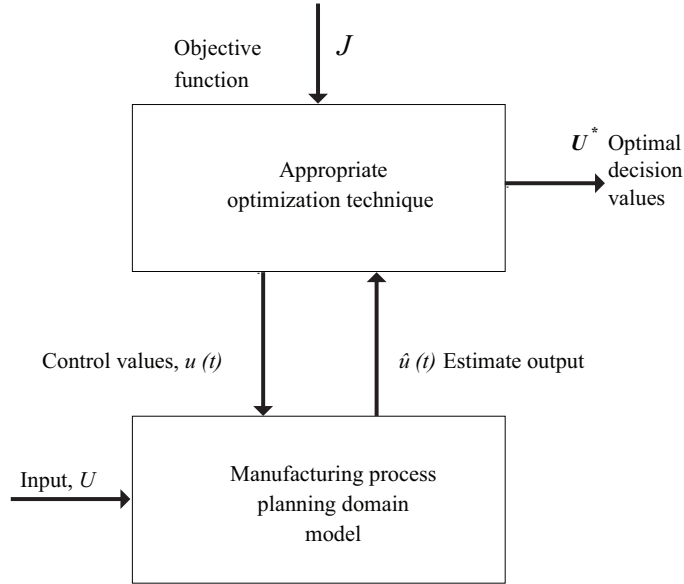
3.0   OPTIMIZATION APPROACH

The proposed optimization approach advocates development of an optimization system. An optimization system is essentially a decision system that provides a steady state operating solution in a multi-dimensional decision variable space. The general form of a steady state model can be written in terms of a non-linear matrix equation shown in Equation (1).

$$U^* = F(U) \tag{1}$$

where U is an r-dimensional input vector, U^* is an n-dimensional output vector and F is an n-dimensional nonlinear matrix function describing the non-linear relationships between U and U^*. The desired performance criteria are optimized subject to system constraints. In general, the complexity of the optimization task increases with increase in non-linearity, increase in system dimensions and multiplicity of local optima. Due to non-robustness of conventional techniques, an alternative approach is to use non-conventional techniques, for example metaheuristics, that are usually non-math-knowledge oriented. The proposed optimization approach is shown schematically in Figure 1.

In Figure 1, an optimization algorithm generates a control profile $u(t)$ and receives the response, $\hat{u}(t)$, from the manufacturing process planning domain model. Depending on the cost function, J, the optimization algorithm eventually finds an optimal control profile U^*. The optimization approach depicted in Figure 1 implies that an optimization model and an optimization algorithm exchange information concerning the problem at hand in order to solve the problem. Knowledge of processes available to the manufacturing system and the processing constraints are encoded in the optimization model. Thus, the framework of approach provides the fundamental services of the problem domain captured in an optimization model and a solution procedure, provided by the algorithm. Guidelines for the decision making process are then provided through an appropriate process planning evaluation model.

Figure 1 Optimization approach to manufacturing process planning in reconfigurable manufacturing systems

3.1 Process Planning Evaluation Model

The process planning evaluation model is defined by an objective function. The objective function for the MPP problem is shown in Equation (2). The evaluation criterion is based on minimizing the total processing costs for multiple parts flowing in the system.

$$\text{Min } F(y) = \text{total processing costs} = \sum_{n=1}^{nf} \sum_{k=1}^{pfn} \sum_{i=1}^{K} [(v_{i,j} * F_{TOC})] \tag{2}$$

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

$ps_{i,j}$ = part similarity coefficient

F_{TOC} = total processing cost function obtained by adding the cost components represented in Equations (3) to (9)

nf = is the number of part families

pfn = is the number of parts in the nth part family

K = the processing types required for producing a part

The part similarity coefficient, $ps_{i,j}$, is a measure of similarity between any two (2) parts of manufacture, i and j, in the production scenario. The parameter, v_{ij}, represents

the change-over costs associated with processing consecutive parts depending on the part load scheduling scheme in the reconfigurable manufacturing system, i.e. it represents the changeover cost from part i to part j. The total processing cost function used in this work is developed based on the suggestions of Zhang and Nee [11]. The modified cost items are defined in Equations (3) to (14). The cost array associated with a proses module used is given by Equation (3):

$$\text{PMC [ ]} = \sum_{i=1}^{K} PMCI_i \tag{3}$$

where, $PMC[\ ]$ is the processing module usage cost array, K is the total number of processing types required to complete the processing of part i, $PMCI$ is the processing module cost index for using PM_i. The cost array associated with a process change, $PCC[\ ]$, is given by Equation (4):

$$PCC = PCCI * \sum_{i=1}^{K-1} \Omega\ (PM_{i+1} - PM_i) \tag{4}$$

where $PCCI$ is the process change cost index and PM_i is the processing module i. In Equation (4),

$$\Omega\ (PM_{i+1} - PM_i) = \begin{cases} 1 & \text{if}\ \ PM_{i+1} \neq PM_i \\ 0 & \text{if}\ \ PM_{i+1} = PM_i \end{cases} \tag{5}$$

The cost array associated with a set-up change, $SCC[\ ]$, is given by Equation (6):

$$SCC = SCCI * \sum_{i=1}^{K-1} [(1 - \Omega\ (PM_{i+1} - PM_i)) * \Omega\ (TAD_{i+1} - TAD_i)] \tag{6}$$

where, $SCCI$ is the set-up change cost index and TAD represents the required PM key characteristic in processing consecutive parts. In Equation (6),

$$\Omega\ (TAD_{i+1} - TAD_i) = \begin{cases} pms_{i,j} & \text{if}\ \ TAD_{i+1} \neq TAD_i \\ 0 & \text{if}\ \ TAD_{i+1} = TAD_i \end{cases} \tag{7}$$

where, $pms_{i,j}$ is the processing module chain similarity coefficient. Also, $TAD_{i+1} = TAD_i$ if the required process modules are in the same stage, otherwise a factor of $pms_{i,j}$ has

to be used, as defined in Equation (7). The cost array associated with reconfiguration, $RC[\ ]$, is given by Equation (8):

$$RC = RCI * \sum_{i=1}^{K-1} [(1 - \Omega(PM_{i+1} - PM_i)) * \Omega(XS_{i+1} - XS_i)] \tag{8}$$

where RCI is the reconfiguration cost index and XS defines a reconfiguration scenario and represents the required key part features for the manufacture of consecutive different part types. In Equation (8),

$$\Omega(XS_{i+1} - XS_i) = \begin{cases} ps_{i,j} & \text{if } XS_{i+1} \neq XS_i \\ 0 & \text{if } XS_{i+1} = XS_i \end{cases} \tag{9}$$

where, $ps_{i,j}$ is the part similarity coefficient between parts i and j.

The cost array associated with use of tools, $TC[\ ]$, is given by Equation (10):

$$TC = TCI * \sum_{i=1}^{K} T_i \tag{10}$$

where TCI is the tool cost index for using tool i and T_i is the processing time required for part i. T_i is defined in Equation (11) as follows:

$$Ti = \begin{cases} Ti \text{ if part } i \text{ visits the standby process module} \\ 0 \text{ if part } i \text{ does not visit the standby process module} \end{cases} \tag{11}$$

The cost array associated with tool change, $TCC[\ ]$, is given by Equation (12):

$$TCC[\ ] = TCCI * \sum_{i=1}^{K-1} [(1 - \Omega(PM_{i+1} - PM_i)) * \Omega(T_{i+1} - T_i)] \tag{12}$$

where, $TCCI$ is the tool change cost index. In Equation (12);

$$\Omega(T_{i+1} - T_i) = \begin{cases} ps_{i,j} & \text{if } T_{i+1} \neq T_i \\ 0 & \text{if } T_{i+1} = T_i \end{cases} \tag{13}$$

Also, this expression in Equation (12) applies only if processing is done by the multi-purpose processing modules. The materials handling cost array is given by Equation (14):

$$HC[\ ] = HCI * \sum_{i=1}^{K-1} d_{i,j} \tag{14}$$

where *HCI* is the materials handling cost index and *d* is the distance between processing modules *i* and *j* in the manufacturing grid. The total processing cost function, F_{TOC}, is the sum of the cost items represented in Equations (3) to (9).

3.2   Optimization Technique

In the proposed approach, the optimization solution technique was provided by a variant of the SA algorithm. The SA algorithm was used to search for an optimal manufacturing process planning profile. The variant implements an advanced local search technique supported by application specific heuristics. The SA solution methodology implements a randomization concept at every critical decision point in the search process. A fast cooling schedule that aims to balance diversification and intensification in the search process was used. Such a schedule is characterized by cooling and reheating, which provides occasional jumps in the search space and thus ensuring an oscillatory balance between diversification and intensification in the search strategy. The generic framework of the SA strategy is heuristic in nature and it simulates the annealing process of metal by probabilistically finding the minimum value of a state-dependent objective function. The flowchart for the SA technique is shown in Figure 2.
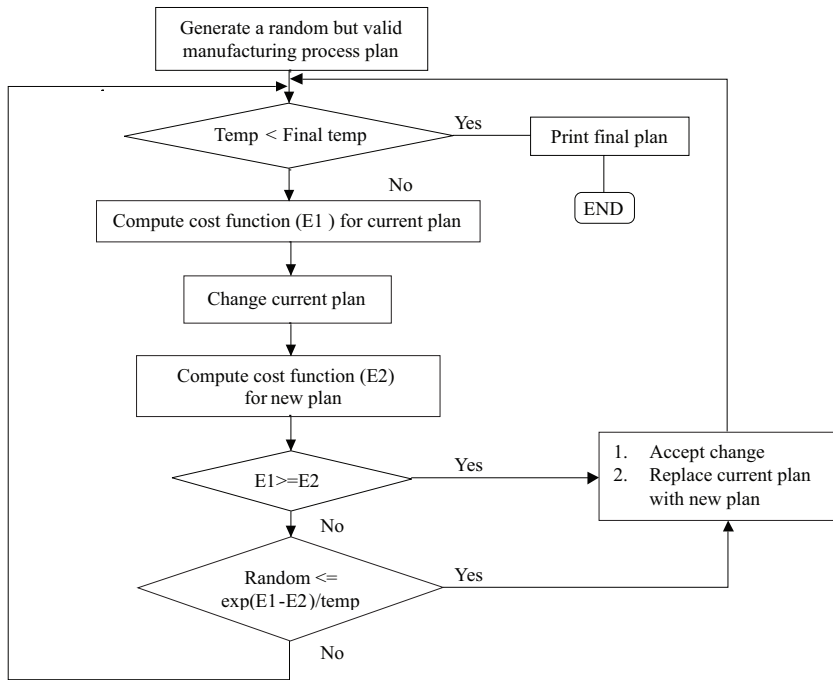

Figure 2   Flow chart for the implemented simulated annealing algorithm

In implementing the SA algorithm, decisions have to be made about the generic parameters and problem specific parameters. An application of the variant of the SA technique is described in the following section.

4.0   APPLICATION OF SIMULATED ANNEALING

4.1   Reconfigurable Manufacturing System Model

In order to test the performance of the SA technique, a reconfigurable manufacturing system testbed was configured from manufacturing modules of a conventional modular production system. The advantage of using such manufacturing modules lies in that the modular stations can be moved or removed and be configured into any desired system for experimental purposes. Implementing various configurations in the testbed was facilitated by modular transporter links and the provision for combining the dedicated manufacturing modules with multipurpose conventional machining centers that provide support to the main production line. A schematic representation of the reconfigurable manufacturing system testbed is shown in Figure 3.
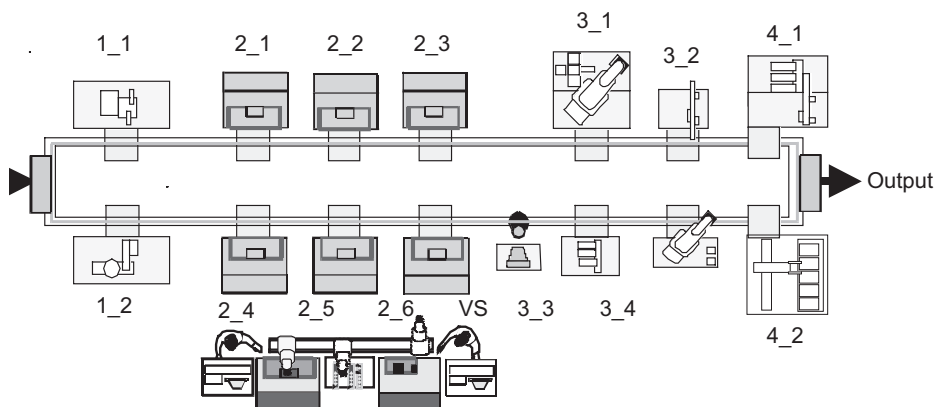

Figure 3   Reconfigurable manufacturing system testbed for this study

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 (4) processing stages. In Figure 3, 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 consists of a mixture of fourteen (14) dedicated processing modules and two (2) multi-purpose processing machines.

The principal modules in the main production line consist of: processing machine primitives (PMPs), modular tooling and jigs (MTJs), modular actuator elements (MAEs) and configurable control systems (CCSs) in contrast to conventional machines [14]. These types of manufacturing modules facilitates easy reconfiguration of the manufacturing system in response to changing production needs. The multipurpose machines, 2_7 and 2_8, are general purpose machining centers that serve as productive reserve capacity in support of the main production line [15]. The flexible transporter links also facilitate reconfigurable flow of parts/products in the system.

4.2   Parameters Used in the Implimented Simulated Annealing Technique

The objective function used in the SA algorithm was defined in Equation (2). All cost items in Equations (3) to (14) were used in the algorithm. The parameters chosen are depicted in the user interface window shown in Figure 4.
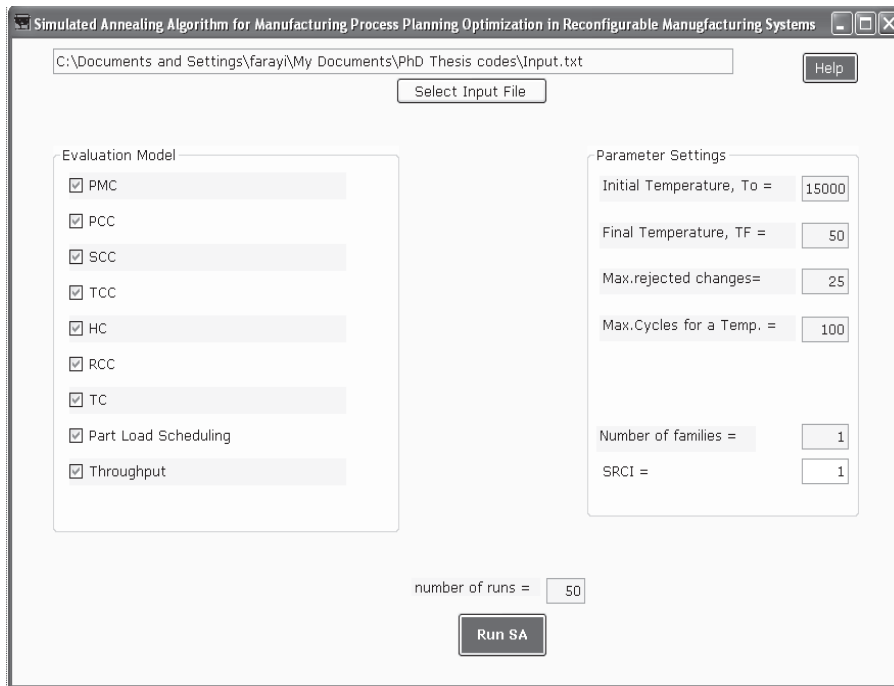
Figure 4   Screenshot showing the parameters used in running the simulated annealing algorithm

A fixed number of rejected changes under each temperature was chosen as the stopping criterion [11]. The SA algorithm was coded in C/C++ and was run on a Pentium 4, 2.0 GHz PC with 512 MB.

5.0   RESULTS AND DISCUSSION

The capability of the SA algorithm to generate optimal manufacturing process plans for the described case study was carried out under the following settings: all processing modules types were assumed to be available and there were no breakdowns. In order to validate the performance of the SA algorithm, attempts were made to solve the MPP problem using a software known as GA Optimization for Excel (GAOE) version 1.2. Table 1 summarizes the comparison of the GAOE results with those of the SA technique.

Table 1   Comparison of software results with those obtained from the simulated annealing run for small-sized problems

P_i	Cost function values, J				Execution times, t			
	GAOE	SA	ΔJ	$\Delta J\%$	GAOE	SA	Δt	$\Delta t\%$
1	51	45	6	11.76	10	8	2	20.00
2	107	92	15	14.02	14	10	4	28.57
3	212	184	28	13.21	17	12	5	29.41
4	267	234	33	12.36	20	14	6	30.00
5	313	275	38	12.14	24	16	8	33.33

In Table 1, it is evident that the quality of the solutions obtained from the SA technique is better than those obtained from the GAOE software. The quality is significantly higher as the size of the problem increases, i.e. as the number of parts in the production scenario, P_i, increases. The same trend is true for the computer execution times. For processing one part, the SA technique improved the quality of the solution by 11.76%. The percentage improvement in terms of the execution time was 20%. Table 1 indicates that for large scale problems, i.e. number of parts greater than five (5), it is better to use the SA technique due to (i) the limitations in encoding more than five (5) parts when using the GAOE software and (ii) improved quality of the solutions obtained through using the SA technique. Therefore, for the case of twenty (20) parts flowing in the manufacturing system, only the SA technique was used to determine an appropriate manufacturing process plan. The simulation performance curve for the SA algorithm in search for an optimal manufacturing process plan for twenty (20) parts is shown in Figure 5.
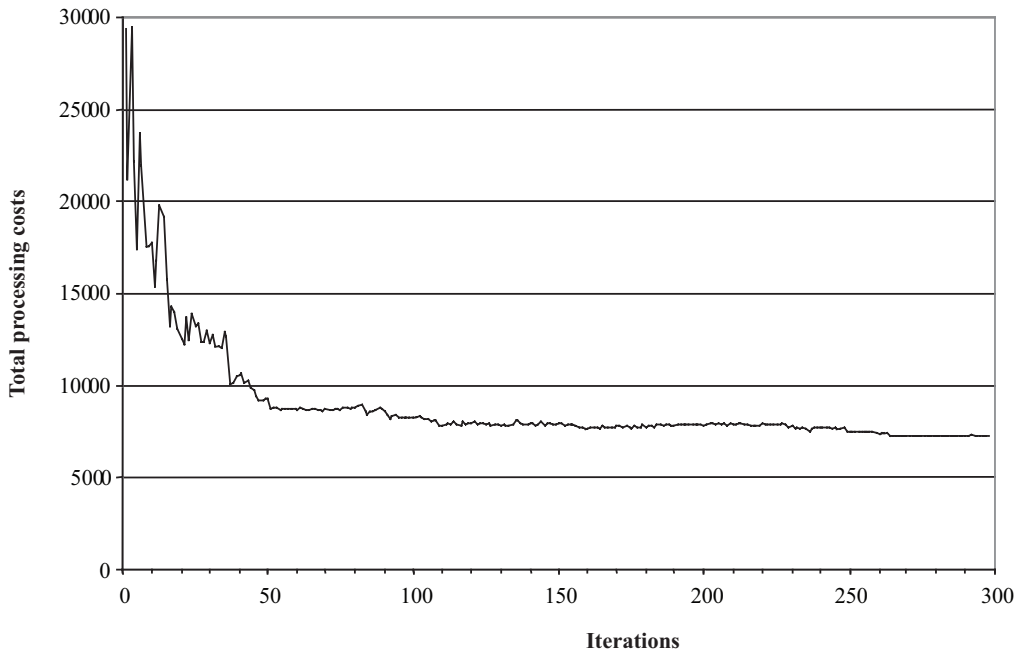
Figure 5   Mean optimization performance curve for the simulated annealing
algorithm

Figure 5 shows the convergence characteristics of the optimization process, which is a plot of the total processing costs against the number of iterations. The optimum cost was found at 7308 and the solution time was twenty-seven (27) minutes. The solution time of twenty-seven (27) minutes may be considered more efficient in comparison to an attempt to generate such an optimal solution manually. Moreover, the application is for non-real time and as an aid to decision making. In this regard, a solution time of twenty-seven (27) minutes may be considered adequate for generating an optimal manufacturing process plan for non-real time applications.

In most runs carried out during the simulation experiments, the final solution was achieved at just before the specified final temperature was reached. This suggests that the algorithmic stopping criterion for the SA was sufficient. One of the recommended manufacturing process plans is shown in Table 2. In Table 2, P_i is the part identification number, PL is the order of part processing while the optimum processing route profile shows the selected process modules and their sequences as recommended by the SA technique.

Table 2 also shows the respective number of changes for each part processing together with the percentage of the available processing modules seized in the processing of each part (refer column f of Table 2). The total number of changes

in the manufacturing process plan shown in Table 2 is 361, while the average percentage of processing modules seized during the manufacturing process is 44.5%. The optimum processing route profiles also indicate that there is provision for repeat processing, i.e. same process module reselected for the same part, and there is minimal use of the productive reserve capacity as evident in column e. Such a comprehensive processing evaluation avails information that allows manufacturing engineers to make more informed decisions regarding the best manufacturing process plans to implement.

Table 2   Manufacturing process plan selected by the simulated annealing algorithm

P_i	Optimum processing route profile	P_L	Processing evaluation					
			a	b	c	d	e	f
1	1_2 2_6 2_5 2_2 2_5 2_2 3_3 4_2	2	7	7	0	1	0	50%
2	1_2 2_6 2_5 2_4 2_4 2_5 2_1 3_3 4_2	9	7	8	0	1	0	44%
3	1_1 2_5 2_5 2_3 2_2 2_3 3_3 4_2	6	6	7	0	2	0	38%
4	1_2 2_5 2_13 3_3 4_2	7	5	4	2	3	1	31%
5	1_2 2_5 2_5 2_2 2_4 2_13 2_4 3_2 3_3 4_1 4_2	12	10	11	2	3	1	56%
6	1_2 2_5 2_13 2_6 2_4 3_3 4_2	13	7	6	2	3	1	44%
7	1_1 2_5 2_1 2_2 2_3 2_3 3_2 3_3 4_1 4_2	16	9	10	0	2	0	56%
8	1_2 2_5 2_5 2_2 2_5 2_4 3_3 3_4 4_1 4_2	20	9	10	0	2	0	50%
9	1_2 2_5 2_5 2_5 2_2 2_4 3_3 4_2	1	6	8	0	3	0	38%
10	1_2 2_5 2_5 2_3 2_2 2_3 3_3 4_2	3	7	8	0	2	0	38%
11	1_2 2_5 2_6 2_6 3_2 3_3 4_1 4_2	19	7	8	0	2	0	44%
12	1_2 2_6 2_6 2_2 3_3 4_2	4	5	6	0	2	0	31%
13	1_2 2_5 3_3 3_4 4_1 4_2	8	6	6	0	1	0	38%
14	1_2 2_6 2_5 2_5 2_5 2_4 3_3 4_2	18	6	8	0	3	0	38%
15	1_2 2_5 2_5 2_6 2_2 2_4 3_3 4_2	5	7	8	0	2	0	44%
16	1_2 2_6 2_5 2_4 2_4 2_5 2_3 2_2 2_5 3_3 4_1 4_2	10	11	12	0	2	0	56%
17	1_2 2_6 2_6 2_6 2_4 2_13 3_3 4_2	17	6	8	0	3	0	38%
18	1_2 2_5 2_1 2_4 2_4 3_3 4_1 4_2	15	7	8	0	2	0	44%
19	1_2 2_5 2_6 2_2 3_2 3_3 3_4 4_1 4_2	14	9	9	0	1	0	56%
20	1_2 2_6 2_1 2_2 2_5 2_5 2_4 2_4 2_5 3_3 4_2	11	9	11	0	3	0	56%
Total changes=361			**146**	**163**	**6**	**43**	**3**	**Ave. 44.5**

Key to Table 2

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

6.0   CONCLUSION

This study has revealed the capability of the SA algorithm to handle manufacturing process planning optimization in multistage multiparts reconfigurable manufacturing lines. The results show that the SA algorithm is able to recommend an optimal manufacturing process plan for a given production scenario. The SA technique also showed significant improvements in obtaining solutions in comparison to a software approach. Moreover, the SA technique has the advantage of handling large problems and thus overcoming the limitations of using software. For non-real time applications similar to the decision support system discussed in this work, the performance of the SA algorithm can be considered sufficient. In addition, the SA algorithm is simple, easy to implement and a near-optimal solution can be obtained due to its capability to escape from local optima. The capability of the SA algorithm to recommend feasible manufacturing process plans for multiple part types with reconfigurable flow indicates that this approach has potential in reconfigurable manufacturing system applications.

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