

ASSESSING THE EFFECTIVENESS OF FLEXIBLE PROCESS PLANS FOR LOADING AND PART TYPE SELECTION IN FMS

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Abstract:

The increased use of flexible manufacturing system (FMS) to provide customers with diversified products efficiently has created a significant set of operational challenges for managers. This technology presents a number of decision problems to be solved by researchers and practitioners. There have been a number of attempts to solve design and operational problems in FMS. In this paper, a special attention has been given to FMS loading along with part type selection, when flexible process plans (FPPs) for each part type are available. A genetic algorithm (GA) based methodology is adopted that selects part types along with their process plans in order to minimize system unbalance while satisfying the constraints of tool slots, available tool copies and planning period duration. An example FMS is taken into consideration and results indicate that availability of FPPs during FMS loading assists the planner in reducing the system unbalance. Other interesting conclusions, such as for a given number of tool copies of each tool type tool loading, is affected by the availability of flexible process plans, are drawn.

Key Words: Flexible Manufacturing System, Flexible Process Plans, Loading, Part Type Selection, Genetic Algorithm.

1. INTRODUCTION

In recent years, there has been a considerable interest in methods for design, modeling, planning, scheduling and performance evaluation of flexible manufacturing systems (FMSs). This is partly due to the fact that flexibility is required by manufacturing companies to stay in a highly competitive and changing business environment. A FMS can be defined as an automated manufacturing system consisting of multi-functional machines that are interconnected by a material handling system. These systems are designed to combine the efficiency of mass-production line with the flexibility of a job shop to best suit the batch production of mid-volume and mid-variety of products. The flexibility of a FMS is mainly due to the capability of performing different operations within the same station and the material handling stations, which provide fast and flexible transfer of parts within the system. Since FMSs are capital intensive, an effective management and control system is needed for their successful implementation.

Managing FMS is more complex than production line and job shop as (i) each machine is quite versatile and capable of performing many different operations, (ii) the system can process several part types simultaneously, and (iii) each part may have alternative routes through the system [1]. For better management, production-planning problem in FMS is subdivided into five stages: part type selection, machine grouping, part-mix ratio determination, resource allocation and loading [1]. In order to ensure the smooth operation of FMS, all these problems must be solved before making the system operational. Among them, part type selection and loading has been researched vastly over past several years as

they play an important role in determining the system performance. Loading in FMS is defined as “assigning operations of selected part types and the tools needed to carry out these operations on available machines, subject to the constraints of the system and meeting a pre-specified objective function” and part type selection is defined as “selection of a set of part types from the total part types that are to be processed in given FMS for immediate and simultaneous processing”.

In FMS, flexible process plans (FPPs) are common due to the presence of versatile machines that provide alternatives for adapting to dynamic environment and improve system performance [2]. FPPs can be generated with the consideration of operation flexibility (possibility of performing an operation on more than one machine), sequencing flexibility (possibility of interchanging the sequence in which required manufacturing operations are performed) and processing flexibility (possibility of producing the same manufacturing feature with alternative operations or sequence of operations) [3]. It is important to mention that a computer controlled flexible automation system is essential to implement FPPs in practice [4]. Part type selection and loading becomes more complex when FPPs for each part type are available. This is due to the fact that availability of FPPs increases the number of options for a part type to be considered during loading. For example, if a part type has three available flexible process plans, then it should be considered twice during loading with each of its three process plans one at a time.

This paper, initially, provides a literature review of manufacturing research on FMS loading and part type selection. Subsequently, an example FMS that is taken into consideration, is described. A genetic algorithm (GA) based methodology that is adopted in the present work is then discussed. Finally, the results obtained from the experiments are discussed and summarized.

2. LITERATURE REVIEW

This section provides a review of relevant literature in the area of part type selection and loading. Review of literature indicates that primarily four approaches viz., mathematical programming approach, multi-criteria decision making approach, simulation based approach and heuristic based approach are used for FMS loading and part type selection [5]. Some of the important contributions are discussed below.

Stecke [1] formulates loading problem as a non-linear 0-1 mixed integer programs (MIP) and suggests various linearizing methods and applied to data from an existing FMS with the objective to balance the assigned workload per machine as much as possible while assigning each operation to only one machine. Gurrero et al. [6] have formulated loading and part type selection problem as a mixed integer linear program, with the objective of balancing machine workloads. It focuses on the existence of alternative routes for each part type and determines the optimal number of tool copies of each tool type that are to be loaded in the tool magazine of each machine tool. Shanker and Tzen [7] have also developed a MIP model with bi-criterion objective of workload balancing amongst the machine and meeting the due dates of the jobs. They considered the scheduling problem in FMS as a composite of two interdependent problems i.e. loading and sequencing.

Generally, under mathematical programming approach category, most of the researchers used integer linear/mixed integer linear programming approach although some non-linear models have also been developed [6]. However, computation time required by mathematical approach is prohibitive [5, 8]. Thus, the common approach is, to model the problem using mathematical programming approach and solve it by heuristics [8]. Many of these heuristics are again based on mathematical programming tools, such as branch and bound, decomposition, Lagrangian relaxation etc. and still require substantial computing time [8]. The heuristics techniques can broadly be divided into two types: (i) heuristics with simple rules such as shortest processing time (SPT) rule and (ii) elaborate heuristics designed for a specific problem environment or objective [8]. However, most of such heuristics are problematic specifically for a particular situation and objective and can not be generalized

and also often get trapped in local optimum and thus, do not give globally optimum results [8]. In the recent past, general-purpose modern heuristic techniques known as meta-heuristics have become popular. These heuristics include tabu-search, simulated annealing, GA and neural networks. Drawback of being trapped in local optimum could be avoided by these modern heuristics and thus, solutions as close as possible to the global optimum can be obtained [8]. Kumar and Shanker [8] have solved part type selection and machine loading of FMS using GA, while considering operation flexibility only. In order to make their GA more effective, they modeled their problem using mixed integer programming approach and developed a strategy consisting of three parts namely: solution coding, solution generation and solution recombination. Tiwari and Vidyarthi [9] have used GA based heuristic to solve the machine loading problems of FMS in order to determine the part sequence and the operation-machine allocation with the objectives of minimizing the system unbalance and maximizing the throughput with the consideration of operation flexibility only. Vidyarthi and Tiwari [5] have proposed a fuzzy based heuristic approach for solving machine loading problem in FMS with the objectives of minimization of the system unbalance and maximization of the throughput. Rai et al. [10] have formulated machine-tool selection and operation allocation in FMS and have solved a fuzzy goal-programming model using GA with the considerations of operation flexibility. Akhilesh et al. [11] have suggested constraint based GA, consisting of three new genetic operators (constraint based initialization, crossover and mutation) to handle a variety of variables and constraints in an FMS environment. Several other researchers have also attempted loading problem separately or together with other problems of production planning in the recent past [12, 13, 14].

Literature review reveals that machine loading in FMS has been analyzed separately as well as in combination with other related problems such as grouping, part type selection and scheduling. Moreover, FMS loading in the presence of FPPs has not been addressed adequately. Researcher community has taken into consideration the aspect of operation flexibility in a single process plan and carried out operation-machine-tool allocation (loading) following operation-by-operation allocation strategy for each part type. However, in general, FPPs can be generated with the considerations of operation, sequencing and processing flexibility. Loading and part type selection problem changes completely in the presence of FPPs as operation-machine-tool allocation (loading), is done with the consideration of entire one process plan of each part type at a time. The present work is an attempt in this direction. It is important to mention that as each part type contains FPPs, thus during loading of various machine tools, selection of the process plan for each selected part type is also determined. In the present work, the loading and part type selection problem is defined in the following manner:

“For a given FMS, the tool magazine capacity of each machine tool as well as number of available tool types and their copies are known. The FMS has to process a variety of part types whose FPPs are known. For a given planning period, determine the various part types that will be processed simultaneously among the available part types and loading of various machine tools of the system subject to satisfying the constraints of tool magazine capacity and number of available tool copies with the objective of minimizing the system unbalance.”

3. DESCRIPTION OF FMS

Figure 1 shows the configuration of FMS that has been taken into consideration in the present work. It consists of four CNC machine tools (i.e. M-1, M-2, M-3 and M-4) with automatic tool interchanging capabilities. Each machine tool has five tool slots in its tool magazine. There is also one load-unload station (i.e. L/UL) for the purpose of loading and unloading the raw stock and finished parts respectively. All machines and load-unload station are well connected through an automated material handling system

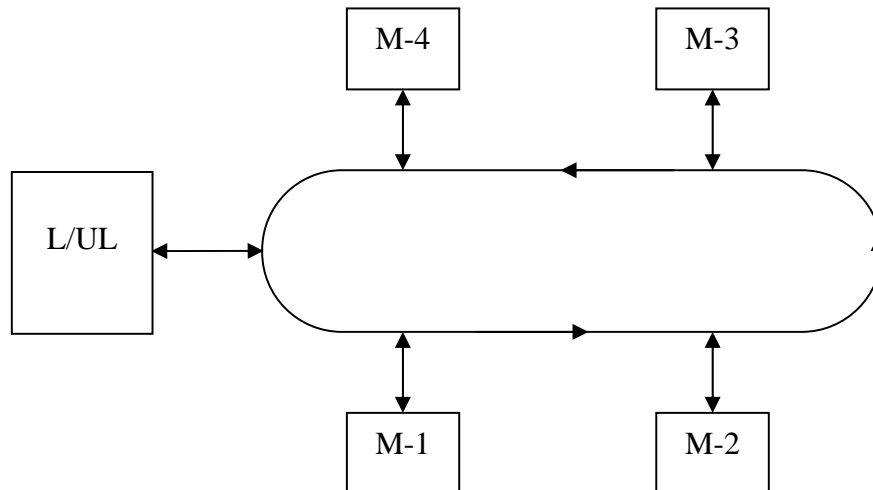


Figure 1: FMS Configuration.

(e.g. conveyor). At each station, a secondary material handling system (e.g. robot, human worker) works to shift the material from the conveyor to the station and vice-versa. Total twenty types of tool are available and they are identified by tool number 1, 2, 3, 4, ..., 20.

Following assumptions that are in line with the previous studies are made in the present work, [5, 9].

- (i) All machines have infinite buffer capacities.
- (ii) No tool replacement will occur in the mid of planning period.
- (iii) All raw materials and customer orders are available at the start of planning period.
- (iv) A part type follows strict processing sequence of operations defined by its process plan.
- (v) Non-splitting of jobs i.e. splitting of jobs is not allowed for a planning period.
- (vi) Availability of sufficient number of pallets and fixtures.
- (vii) Transportation time as well as loading and unloading times are considered to be very small in comparison to processing time and hence assumed to be negligible.
- (viii) It has also been assumed that each tool occupies only one tool slot in the tool magazine of each machine tool.

4. ADOPTED METHODOLOGY

The present work utilizes GA based approach to solve the part type selection and loading of FMS. GA is a computerized search algorithm and it works on the Darwin's theory of survival of the fittest. Encoding/representation is the first step of GA, in which variables or expected solutions of a problem are coded into some useful form. Generally, in GA, a fitness function is derived from the objective function and it is used in successive generations for evaluation of the individuals that represent the expected solutions. In literature, a number of GA operators have been used to solve a variety of problems [15]. A simple GA is composed of three probabilistic operators namely selection, crossover and mutation. For a given fitness function, better individuals are selected from a population by selection operator after giving due consideration to system's constraints and a mating pool is formed. Usually, off-springs are produced by applying crossover and mutation operators on the individuals of mating pool. Individuals of parent population and off-springs produced are used in the process of reproduction for creating new population for the next generation. The cycle of evaluation-selection-reproduction continues until a satisfactory solution is found [16, 17]. For more information, interested readers can refer to standard books on GA [15, 16, 17, 18, 19]. The adopted methodology is discussed in following subsections.

4.1 Encoding/representation

In GA, encoding is used to code the variables (i.e. the expected solutions) of the problem and it must represent the characteristics of the problem properly as it affects the subsequent working of GA significantly. As the present study considers the availability of FPPs for each part type, thus part type selection needs to be carried out along with the selection of best process plan among the given FPPs for each part type. The best process plan for a part type is one that assists in meeting the objective function i.e. minimizing the system unbalance. Thus, in this study, for a given planning period, each part type is allocated to its best process plan after giving due consideration to system's constraints of tool magazines capacities and number of available tool copies so as to minimize the system unbalance. Keeping the above characteristic of the problem in mind, the present work uses sequence oriented permutation type of encoding. In this scheme of representation, part type is combined together with its process plan to form a bit (gene) of a chromosome. For example, if there are four part types A, B, C and D and each part type can be processed through any of its available FPPs 1, 2 and 3, then this information can be suitably encoded as: B3, D1, C2, A3. In this representation, alphabets represent part types and numerals represent process plans. Thus, B3 represents processing of part type B by following its process plan number 3, D1 represents processing of part type D by following its process plan number 1, C2 represents processing of part type C by its process plan number 2 and similarly A3 represents processing of part type A by its process plan number 3.

4.2 Initialization and selection

In the present work, initial population of GA is generated randomly as the performance of GA is found better with a random start than from a pre-selected starting population [20]. This initial population is to be operated first by the selection operator to form a mating pool. Selection is applied on the parent population with the aim to select fitter individuals for the given objective and satisfying the system's constraints as well. The present work utilizes Rank Selection method, as the limitation of proportionate selection methods (such as "roulette wheel" and "stochastic universal" sampling) of being converging prematurely can be prevented effectively to a great extent by this method [18]. In this method, individuals in the population are ranked according to their fitness, and the expected value of each individual depends on its rank rather than on its absolute fitness [21]. Thus, a mating pool consisting of selected individuals is formed.

4.3 Crossover

This study considers two-point crossover approach and it is applied on the individuals of mating pool. For two-point crossover, two strings (individuals) are selected randomly from the mating pool to make a pair. For each pair, essentiality of carrying out crossover is determined using crossover probability (0.8). In two-point crossover, crossing site/position is selected randomly twice from one to four.

For example:

Parent string 1: A1, **B2**, **C3**, D3.
Parent string 2: A1, **B1**, **D3**, C2.

Let, for crossover, positions two and three are selected as shown in bold. Thus, bits from second position to third position are exchanged in the parent strings, keeping other bits unchanged. Thus, off-springs produced are:

Offspring 1: A1, **B1**, **D3**, D3.
Offspring 2: A1, **B2**, **C3**, C2.

4.4 Mutation

In previous research, several mutation operators are proposed for the permutation type of representation such as inversion, insertion, displacement and reciprocal exchange [15, 22]. The present work utilizes reciprocal exchange type of mutation operator and it is applied on the off-springs produced after the crossover operation. The mutation operator used in this study differs from its existing cousins as it works slightly in a different way. This is due to the fact that every bit of an individual has two digits, first one for part type and second one for the process plan number through which the part shown by the first digit will be processed. Similar to crossover, in mutation also, the essentiality of carrying out mutation is performed using mutation probability (0.2). If mutation is desired, then it is essential to determine the position at which mutation should be carried out as each gene consists of two digits (first digit is part type and the second digit is process plan). This is carried out with 50% probability as mutation will be having equal chance to be performed either on part type or process plan. Now again, positions on which mutation is to be performed (i.e. from one to four) are selected randomly twice and part types/process plans at these positions are interchanged. For example, A1, B1, D3, C2 represents a string before mutation. Assuming that part types are to be interchanged and the positions two and four are selected, then the string after mutation will be A1, C1, D3, B2.

4.5 Repairing

After crossover/mutation, some illegal off-springs may generate i.e. one or two part types may repeat in an individual. For example, if an individual (string) after mutation is A1, C1, A3, D2 then it is an illegal offspring as part type A gives rise to a conflict situation. Thus, a repairing strategy is required to resolve this illegitimacy of off-springs. In the present work, after mutation operation, all the individuals are checked to ensure that no part type repeats in any individual. Moreover, A - B - C - D - A repairing procedure is used i.e. all the individuals are checked from left to right and if at any position part type repeats, it shall be replaced by the next part type according to the above mentioned repairing procedure.

4.6 Reproduction

After applying crossover, mutation and repairing strategy, all the off-springs thus generated are combined with parent population to form extended population. From this extended population, population for next generation is formed, by taking all the individuals of mating pool (i.e. off-springs produced after crossover and mutation operations) and the remaining individuals are taken from the previous population in the order of their fitness values. The above approach ensures that elitism way is embedded with in the rank selection. Elitism, first proposed by De Jong [23] is a methodology that considers the transfer of few good individuals from the previous population to the population of next generation and it is an important consideration in GA.

4.7 Fitness function

The present work considers the minimization of system unbalance as an objective function, which can be defined as the sum of un-utilized and/or over-utilized time on all the machines available in the system. Considering a planning period of eight hours, various individuals of a population are evaluated using the following objective function [9]:

$$\text{Maximize 'f'} = (\text{SU}_{\text{max}} - \text{SU}_{\text{seq}}) / (\text{SU}_{\text{max}} - \text{SU}_{\text{min}}).$$

Where:

$$\text{SU}_{\text{max}} = \text{Maximum system unbalance [= 1920 minutes (4 machine x 8 hours x 60 minutes)].}$$

SU_{min} = Minimum system unbalance (= 0 minute).

SU_{seq} = System unbalance corresponding to a particular sequence of part types (i.e. individual).

It is important to mention that in the present work during the evaluation of various individuals SU_{seq} is determined, while taking care of the constraints of the system. In this study, various constraints (tool magazine's capacity, number of tool copies of available tool types and duration of planning period) are grouped into two categories viz. system unbalance constraint (SUC) and loading constraint (LC). SUC is caused by the condition of non-decrement of system unbalance as the adopted methodology selects a part type only if it helps in reducing the system unbalance otherwise it is rejected. LC is imposed by the non-availability of tool slot and /or tool copies for the tool types required to process the part type under consideration. Thus, during the evaluation of an individual, only those part types are loaded, which satisfy both the above mentioned categories of constraints.

The flow chart representing the adopted methodology in the present study is shown in Fig. 2 and it is coded in C language and executed on Pentium IV processor computer. GA parameters values such as crossover probability and mutation probability play an important role in determining the solution quality. In the present work, the values of population size and generation gap (G_GAP) are taken as 15 and 0.7 respectively. G_GAP indicates the fraction of population to be reproduced to carry out crossover and mutation, G_GAP=0.7 means that 7 strings are to be selected from a population of 10 strings to generate off-springs after crossover and mutation. Crossover probability and mutation probability are in line with the previous studies with the values of 0.8 and 0.2 respectively [9].

4.8 Determination of Optimal Number of Generations

Determination of optimal (maximum) number of generations (MAX_GEN) in GA is an important consideration in order to find a global optimum solution. Tables I-IV show the details of four production orders that are taken into consideration. For each production order, considering two number of tool copies

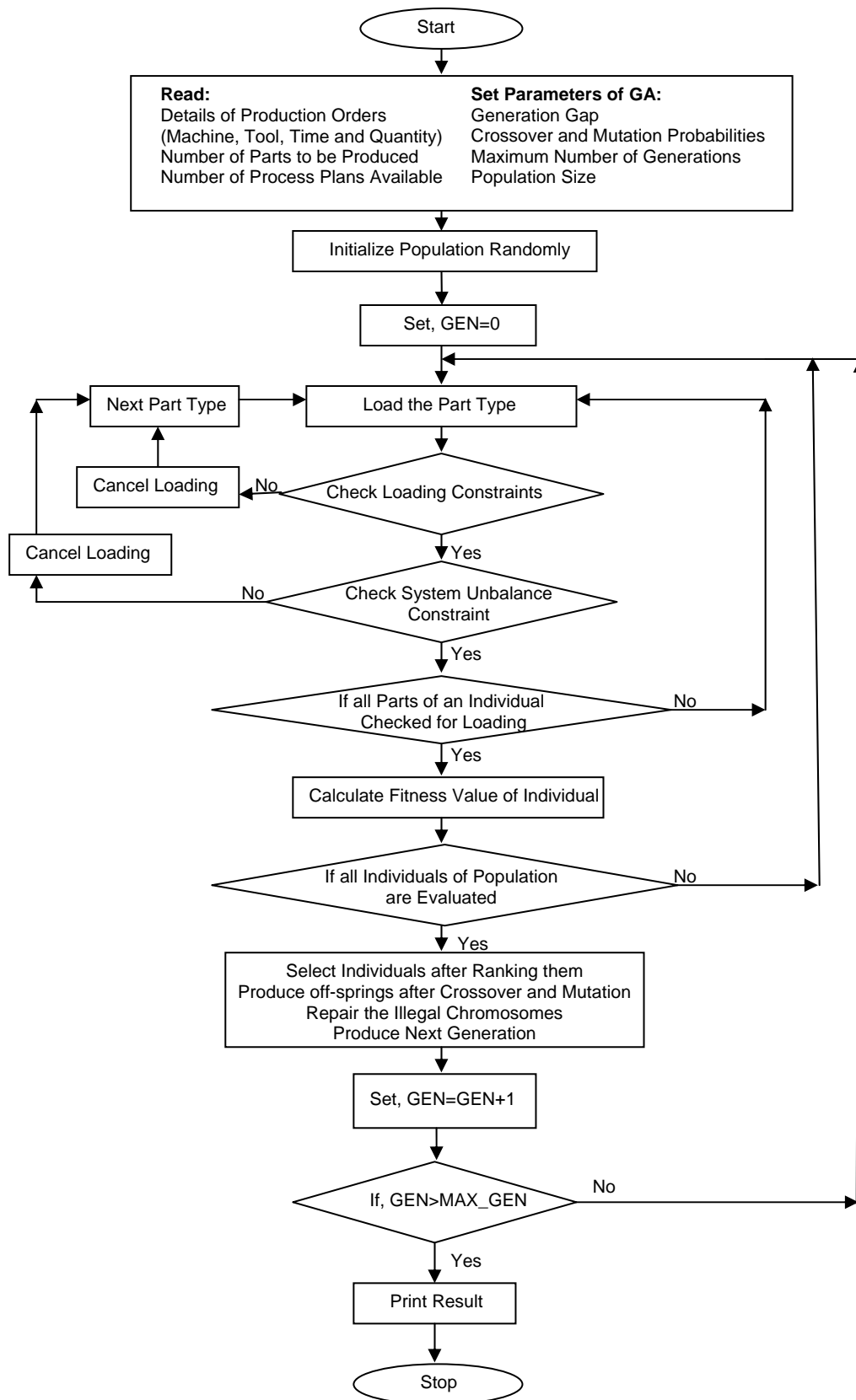


Figure 2: Flow chart of adopted methodology.

Table I: Production order 1 details.

Part type	Qty	PP No.	Flexible Process Plans M-i (t) _k			
E	01	1	M-2 (40) ₄	M-1 (110) ₇	M-3 (109) ₂	M-1 (106) ₃
		2	M-3 (78) ₄	M-2 (60) ₁₀	M-3 (93) ₈	M-1 (106) ₃
		3	M-3 (35) ₆	M-1 (130) ₁₀	M-3 (93) ₈	M-4 (140) ₃
F	02	1	M-1 (82) ₁	M-1 (99) ₃	M-2 (50) ₄	M-3 (129) ₉
		2	M-2 (103) ₁	M-1 (99) ₃	M-3 (32) ₄	M-4 (81) ₉
		3	M-4 (107) ₅	M-2 (56) ₃	M-4 (86) ₁₁	M-4 (69) ₁₅
H	01	1	M-1 (76) ₁	M-2 (117) ₁₉	M-2 (70) ₂₀	M-4 (106) ₁₈
		2	M-2 (106) ₁₁	M-3 (117) ₁₂	M-1 (127) ₁₃	M-4 (106) ₁₈
		3	M-4 (93) ₁₁	M-1 (49) ₁₂	M-2 (134) ₁₃	M-1 (132) ₁
J	01	1	M-1 (29) ₁₀	M-2 (107) ₁₁	M-2 (113) ₁₄	M-4 (69) ₁₅
		2	M-2 (41) ₁₀	M-1 (53) ₁₆	M-3 (42) ₈	M-2 (134) ₁₉
		3	M-2 (70) ₁₉	M-4 (91) ₁₁	M-3 (42) ₈	M-4 (69) ₁₅

Legend: PP No: Process Plan Number, Qty: Production quantity, M-i (t)_k: Required operation will be carried out on machine i with tool-type k and it requires t units (minute) of processing time.

Table II: Production order 2 details.

Part type	Qty	PP No.	Flexible Process Plans M-i (t) _k			
C	01	1	M-1 (67) ₁₂	M-3 (90) ₉	M-2 (117) ₁₁	M-1 (82) ₃
		2	M-1 (67) ₁₂	M-4 (120) ₉	M-2 (47) ₁₉	M-2 (85) ₃
		3	M-4 (134) ₁₅	M-4 (40) ₁₈	M-2 (47) ₁₉	M-1 (82) ₃
B	02	1	M-1 (114) ₁	M-3 (119) ₈	M-2 (66) ₁₀	M-2 (116) ₄
		2	M-2 (126) ₁	M-1 (25) ₁₆	M-3 (29) ₁₇	M-1 (96) ₁₂
		3	M-2 (98) ₃	M-1 (25) ₁₆	M-1 (106) ₁₀	M-3 (84) ₁₂
F	02	1	M-1 (82) ₁	M-1 (99) ₃	M-2 (50) ₄	M-3 (129) ₉
		2	M-2 (103) ₁	M-1 (99) ₃	M-3 (32) ₄	M-4 (81) ₉
		3	M-4 (107) ₅	M-2 (56) ₃	M-4 (86) ₁₁	M-4 (69) ₁₅
H	01	1	M-1 (76) ₁	M-2 (117) ₁₉	M-2 (70) ₂₀	M-4 (106) ₁₈
		2	M-2 (106) ₁₁	M-3 (117) ₁₂	M-1 (127) ₁₃	M-4 (106) ₁₈
		3	M-4 (93) ₁₁	M-1 (49) ₁₂	M-2 (134) ₁₃	M-1 (132) ₁

Legend: PP No: Process Plan Number, Qty: Production quantity, M-i (t)_k: Required operation will be carried out on machine i with tool-type k and it requires t units (minute) of processing time.

Table III: Production order 3 details.

Part type	Qty	PP No.	Flexible Process Plans M-i (t) _k			
A	02	1	M-1 (104) ₁	M-2 (130) ₇	M-3 (118) ₆	M-4 (100) ₁₃
		2	M-2 (110) ₁	M-1 (68) ₇	M-2 (110) ₆	M-4 (100) ₁₃
		3	M-3 (101) ₂	M-2 (120) ₄	M-3 (118) ₆	M-1 (84) ₁₀
C	01	1	M-1 (67) ₁₂	M-3 (90) ₉	M-2 (117) ₁₁	M-1 (82) ₃
		2	M-1 (67) ₁₂	M-4 (120) ₉	M-2 (47) ₁₉	M-2 (85) ₃
		3	M-4 (134) ₁₅	M-4 (40) ₁₈	M-2 (47) ₁₉	M-1 (82) ₃
E	01	1	M-2 (40) ₄	M-1 (110) ₇	M-3 (109) ₂	M-1 (106) ₃
		2	M-3 (78) ₄	M-2 (60) ₁₀	M-3 (93) ₈	M-1 (106) ₃
		3	M-3 (35) ₆	M-1 (130) ₁₀	M-3 (93) ₈	M-4 (140) ₃
J	03	1	M-1 (29) ₁₀	M-2 (107) ₁₁	M-2 (113) ₁₄	M-4 (69) ₁₅
		2	M-2 (41) ₁₀	M-1 (53) ₁₆	M-3 (42) ₈	M-2 (134) ₁₉
		3	M-2 (70) ₁₉	M-4 (91) ₁₁	M-3 (42) ₈	M-4 (69) ₁₅

Legend: PP No: Process Plan Number, Qty: Production quantity, M-i (t)_k: Required operation will be carried out on machine i with tool-type k and it requires t units (minute) of processing time.

Table IV: Production order 4 details.

Part type	Qty	PP No.	Flexible Process Plans M-i (t) _k			
D	02	1	M-3 (49) ₂	M-1(137) ₅	M-2 (115) ₁₄	M-1 (68) ₇
		2	M-2 (114) ₄	M-4 (118) ₅	M-4 (120) ₁₃	M-2 (53) ₇
		3	M-3 (140) ₄	M-2 (38) ₂₀	M-4 (120) ₁₃	M-1 (68) ₇
E	03	1	M-2 (40) ₄	M-1 (110) ₇	M-3 (109) ₂	M-1 (106) ₃
		2	M-3 (78) ₄	M-2 (60) ₁₀	M-3 (93) ₈	M-1 (106) ₃
		3	M-3 (35) ₆	M-1 (130) ₁₀	M-3 (93) ₈	M-4 (140) ₃
F	01	1	M-1 (82) ₁	M-1 (99) ₃	M-2 (50) ₄	M-3 (129) ₉
		2	M-2 (103) ₁	M-1 (99) ₃	M-3 (32) ₄	M-4 (81) ₉
		3	M-4 (107) ₅	M-2 (56) ₃	M-4 (86) ₁₁	M-4 (69) ₁₅
I	01	1	M-1 (117) ₇	M-2 (65) ₁₀	M-2 (90) ₇	M-3 (120) ₈
		2	M-2 (123) ₇	M-1 (36) ₁₀	M-3 (107) ₂	M-4 (110) ₃
		3	M-3 (77) ₁₇	M-2 (127) ₂₀	M-1 (67) ₇	M-4 (110) ₃

Legend: PP No: Process Plan Number, Qty: Production quantity, M-i (t)_k: Required operation will be carried out on machine i with tool-type k and it requires t units (minute) of processing time.

of each tool type, three runs are performed using randomly generated population of population size fifteen. Three runs are taken into consideration, as GA does not ensure reaching to global optimum solution always. Fig. 3 shows the results obtained for production order number 1.

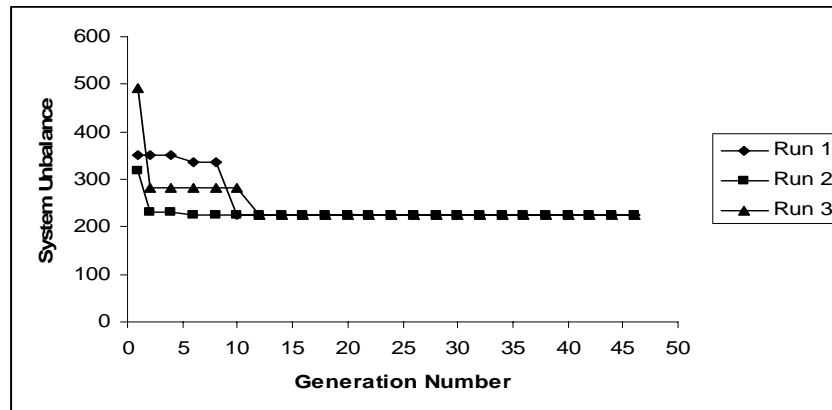


Figure 3: Determination of optimal number of generation for production order 1 (Table I).

For other production orders, the results are not presented here for want of space. However, the trend remains the same. Figure 3 clearly shows that the solution does not improve beyond twenty-five numbers of generations. Moreover, system unbalance stabilizes well before this number. This observation is also true for remaining three production orders. Thus, in the present work, MAX_GEN is taken as twenty-five.

5. EXPERIMENTAL INVESTIGATION

Experiments are designed and conducted using adopted methodology in two manufacturing environment viz. flexible process plan environment and single process plan environment. Flexible process plan environment represents that FPPs are available during loading and part type selection, while single process plan environment represents that only one process plan is available for loading and part type selection. Table V shows the various part types along with their FPPs. It is important to mention that process plan number 1, as shown in Table V, is taken as the process plan available in single process plan environment. Table VI shows the various variables/parameters that are considered in the present work along with their range/ values employed.

Eight case studies are generated randomly from the part types shown in Table V. For each case study, five runs using randomly generated populations are carried out and a run that yields minimum system unbalance is taken as global optimum. As described earlier, this is due to the fact that GA does not ensure convergence at global optimum always. Table VII shows the comprehensive results obtained from these eight case studies. As mentioned already that various constraints (tool magazine's capacity, number of tool copies of available tool types and duration of planning period) considered in the present work are grouped into two categories viz. system unbalance constraint (SUC) and loading constraint (LC). The results obtained are discussed according to the objective of the paper in the following subsections.

5.1 Effectiveness of Flexible Process Plans over Single Process Plan

Figure 4 shows the affect of availability of FPPs during FMS loading as compared to single process plan for case study 5 (Table VII). It clearly shows that availability of FPPs during loading and part type selection reduces system unbalance irrespective of number of available tool copies. This is due to the fact that more alternatives are available during part type selection and loading in flexible process plan environment as compared to single process plan environment. This observation is also true for other case studies.

Table V: Flexible process plans of various part types.

Part Type	PP No.	Flexible Process Plans (M-i (t) _k)			
A	1	M-1 (104) ₁	M-2 (130) ₇	M-3 (118) ₆	M-4 (100) ₁₃
	2	M-2 (110) ₁	M-1 (68) ₇	M-2 (110) ₆	M-4 (100) ₁₃
	3	M-3 (101) ₂	M-2 (120) ₄	M-3 (118) ₆	M-1 (84) ₁₀
B	1	M-1 (114) ₁	M-3 (119) ₈	M-2 (66) ₁₀	M-2 (116) ₄
	2	M-2 (126) ₁	M-1 (25) ₁₆	M-3 (29) ₁₇	M-1 (96) ₁₂
	3	M-2 (98) ₃	M-1 (25) ₁₆	M-1 (106) ₁₀	M-3 (84) ₁₂
C	1	M-1 (67) ₁₂	M-3 (90) ₉	M-2 (117) ₁₁	M-1 (82) ₃
	2	M-1 (67) ₁₂	M-4 (120) ₉	M-2 (47) ₁₉	M-2 (85) ₃
	3	M-4 (134) ₁₅	M-4 (40) ₁₈	M-2 (47) ₁₉	M-1 (82) ₃
D	1	M-3 (49) ₂	M-1 (137) ₅	M-2 (115) ₁₄	M-1 (68) ₇
	2	M-2 (114) ₄	M-4 (118) ₅	M-4 (120) ₁₃	M-2 (53) ₇
	3	M-3 (140) ₄	M-2 (38) ₂₀	M-4 (120) ₁₃	M-1 (68) ₇
E	1	M-2 (40) ₄	M-1 (110) ₇	M-3 (109) ₂	M-1 (106) ₃
	2	M-3 (78) ₄	M-2 (60) ₁₀	M-3 (93) ₈	M-1 (106) ₃
	3	M-3 (35) ₆	M-1 (130) ₁₀	M-3 (93) ₈	M-4 (140) ₃
F	1	M-1 (82) ₁	M-1 (99) ₃	M-2 (50) ₄	M-3 (129) ₉
	2	M-2 (103) ₁	M-1 (99) ₃	M-3 (32) ₄	M-4 (81) ₉
	3	M-4 (107) ₅	M-2 (56) ₃	M-4 (86) ₁₁	M-4 (69) ₁₅
G	1	M-1 (125) ₁₂	M-2 (92) ₆	M-1 (33) ₁₆	M-3 (32) ₉
	2	M-3 (47) ₂	M-2 (89) ₁₄	M-1 (33) ₁₆	M-4 (70) ₅
	3	M-3 (77) ₁₂	M-3 (110) ₆	M-1 (33) ₁₆	M-4 (46) ₉
H	1	M-1 (76) ₁	M-2 (117) ₁₉	M-2 (70) ₂₀	M-4 (106) ₁₈
	2	M-2 (106) ₁₁	M-3 (117) ₁₂	M-1 (127) ₁₃	M-4 (106) ₁₈
	3	M-4 (93) ₁₁	M-1 (49) ₁₂	M-2 (134) ₁₃	M-1 (132) ₁
I	1	M-1 (117) ₇	M-2 (65) ₁₀	M-2 (90) ₇	M-3 (120) ₈
	2	M-2 (123) ₇	M-1 (36) ₁₀	M-3 (107) ₂	M-4 (110) ₃
	3	M-3 (77) ₁₇	M-2 (127) ₂₀	M-1 (67) ₇	M-4 (110) ₃
J	1	M-1 (29) ₁₀	M-2 (107) ₁₁	M-2 (113) ₁₄	M-4 (69) ₁₅
	2	M-2 (41) ₁₀	M-1 (53) ₁₆	M-3 (42) ₈	M-2 (134) ₁₉
	3	M-2 (70) ₁₉	M-4 (91) ₁₁	M-3 (42) ₈	M-4 (69) ₁₅

Legend: PP No.: Process Plan number, M-i(t)_k: Required operation will be carried out on machine i with tool type k and requires t units (minute) of processing time

Table VI: Parameters and their range considered in the present work.

S.No.	Parameter	Range/Value
1.	Duration of planning period	8 hours
2.	Number of tool types	20
3.	Number of tool copies of each tool type	1-4
4.	Manufacturing environment	FPP/SPP
5.	Number of part types in a production order	4
6.	Number of operations on each part type	4
7.	Processing time of each operation of part types	25-140 minutes
8.	Production quantity of each part type	1-3
9.	Number of tool slots available in the tool magazine of each machine tool	5
10.	Number of tool slots required by each tool type	1

Legend: SPP: Single Process Plan Environment, FPP: Flexible Process Plan Environment

Table VII: Results for considered case studies.

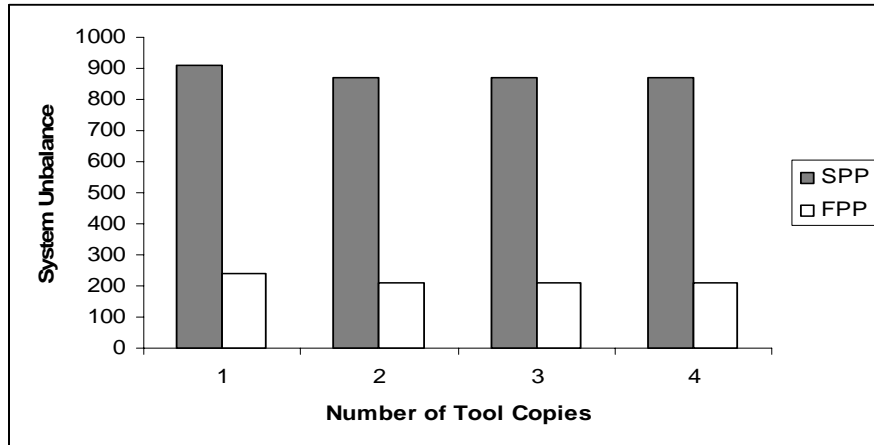
Case study No.	Item	No of Tool Copy = 1		No. of Tool Copy = 2		No. of Tool Copy = 3		No. of Tool Copy = 4		
		SPP	FPP	SPP	FPP	SPP	FPP	SPP	FPP	
1	SU	567	369	567	225	567	225	567	225	
	PT & PP Selected	F1,H1, J1	E2, F2, H2, J2	F1,H1,J1	E2, F2, H2,J3	F1,H1, J1	E2, F2 H2, J3	F1,H1, J1	E2, F2 H2, J3	
	PT Left Unassigned	E(SUC)	--	E(SUC)	--	E(SUC)	--	E(SUC)	--	
	Tool Loading	M-1	1, 3, 10	16, 13, 3	1, 3, 10	13, 3	1, 3, 10	13, 3	1, 3, 10	13, 3
		M-2	19, 20, 4, 11, 14	10, 19, 11, 1	19, 20, 4, 11, 14	11, 19, 1, 10	19, 20, 4, 11, 14	11, 19, 1, 10	19, 20, 4, 11, 14	11, 19, 1, 10
		M-3	9	8,12,4	9	12,8,4	9	12,8,4	9	12,8,4
M-4		18,15	18, 9	18,15	18,11,15,9	18,15	18,11,15,9	18,15	18,11,15,9	
2	SU	622	405	622	364	622	364	622	364	
	PT & PP Selected	B1, F1	B1,C3, H2	B1,F1	B3,C1, F3,H2	B1,F1	B3,C1 F3,H2	B1,F1	B3,C1 F3,H2	
	PT Left Unassigned	C(SUC) H(SUC)	F(LC)	C(SUC) H(SUC)	--	C(SUC) H(SUC)	--	C(SUC) H(SUC)	--	
	Tool Loading	M-1	1, 3	1, 3, 13	1, 3	12, 3, 13, 16, 10	1, 3	12, 3, 13, 16, 10	1, 3	12, 3, 13, 16, 10
		M-2	10, 4	10, 4, 19, 11	10, 4	11, 3	10, 4	11, 3	10, 4	11, 3
		M-3	8, 9	8, 12	8, 9	9, 12	8, 9	9, 12	8, 9	9, 12
M-4		--	15, 18	--	18, 5, 11, 15	--	18, 5, 11, 15	--	18, 5, 11, 15	
3	SU	660	299	481	276	481	276	481	276	
	PT & PP Selected	A1,C1	A3, E1, J3	A1, C1, E1	A1, C1, E3	A1, C1, E1	A1, C1, E3	A1, C1, E1	A1, C1, E3	
	PT Left Unassigned	E (LC) J (SUC)	C (SUC)	J (SUC)	J (SUC)	J (SUC)	J (SUC)	J (SUC)	J (SUC)	
	Tool Loading	M-1	1, 12, 3	10, 3, 7	7, 3, 1, 12	12, 3, 10,1	7, 3, 1,12	12, 3, 10,1	7, 3, 1, 12	12, 3, 10,1
		M-2	7, 11	4, 19	4, 7, 11	11, 7	4, 7, 11	11, 7	4, 7, 11	11, 7
		M-3	6, 9	2, 6, 8	2, 6, 9	9, 6, 8	2, 6, 9	9, 6, 8	2, 6, 9	9, 6, 8
M-4		13	11,15	13	3,13	13	3,13	13	3,13	
4	SU	1044	445	884	233	884	233	884	233	
	PT & PP Selected	D1, F1	E3, I3	D1, I1	D2, E2	D1, I1	D2, E2	D1, I1	D2, E2	
	PT Left Unassigned	E(SUC) I(LC)	D (SUC) F (LC)	E(SUC) F(SUC)	F (SUC) I(SUC)	E (SUC) F (SUC)	F (SUC) I(SUC)	E (SUC) F (SUC)	F (SUC) I(SUC)	
	Tool Loading	M-1	5, 7, 1, 3	10, 7	5, 7	3	5, 7	3	5, 7	3
		M-2	14, 4	20	14, 10,7	10, 4, 7	14, 10, 7	10, 4, 7	14, 10, 7	10, 4, 7
		M-3	2, 9	6, 8, 17	2, 8	4, 8	2, 8	4, 8	2, 8	4, 8
M-4		--	3	--	5, 13	--	5, 13	--	5, 13	

Table VII: Results for considered case studies (continued).

Case study No.	Item	No. of Tool Copy = 1		No. of Tool Copy = 2		No. of Tool Copy = 3		No. of Tool Copy = 4		
		SPP	FPP	SPP	FPP	SPP	FPP	SPP	FPP	
5	SU	908	238	868	211	868	211	868	211	
	PT & PP Selected	B1,E1, G1	B1,E1, G2,J3	B1,E1,J1	B1,E3, G1,J3	B1,E1,J1	B1,E3, G1,J3	B1,E1,J1	B1,E3, G1,J3	
	PT Left Unassigned	J (LC)	--	G (SUC)	--	G (SUC)	--	G (SUC)	--	
	Tool Loading	M-1	12, 16, 7, 3, 1	7, 3, 16, 1	10, 3, 7, 1	12, 16, 10, 1	10, 3, 7, 1	12, 16, 10, 1	10, 3, 7, 1	12, 16, 10, 1
		M-2	6, 4, 10	4, 19, 14, 10	11, 14, 4, 10	6, 19, 10, 4	11, 14, 4, 10	6, 19, 10, 4	11, 14, 4, 10	6, 19, 10, 4
		M-3	9, 2, 8	2, 8	2, 8	9, 8, 6	2, 8	9, 8, 6	2, 8	9, 8, 6
		M-4	--	11, 15, 5	15	11, 15, 3	15	11, 15, 3	15	11, 15, 3
6	SU	236	236	236	170	236	170	236	170	
	PT & PP Selected	A1,F1	A1,F1	A1,F1	A1,F2,I3	A1,F1	A1,F2,I3	A1,F1	A1,F2,I3	
	PT Left Unassigned	H(SUC) I (SUC)	H (LC) I (LC)	H(SUC) I (SUC)	H (SUC)	H(SUC) I (SUC)	H (SUC)	H(SUC) I (SUC)	H (SUC)	
	Tool Loading	M-1	1,3	1,3	1,3	3,7,1	1,3	3,7,1	1,3	3,7,1
		M-2	7,4	7,4	7,4	1,20,7	7,4	1,20,7	7,4	1,20,7
		M-3	6,9	6,9	6,9	4,17,6	6,9	4,17,6	6,9	4,17,6
		M-4	13	13	13	9,3,13	13	9,3,13	13	9,3,13
7	SU	765	188	765	188	765	188	765	188	
	PT & PP Selected	E1,H1	E2,G1,J3	E1,H1	E2,G1,J3	E1,H1	E2,G1,J3	E1,H1	E2,G1,J3	
	PT Left Unassigned	G(SUC) J (SUC)	H (SUC)	G(SUC) J (SUC)	H(SUC)	G(SUC) J (SUC)	H (SUC)	G(SUC) J (SUC)	H (SUC)	
	Tool Loading	M-1	1,7,3	12,16,3	1,7,3	12,16,3	1,7,3	12,16,3	1,7,3	12,16,3
		M-2	19, 20, 4	6, 19, 10	19, 20, 4	6, 19, 10	19, 20, 4	6, 19, 10	19, 20, 4	6, 19, 10
		M-3	2	9, 8, 4	2	9, 8, 4	2	9, 8, 4	2	9, 8, 4
		M-4	18	11,15	18	11,15	18	11,15	18	11,15
8	SU	506	292	506	266	506	266	506	266	
	PT & PP Selected	A1,J1	A1,J3	A1,J1	A1,I3	A1,J1	A1,I3	A1,J1	A1,I3	
	PT Left Unassigned	D(LC) I (LC)	D(SUC) I (LC)	D(LC) I (LC)	D (SUC) J (SUC)	D(LC) I (LC)	D (SUC) J (SUC)	D(LC) I (LC)	D (SUC) J (SUC)	
	Tool loading	M-1	1,10	1	1,10	7,1	1,10	7,1	1,10	7,1
		M-2	7, 1 1, 14	19, 7	7, 11, 14	20, 7	7, 11, 14	20, 7	7, 11, 14	20, 7
		M-3	6	8, 6	6	17, 6	6	17, 6	6	17, 6
		M-4	13, 15	11, 15,13	13, 15	3, 13	13, 15	3, 13	13,15	3,13

Legend: SU : System Unbalance, PT : Part Type, PP : Process Plan, LC : Loading constraint, SUC: System Unbalance Constraint, M-i : ith machine tool, SPP : Single Process Plan Environment, FPP : Flexible Process Plans environment

Thus, it can safely be concluded that availability of FPPs reduces system unbalance and they are effective over single process plan in reducing the system unbalance, during FMS loading and part type selection. As the present study considers the availability of only three flexible process plans during loading and part type selection, so it serves as a pillar for FMS loading and part type selection in which either less or more than three FPPs per part type are available.



Legend: SPP: Single Process Plan Environment, FPP: Flexible Process Plan Environment

Figure 4: Variation of system unbalance with process plan type (for case study 5).

5.2 Affect of Availability of Flexible Process Plans on Part Type Selection

Table VII shows that for case study 7, under single process plan environment when one tool copy of each tool type is available, part types E and H are selected and part types G and J remain unassigned due to SUC. However, under flexible process plan environment when one tool copy of each tool type is available, selected part types are E, G and J and part type H is left unassigned due to SUC. Moreover, the selected part types E, G and J are to be processed following their process plan number 2, 1 and 3 respectively. It clearly reveals that availability of flexible process plans affects the part type selection, when it is considered simultaneously with loading. This is due to the fact that under flexible process plan environment, more than one alternative are available for each part type for its consideration during loading. The above observation is also true for other case studies. Thus, it can safely be concluded that availability of flexible process plans affects the part type selection when it is considered simultaneously with loading.

5.3 Affect of Availability of Flexible Process Plans on Tool Loading

Table VII shows that for case study 8, under single process plan environment, when one number of tool copy of each tool type is available, tool types 1 and 10 are to be loaded on M-1, tool types 7, 11 and 14 on M-2, tool type 6 on M-3 and 13 and 15 tool types are to be loaded on M-4 respectively. However, under flexible process plan environment when one number of tool copy of each tool type is available, tool loading changes completely and now tool type 1 is to be loaded on M-1, tool types 19 and 7 on M-2, tool types 8 and 6 on M-3 and on machine M-4, 11, 15 and 13 number tool types are to be loaded. This is due to the fact that different part types are selected for processing under single process plan and flexible process plan environment. Other case studies also confirm this observation for different number of tool copies. Thus, it can safely be concluded that for a given production order and

number of available tool copies, tool loading depends on the manufacturing environment (i.e. single process plan/flexible process plan manufacturing environment).

5.4 Determination of Optimal Number of Tool Copies

Figure 5 shows the affect of tool copies on system unbalance for case studies 2, 4 and 6 respectively under flexible process plan environment. It clearly shows that when the number of available tool copies is more than one, system unbalance reduces. This is due to the fact that as the number of tool copies increases, it increases the tool supply and assists the planner in loading and part type selection. However, there is no change in system unbalance when the number of available tool copies is varied from two to four. This observation is true for other case studies also.

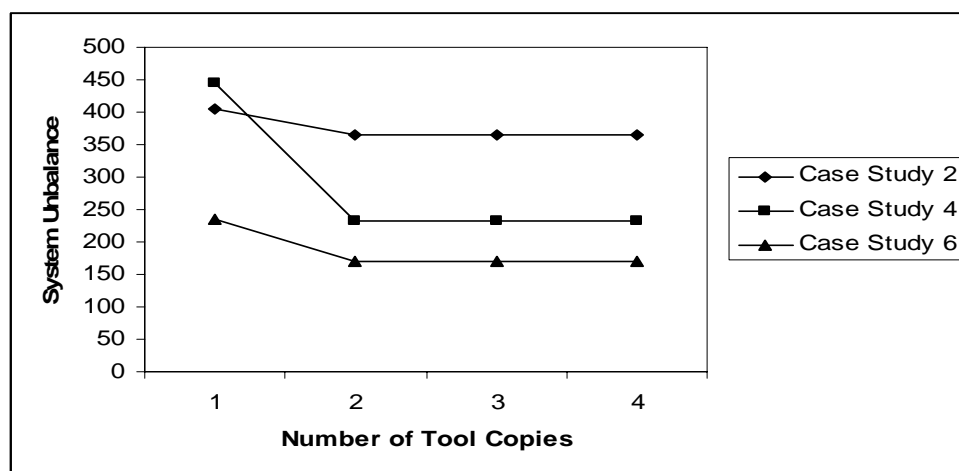


Figure 5: Affect of number of tool copies on system unbalance.

Thus, it can safely be concluded that optimal number of tool copies under flexible process plan environment is 'two'. However, in general, the optimal number of tool copies may be more than two and depends on system configuration, part types that are to be processed and objective function. This observation indicates that availability of larger number of tools does not always help in reducing system unbalance and there is always an optimum level of tool copies at which the system unbalance is at minimum. However, under single process plan environment, when number of tool copies is increased from one to four in step of one, improvement in system unbalance is observed in three case studies viz. case studies 3, 4 and 5 respectively (Table VII) and for other case studies viz. case studies 1, 2, 6, 7, and 8, system unbalance remains same. Thus, on the basis of present case studies it seems unrealistic to comment on the optimal number of tool copies in single process plan environment. Few more case studies need to be conducted to reach to a conclusion.

6. CONCLUSIONS AND FUTURE SCOPE OF WORK

This paper addresses the problem of FMS loading and part type selection, when flexible process plans for each part type are available. The following conclusions are drawn from the results of the taken case studies.

1. Availability of flexible process plans is better over single process plan as they are quite effective in reducing the system unbalance during FMS loading and part type selection.
2. Part type selection, when considered simultaneously with loading, is influenced by the availability of flexible process plans.
3. For a given number of tool copies, tool loading (i.e. machine-tool allocation) in the tool magazines of the machine tools of FMS is affected by the availability of flexible process plans.
4. Two number of tool copies of each tool type are optimum when flexible process plans for each part type are available.

The present work can be extended in several ways. The system model can also include transportation time, availability of limited buffer capacities and pallets and fixtures. It can be extended by incorporating the aspect of due dates of the part types. Considering other objectives such as can also extend this work: maximization of throughput, minimization of part movement as well as multiple objectives (e.g. minimization of system unbalance and maximization of throughput etc.). The above problem can also be attempted by using other meta-heuristic techniques such as tabu-search and simulated annealing, and comparison of efficiency of GA with these techniques can be done.

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