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Application of simulated annealing algorithm for multi-criteria operation planning in flexible manufacturing systems

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Simulated Annealing (SA) algorithm.

Abstract. This paper considers a multi-objective model in which operation planning and tool assignment are simultaneously in a Flexible Manufacturing System (FMS). In this regard, the main characteristics of FMS have been analyzed. Then, a comprehensive model, including major system parameters and cost components, has been designed and presented. The proposed model contains cost factors, including machining cost, earliness or tardiness penalties, tool and part movement or switch costs, and idle time costs of tools and machines. Then, a multi-objective model for the problem has been proposed, in which the relative importance of each cost through weighting these costs based on the decision-making goals and the sum of the mentioned costs have been considered simultaneously. Based on the complex nature of the problem, standard solution techniques have yet to be employed. Therefore, to reduce computational times, the Simulated Annealing (SA) algorithm has been used for about 30 minutes (10,000 movements). The total production costs have been decreased from 7,000 to 4333 units using the SA algorithm. Based on the results, a 38% reduction in total production costs has been achieved. Computational results revealed that the proposed method is quite efficient in the multi-objective optimization of FMS within a short computational time.

1. Introduction

The rapid growth in different aspects of technology, production diversity, and the rapid growth of computer sciences have brought about changes in the way companies operate in such a way that mass production systems have been replaced by systems with more diversity and flexibility, such as Flexible Manufacturing Systems (FMSs). Nowadays, the production time has been shortened, production variety has been increased, and companies' attitudes towards flexible indicators and speed of operation have changed [1]. In such a situation, rapid and economical decision-making strategies to maximize the capacities are inevitable and directly related to system productivity.

FMS methodology has been originally developed to meet the medium-sized and medium-varied production requirements in Europe and has grown significantly over the last two decades. In general, the main components of a FMS are:

1. Work stations such as CNC machines, assembling and measuring equipment, and washing stations;

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2. Automatic transfer systems such as loading and unloading stations, material handling equipment, and robots;
3. Tooling mechanisms like replacement and transfer of tools;
4. Central computer control.

These systems have more sophisticated technology than mass production lines, which requires a relatively high investment. Therefore, using such systems has economic justification when utilized with maximum efficiency and minimum waste. Generally, production planning is an optimal determination of the type, number, sequence, and production time of products; resources and production commitments are required to reduce production costs [2,3].

In FMSs, the variety and multiplicity of factors affecting production, including rapid changes from product to product, the necessity of timely production, the urgent need for materials and components, and workload balancing of the machinery, are of great importance for experts and production planners.

2. Literature survey

Nowadays, allocating parts to different machines and tool assignment management have become important research subjects. In this regard, various allocation policies have been studied and compared by Abu-Ali and Shouman [4]. Different types of distribution strategies have also been investigated, among which random distribution, closest parts, farthest parts, shortest and longest idle times, and smallest parts have been considered. In order to compare different policies, several performance criteria have been used, including production rate, total production time, mean operating time, average tardiness, and the number of tardy parts.

Tool management is also one of the key issues in FMS, which has attracted the attention of many researchers. The problem of switching tools in FMS has been examined by Selim et al. [5]. In this study, the useful life of a tool has been considered as a replacement factor. The system consists of several parts that should be processed on a CNC machine. Minimizing the overall time of the operation was the goal of the study for solving, for which a mixed linear programming model has been proposed. Furthermore, several innovative algorithms were proposed to solve the problem quickly, and finally, the obtained results were compared.

The problem of parts and tools allocation in a multi-station FMS has been studied by Pacciarelli [6]. Balancing the workload of stations, along with minimizing the total number of tools required, were the objectives of the problem. Two tool assignment policies were described and reviewed as follows:

1. Static tool allocation, in which the tools could not move around the system, and re-equipment of the tool is only possible at the start of the shift or at the time of emergency, such as tool breakdown;
2. Dynamic tool allocation, in which the tools can move between workstations employing a tool transfer system. In designing and solving a model, integer programming, branching, and bounding methods have been used. However, tool allocation has only been considered statically in the proposed model.

In most proposed models, effective parameters in planning are considered as cost (profit or loss). Various costs in providing a plan have been considered to develop an FMS. These costs include machining costs [7,8], timely delivery failure (both earliness and tardiness), replacement and movement of parts between stations [9,10], and tool changers and idle machines [11]. Each of these costs is of particular importance; minimizing such costs could be considered a goal in production planning. FMSs contain a set of hardware and software capabilities that are mutually dependent so that any changes in one part of the system will affect the other parts. Therefore, in FMS programming, all important factors in system performance should be considered simultaneously. However, in many studies, only a limited number of parameters have been considered, and a comprehensive model that includes a set of these goals has not been presented simultaneously. In this situation, it seems that the design of comprehensive mathematical models of FMS (influenced by all of the above parameters) and their quick solution with efficient optimization methods is an efficient way to respond to the challenges and needs of modern production systems.

A production planning problem (including part loading, tool loading, and part scheduling) in FMS has been addressed by Gamila and Motavalli [7]. A set of tools with specific life and a set of machines that can produce a variety of parts have been considered assumptions. In order to select the machines and assign operations and required tools for the machines with the purpose of minimizing the maximum completion material and handling the total processing times, a mathematical model has been developed. Next, two of the most important FMS planning problems, loading and routing, have been integrated and formulated. Then the output from the integrated planning model was taken, and a detailed operation schedule was generated. The results demonstrated the efficiency of the proposed model.

The total completion time for a single machine sequencing problem subject to tool wear has been minimized by Selim Akturk et al. [10]. For an optimal schedule, several structural properties have been established in which the complexity of the problem has been stated, and a dynamic program for its exact solution has been suggested. Furthermore, the performance of the Shortest Processing Time (SPT) has been analyzed. It has been demonstrated that if the tool changing time was not being considered or if the number of required tools was two or less, SPT was considered optimal. Finally, based on the computational studies, it has been reported that SPT performed quite efficiently in practice. A mathematical model has been modified to optimize the material flow in an FMS. For modifying the proposed model, the waiting time has been considered due to the unavailability of machines. To optimize the material flow of the system, a Real Coded Genetic Algorithm (RCGA) has been implemented into a job shop scheduling FMS. Based on the results, RCGA could be applied to solve the problems of flexible job shop FMS [11].

Bayesian Optimization Algorithm (BOA) has been adopted to solve the Flexible Job-shop Scheduling Problem (FJSP). Based on the experimental tests, it has been concluded that a better solution has been achieved using the proposed hybrid Evolutionary Algorithm (EA) based on BOA with a grouping mechanism compared to the original algorithm, and the robustness of the algorithm has also been improved. Meanwhile, the data could be grouped differently, dividing the whole population into sub-populations and performing experiments separately on different machines in a distributed environment. Using the proposed procedure not only could optimize the answer but could also enhance efficiency and reduce time [12].

In view of the complex structure of FMS and the difficulty of production planning, a general FMS scheduling model has been built, and a multi-level flexible scheduling algorithm has been proposed. The proposed procedure has been analyzed and verified by the plan layout, and the adaptability of the model has been confirmed. A general flexible production scheduling algorithm was proposed, and a multi-level scheduling system based on the proposed algorithm has been developed. In order to carry out the experiments, two kinds of system structures have been used, which verify the correctness of the model and the algorithm and provide possibilities for further research on scheduling and simulating FMS [13].

A mathematical model for designing material handling flow paths based on a single objective model for minimizing the total material flow time interval has been proposed by Hermann [14]. Moreover, the continuity of the flow path between the origin-destination pair, traffic congestion, capacity of the material handling system, vehicle collision avoidance, and prohibition flow through non-selected arcs have been considered as the constraints. In order to tackle the problem, two heuristic methods have been proposed. The fixed costs and selectively included have been adjusted using the Fixed Charge Adjustment Heuristic (FCAH) as the first method in the flow network until a feasible solution has been obtained. To explore the problem space, the second method has been used as a Space Search Heuristic (SSH).

The same single objective function has been discussed by Hermann [15]. To optimize the stated problem, two heuristic algorithms have been proposed (greedy heuristic and packing composite heuristic).

In a study, the implementation of manufacturing flexibility at the shop floor level has been considered. The main objective of the study was to study the performance of flexibility-based manufacturing systems with traditional ones. To achieve the objectives, a simple demo simulation model of the existing and proposed manufacturing system has been built, and the performance has been compared on the following performance measures, i.e., total production and total production time. The introduction of flexibility caused a decrease in makespan time, with maximum reduction in the makespan time occurring when routing flexibility has been increased from 0 to 1. Also, the total production of parts increased with the increase in the level of flexibility [16].

Scheduling of dynamic machine-tool selection in an FMS has been considered in a study [17]. Due to the NP-hard nature of the study, a modified EA has been used to solve the problem. Furthermore, the related results are compared with those obtained by a Branch-and-Bound (B&B) method. It has been found that the EA with the island model has good results regarding the objective function values and CPU times.

An Advanced Grey Wolf Optimization (AGWO) algorithm has been used to schedule between the Material Handling Robots (MHRs) and the jobs under production in the FMS [18]. The proposed FMS layout comprised the tandem flow path configurations for the movements of MHRs. The FMS consists of six Flexible Manufacturing Cells (FMCs) partitioned into six zones and served by six MHRs deployed in each partitioned zone for efficient material handling operations. To develop the coexistent schedule between MHRs and jobs, a combined objective function has been formulated by combining the two diverging objectives and solved using the AGWO algorithm. The combined objective function yield for coexistent production scheduling in FMS, operating with nineteen Work Centers (WCs) and six MHRs to produce thirty-six jobs and sixty-six types of jobs in varying batch production quantities, has also been reported.

The Flexible Flow Shop (FFS) scheduling problem is one of the most common manufacturing environments in which there is more than one machine in at least one production stage. In such a system, additional renewable resources are assigned to the jobs or machines to decrease the processing times, which can lead to reduced total completion time. For this purpose, a Mixed Integer Linear Programming (MILP) model is proposed to minimize the maximum completion time (makespan) in an FFS environment. Therefore, a Particle Swarm Optimization (PSO) algorithm, as well as a hybrid PSO and SA algorithm named SA-PSO, are developed to solve the model. Through numerical experiments on randomly generated test problems, the authors demonstrate that the hybrid SA-PSO algorithm outperforms the PSO, especially for large-size test problems [19].

3. Research motivations and description

There has been an extensive body of research in which modeling and optimization of FMSs have been considered. However, to the best of our knowledge, there is no study in which modeling and optimization of an FMS incorporating all the costs (including machining cost, earliness and tardiness penalties, tool and part movement or switch costs, and idle time costs of tools and machines) simultaneously using heuristic algorithms considered. In the present study, the problem of part scheduling, tool allocation, and production operations for carrying out machinery concerning the paths of production (machines and tools) has been addressed. Such issues arise in many manufacturing units where each part requires several processes (auto part-making companies), and each process may be performed on different machines using different tools. Therefore, the determination of what operation, on which part, by which machine, and by which tool should be carried out to satisfy the production obligations while minimizing the total cost of the system is the goal of an FMS. Thus, first, the structure and characteristics of an FMS have been described and modeled along with the desired objectives. Next, the proposed solution method (SA algorithm) and how it is adapted to the problem has been explained. Finally, a numerical example was solved using the proposed algorithm, and computational results have been presented and compared.

In this study, the system has some flexible machines, each capable of performing a variety of operations. These machines are equipped with magazines in which a limited number of tools for various operations could be handled. Each tool must be replaced when its known limited useful lifetime ends. Therefore, a limited number of spare parts are available for this purpose. Several parts should be produced in a work shift; each part has a number of distinctive and predefined consecutive production processes. They also have their delivery times, in which untimely delivery would result in additional costs. Some of the production processes are common among the parts. In contrast, each production process can also be processed with several types of tools and on different machines. However, the time and cost of performing a particular process vary from machine to machine and using various tools.

The parts move through the workstations using an automatic transportation system. Moreover, the system is equipped with a central inventory of tools, through which the necessary tools are provided and shared among the machines. Moving or replacing parts and tools in the system involves time and costs. In addition, operating times and costs are changed by assigning components to different machines and assigning various tools to them.

According to the information given, the main objective is to schedule the production processes of the machines and allocate the necessary tools to minimize the total weighted production costs simultaneously. Different types of costs are as follows [20]:

1. **Machining cost:** This cost is directly related to the production and machining of the parts. Performing any operation requires the time and cost of machining. In FMS, since the machines are usually multifunctional and capable of performing various operations, each production process may be processed by a variety of machines and with different tools. Therefore, the method of allocating the parts to the machines is very important and has a significant effect on production costs;

2. **Untimely production cost:** Involving scheduling delivery times in planning is based on the ability to produce complex and expensive components. Delivery times are usually of particular importance, and failure to timely delivery of parts may result in high costs for these systems. Expenses in this regard (due to improper delivery time) have been categorized into two groups: tardiness and earliness penalties. Usually, tardiness fines are more distinct; delay in the final product assembly, contractual penalties, and customer loss risk belong to this group. Earliness-imposed fines usually have fewer amounts, including capital dwelling, storage, and the possibility of corruption and product damage;

3. **Part replacement cost**: A machine may process several parts during a work shift. In this case, loading one part after another requires re-preparation of the machine. The time required for this preparation depends on the type of part before and after the replacement. Depending on the amount of this time and the type of machine, the cost of part replacement is considered for the system;

4. **Part movement cost:** In a specific production plan if the operation of a part is assigned to different machines, the part moves by an automatic transport

system through machines. The time spent on this movement is considered as the cost of part movement;

5. Tool life cost: Each machining process is performed by a suitable and limited lifetime tool. After the end of the tool's life, the tool should be replaced. Based on the type of tool used and the machining time, the cost of the tool is considered in terms of the useful life of the tool and its price;

6. Tool replacement cost: In order to carry out a variety of operations with a single machine, the tools must be replaced by a tool magazine. Replacing tools takes time (and cost). This cost is relatively small but sometimes cannot be ignored;

7. Tool transferring cost: This cost is associated with the part replacement cost. If the machine does not have the proper tools to perform a process, the tool will be transferred to the machine by an automatic tool transmission which is costly and time-consuming;

8. Idle machine cost: In some cases, machines could be waiting for the parts depending on the sequence of the selected operation. Based on the amount of time and type of the machine, a machine's idle time cost is considered in the system. These costs are present in most manufacturing systems; however, depending on the type of system under study, their amount and number can be set in the model.

4. The overall sequence in the production plan

Various operations can be carried out using different machines. Therefore, numerous cases exist for assigning machines and operation sequences in the system. In FMS, there are usually a few machines; each is capable of performing various operations. The components produced in this type of system also have a high diversity and low numbers. Various operations can be performed by various machines. Therefore, there are several methods to allocate equipment and sequence of operations in the system.

In order to introduce the method used to display the production program, the following example is presented. In the assumed system, three parts, each with three different processes, should be produced (Figure 1). The operations of each part have prerequisite conditions (earliness and tardiness), according to which they are numbered. For example, Part (1) has three processes; the first process (Operation 1) must be performed before the second process (Operation 2). The number of machines in the system is 3, and the number of tools required is 5. Each machine is capable of performing various operations. Each operation may also be performed by various tools.

In the tree charts (Figure 1), machines capable of performing each part's operation, along with appropriate tools for that process, are represented. Thus, there are many states in the system to allocate machines and tools to the operation. However, each process time is different by assigning it to different machines and using different tools. Such times are marked with each selection. As an example, Operation 1 of Part 1 can be done in three different ways, as follows:

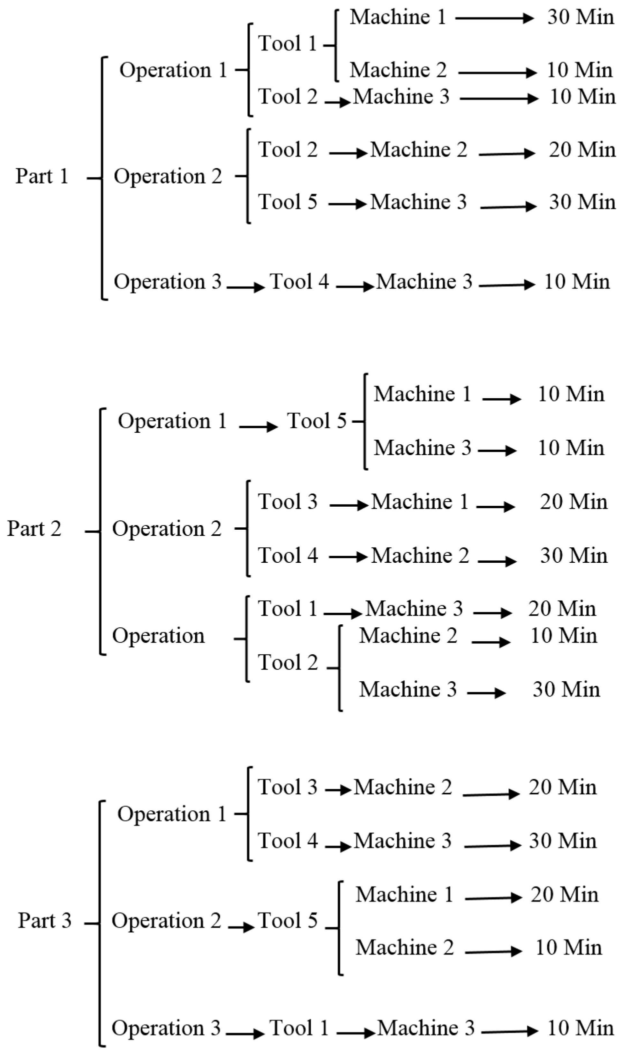

Figure 1. Schematic illustration of tool assignment and process planning.

1. Tool 1 and Machine 1, in 30 minutes;
2. Tool 1 and Machine 2, in 10 minutes;
3. Tool 2 and Machine 3, in 10 minutes.

In order to easily investigate the problem, all possible states of allocation can be represented as a string of combinations of "part/operations/tools/machines". Depending on the number of possible states for each operation, one or more members of the string are related to that operation. For the given problem, the string of possible states is as follows (Table 1).

Table 1. String of possible states for example 1.

1111	1113	1122	1253	1341	2152	2153	2231	2242	2313	2322	2323	3132	3143	3251	3252	3313

Table 2. A possible answer for example 1.

1111	1222	1341	2152	2231	2313	3132	3251	3313

Table 3. Primary production plan.

Operation sequence	1111	2151	1253	2242	3132	1343	2323	3251	3313
Processing time	20	10	30	30	20	10	30	20	20

Table 4. Optimized production plan.

Operation sequence	1112	2151	1222	2231	3143	1343	3252	2322	3313
Processing time	10	10	20	20	30	10	10	10	10

In the above string, each member represents an operation of a part by a specific tool using a definite machine. For each member of the string, the first number indicates the number of the part, the second number indicates the operation number of the part, the third number represents the number of the used tool, and the fourth number represents the number of the used machine.

For example, for the first operation of the second part, there are two different assignment modes based on the corresponding string: 1. the 7th member of the string (2152) indicates that the first operation of the second part was performed by the 5th tool and on the second machine; 2. the 8th member of the string (2153) identifies the allocation of the 5th tool and the third machine to this operation. It should be noted that this string indicates the only possible allocations, and the scheduling, repeatability (or not), and operational conditions are not specified.

Now, in order to create a plan, a non-repetitive operation can be made, provided that all production processes are completed in accordance with the preconditions for the operation. This string, which represents one of the possible answers to the problem, is called an answer string. A sample of this string is shown in Table 2.

The above string (production plan) involves the process of all parts. The length of this string (9) will be equal to the total number of operations in the production plan. By performing this program, all parts will be produced using appropriate tools and machines. It should be noted that the ordering of the members of the answer string is the sequence of various operations. Furthermore, an acceptable answer should also satisfy the system's limitations. These limitations are the time available for each machine and the number of available tools.

As mentioned earlier, there are many states to allocate tools and machines to various operations. In general, the number of possible solutions for a problem is equal to $n!$, where n is the number of members of the string. For instance, the number of possible answers for the given problem ($n = 18$) is more than 6.4×10^4.

Many of these allocation possibilities are unacceptable due to the non-satisfaction of system constraints. There are many other states (production plans) that guarantee the production of components on proper equipment based on preconditions and constraint satisfaction. But the main point in optimizing a production plan is that an optimal program should create the best values for the desired performance indicators. In the proposed model, the functional index of the system (target function) is the total sum of the production costs.

Two different solutions to the given problem (one random answer (Table 3) and one optimal answer (Table 4)) are compared. The sequence of operations for these responses, along with the processing times of each operation, is shown in the following. The idle times for machines 1 to 3 are 35, 40, and 55 minutes respectively. Nevertheless, for the final production plan, none of them have idle time.

To compare the two solutions, the Gant chart of each is presented in Figure 2. For replacing parts on machines, 5 minutes is considered. As it is clear in Figure 2, the completion times of the parts are very different. In the first production program, the completion time of parts 1 through 3 was 60, 100, and 140 minutes respectively, while these times in the final production program decreased to 45, 60, and 70

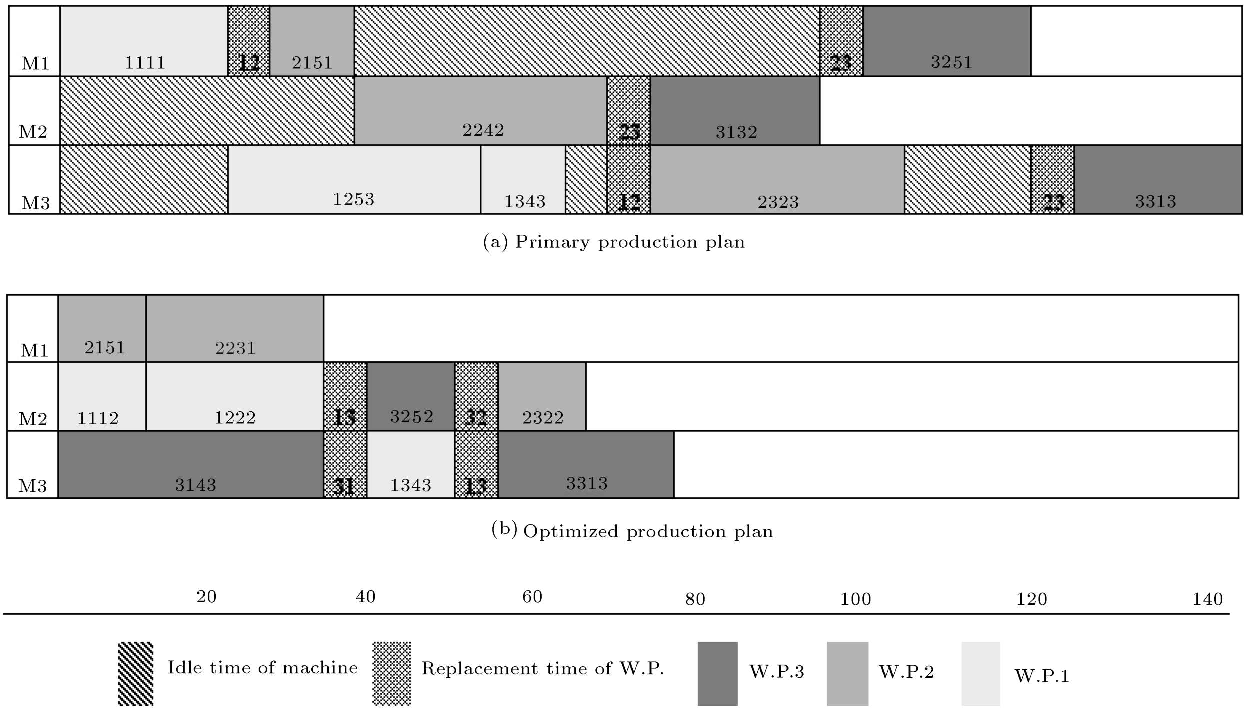

Figure 2. Schematic illustration of Gant chart for two different production programs.

minutes. Also, in the initial production program, the machines have idle times. The idle times for machines 1 through 3 are 55, 35, and 40 minutes respectively, while in the final production program, none have an idle time.

Relatively, the importance of production planning in FMSs can be highlighted. Given the fact that the issue has small dimensions, the importance of this issue is more pronounced in larger issues.

5. Mathematical model of the problem

In this section, a mathematical model that contains problem characteristics and satisfies its objectives and constraints is presented.

Nomenclature

M	Machine $M = 1, 2, 3, \cdots, m$
P	Part $P = 1, 2, 3, \cdots, n$
O	Operation $O = 1, 2, 3, \cdots, q$
T	Tool $T = 1, 2, 3, \cdots, k$
M_i	Machine used to carry out ith operation
P_i	Part that is part of ith operation
T_i	Tool used to conduct ith operation
t_P^{dd}	Delivery time of part P
t_M^{av}	The availability time of the M machine
$t_{x,y}^{se}$	Loading time of part y after part x
t_i^c	The completion time of the ith operations
$t_{i,M}^{cm}$	Time taken from the M machine at the start of the ith operation
$t_{i,P}^{cp}$	Time taken for the P part at the start of the ith operation
t_i^m	Machining time of the ith operation
$t_{T,M}^{tb}$	Total time of consumption of tool T in machine M
$t_{i,M,T}^t$	Tool time on the machine M for doing the ith operation
N_T	Number of available tools of type T
N_M^t	Transferring a number of tools on machine M
N_M	Total number of tools used in the machine M
$N_{T,M}$	The number of tools of T type used in the machine M
H_M	Machine tooling capacity in the machine M
L_T	Useful life of tool of T type
I	Length of the response string
I_t	Possible string lengths
C_M^m	Machinating cost coefficient for machine M per unit time
C_P^t	Tardiness cost coefficient for part P per unit time

C_P^e	Earliest cost coefficient for part P per unit time
C_M^g	Part replacement cost coefficient for machine M per unit time
C_P^m	Cost of movement of part P between two machines per unit number
C_T^p	Consumption cost coefficient of tool T for unit number (tool price T)
C_T^g	Replacement cost factor of tool T per unit number
C_T^m	Transmission cost of tool T between tool warehouse and machine per unit number
C_M^l	Idle cost coefficient for machine M per unit time

Parameters

$$X_{i,M} = \begin{cases} 1 & \text{If machine } M \text{ is used to perform} \\ & i\text{th operation} \\ 0 & \text{Otherwise} \end{cases}$$

$$Y_{i,P} = \begin{cases} 1 & \text{If the } i\text{th member of} \\ & \text{the string completes the} \\ & \text{operation of the part } P \\ 0 & \text{Otherwise} \end{cases}$$

$$Z_p = \begin{cases} 1 & \text{if the part } P \text{ has tardiness} \\ & \left[t_P^{dd} - \sum_{i=1}^{I} Y_{i,P} * t_i^c\right] < 0 \\ 0 & \text{Otherwise} \end{cases}$$

$$U_{i,k,M} \begin{cases} 1 & \text{If there is a replacement between part} \\ & i\text{th and } k\text{th} \\ 0 & \text{Otherwise} \end{cases}$$

k: The first member of the answer string after i, which has the same machine number (M) with the ith member

$$V_{i,a} = \begin{cases} 1 & \text{If the machines that are used for the } i\text{th} \\ & \text{and } n\text{th members are different} \\ 0 & \text{Otherwise} \end{cases}$$

$$W_{i,T} = \begin{cases} 1 & \text{If tool } T \text{ is used to perform } i\text{th} \\ & \text{member's operations} \\ 0 & \text{Otherwise} \end{cases}$$

$$R_{i,b} = \begin{cases} 1 & \text{If for the } i\text{th and } b\text{th members} \\ & \text{the tools used are different} \\ 0 & \text{Otherwise} \end{cases}$$

b: The first member of the answer string after i, which has the same machine number as the ith member,

$$S_{i,T,M} = \begin{cases} 1 & \text{If for the } i\text{th part, the machine } M \\ & \text{and tool } T \text{ are used} \\ 0 & \text{Otherwise} \end{cases}$$

$$T_{i,M} = \begin{cases} 1 & \text{If the } i\text{th member is the last member of} \\ & \text{the string in which the machine } M \\ & \text{has been used} \\ 0 & \text{Otherwise} \end{cases}$$

$$A_{i,P,O} = \begin{cases} 1 & \text{If for the } i\text{th string,} \\ & \text{the operation } O \text{ is performed for part } P \\ 0 & \text{Otherwise} \end{cases}$$

6. Multi-objective model of the problem

The proposed model of the problem is a multi-objective model, in which the objective equation is the sum of different costs. Weights in multi-objective models coordinate decision-making variables and also determine the relative importance of goals. Thus, in the objective function of the following model, each goal is first converted to a cost by a coefficient, then combined with each other:

$$\begin{aligned} \min C = & \sum_{M=1}^{m} \sum_{i=1}^{I} C_M^m . X_{i,M} . t_i^m \\ & + \sum_{P=1}^{n} abs\Big\{(Z_P . C_P^t + (1 - Z_P) . C_P^e). \\ & (t_P^{dd} - \sum_{i=1}^{I} Y_{i,P} . t_i^c)\Big\} \\ & + \sum_{M=1}^{m} \sum_{i=1}^{I} C_M^g . t_{P_i P_K}^{se} . U_{i,k,M} \\ & + \sum_{i=1}^{I} C_P^m * V_{i,a} + \sum_{T=1}^{k} \sum_{i=1}^{I} C_T^p . \frac{t_i^m}{L_T} . W_{i,T} \\ & + \sum_{i=1}^{I-1} C_T^g . R_{i,b} + \sum_{M=1}^{m} C_T^m . N_M^t \\ & + \sum_{M=1}^{m} \sum_{i=1}^{I} C_M^l . (T_{i,M} . t_i^c) - (X_{i,M} . t_i^M), \end{aligned} \tag{1}$$

subject to:

$$\sum_{i=1}^{I} T_{i,M} . t_i^c \leq t_M^{av} \qquad \forall M = 1, 2, 3, ..., m, \tag{2}$$

$$\sum_{i=1}^{I} \frac{t_i^m}{L_T}.W_{i,T} \leq N_T$$

$$\forall T = 1, 2, 3, ..., k, \tag{3}$$

$$if A_{i,P,O} = 1; \qquad A_{j,P,O-1} = 1 \Rightarrow t_j^c < t_i^c$$

$$\forall P = 1, 2, 3, ..., n; \qquad \forall O = 1, 2, 3, ..., q-1, \tag{4}$$

$$\sum_{i=1}^{I} Y_{i,P} = 1 \qquad \forall P = 1, 2, 3, ..., n, \tag{5}$$

$$\sum_{i=1}^{I} A_{i,P,O} = 1 \qquad \forall i = 1, 2, 3, ..., I;$$

$$\forall P=1, 2, 3, ..., n; \qquad \forall O=1, 2, 3, ..., q, \tag{6}$$

where:

$$t_i^c = \max(t_{i,M}^{cm}, t_{i,P}^{cp}) + t_i^m$$

$$\forall i = 1, 2, 3, ..., I, \tag{7}$$

$$N_M^t = N_M - H_M$$

$$\forall M = 1, 2, 3, ..., m, \tag{8}$$

$$N_M = \sum_{T=1}^{k} N_{T,M}$$

$$\forall M = 1, 2, 3, ..., m, \tag{9}$$

$$N_{T,M} = fix\left(\frac{t_{T,M}^{tp}}{L_T}\right) + 1$$

$$\forall T = 1, 2, 3, ..., k; \qquad M = 1, 2, 3, ..., m, \tag{10}$$

$$t_{T,M}^{tp} = \sum_{i=1}^{I} t_{i,T,M}^{t}$$

$$\forall T = 1, 2, 3, ..., k; \qquad M = 1, 2, 3, ..., m, \tag{11}$$

$$t_{i,T,M}^{t} = S_{i,T,M}.t_i^m$$

$$\forall i = 1, 2, 3, ..., I; \qquad \forall T = 1, 2, 3, ..., k;$$

$$M = 1, 2, 3, ..., m. \tag{12}$$

In the cost function (1), the important costs in an FMS are considered. The objective function has eight sentences, each representing one of the costs in the system. These sentences represent machining costs, timely delivery, part replacement, part movement, tool life cost, tool replacement, tool transfer, and idle, respectively. Each sentence is weighted by the cost coefficients explained in the previous section. Obviously, the components of the cost are adjustable and varied according to the type and structure of the system.

Eq. (2) shows the time constriction of machines. Each machine has an availability time that can be considered as a work shift. The left-hand side of the equation is the total time that each machine was engaged during the work shift, which should not exceed the availability time. The number of spare tools is expressed by relation (3). There are a limited number of tools available. In an acceptable solution, the number of tools required for each type should not exceed its available number. Eq. (4) refers to the limitation on priority and the duration of operation of each part. As previously explained, each part has several different operations, which should consider the preconditions for the operation.

Eq. (5) has two meanings: (a) ensures that the processing of all parts is completed, and (b) only one member of the processing string completes the processing of part P. Eq. (6) refers to the fact that every operation must be performed only once by a tool and on a machine. In an acceptable solution, a workflow cannot be assigned to multiple tools or machines.

7. Designing a method for solving and presenting proposed algorithms

Many of the scheduling and planning issues of the production systems are complex and difficult to solve. Therefore, their optimal solution at acceptable computational times is not feasible. Over the past few decades, several algorithms have been proposed to solve complex and large-scale models inspired by the natural system and other physical phenomena. Locally optimized search algorithms, such as the SA algorithm, are widely used to solve such problems. The main principles of these algorithms are to create and evaluate a limited number of acceptable solutions to reach the optimal answer at acceptable times [21–23].

7.1. SA algorithm

As different algorithms (including SA, Genetic Algorithm (GA), Tabu Search (TS), Ant Colony (AC), Bee Colony (BC), PSO, etc.) have different procedures for finding the optimum condition, they are used for different optimization purposes. Among the proposed algorithms, PSO and SA, due to their advantages, are mostly employed. Easy programming (few input parameters to adjust) and fast convergence are the major merits of the PSO algorithm. Whereas, in high dimensional space, falling into local optimum traps may be considered a weakness for the PSO algorithm.

Based on the SA mechanism, this algorithm could avoid getting trapped into local optimum, which can be considered major excellence over other algorithms.

The SA algorithm was first proposed by Kirkpatrick in 1982 to solve the combined optimization problems. This algorithm is a local searcher which randomly generates and evaluates a new neighborhood through either of the following two situations. This search engine randomly generates and evaluates a new neighborhood. Moving to this answer will occur in either of the following two situations: (1) the new answer is better than the current one, and (2) the value of the probability function is larger than a randomly generated number of the domain (0, 1]. Otherwise, the algorithm will generate a new answer. This step continues until the algorithm stops the condition (number of iterations, calculation time, etc.). The value of the probability function for each time is calculated by the following equation [24–27]:

$$P_r(solution\_cyrrent_{k+1} = solution\_neighbour_k) = \exp\left(-\frac{\Delta Z}{c_k}\right), \tag{13}$$

$$c_{k+1} = \alpha c_k. \tag{14}$$

In Eq. (13), ΔZ is the difference between the values of the current answer and the new answer. The index k is the number of iterations, c_k is the control parameter called temperature. At the beginning of the search, the initial temperature value, c_k, is chosen; consequently, the algorithm has a greater chance of moving to non-improving solutions. But when the number of these moves increases, this temperature gradually decreases according to a cooling schedule function (Eq. (14)); hence, the probability of choosing worsening solutions decreases with an increasing number of moves. In other words, at the beginning of the search, the role of the random nature of the algorithm in adopting new neighborhoods is more important than the role of its definite nature. As the search progresses, moves are often based on the improvement of the objective function and the role of the random nature of the algorithm in reducing the acceptance of the new answer [16]. Different steps of the SA algorithm to simultaneously solve tool assignment and production planning are presented as follows:

Step 1: Receiving problem inputs and search parameters (parts, operations, tools, machines, cost coefficients, cooling function, motion function, etc.);

Step 2: Establishing a valid production plan (answer) as a starting point and calculate its cost;

Step 3: Generating and evaluating a new random neighborhood;

Step 4: Assessment of the acceptance conditions of the new answer; if the cost of the new production plan is less than the current answer, or the possibility of accepting a worse response is more than one random number in the interval (0,1], move to Step 5; otherwise, go back to Step 3;

Step 5: Updating the parameters and checking the stop criteria; if the stop criteria are not set, go back to Step 3; otherwise, stop searching and deliver the best sequences and outputs.

7.2. Providing examples and computational results

In this section, the structure of a production scheduling problem and the suggested methods for solving it have been described in the form of a numerical example with real dimensions, and the computational results will be presented. In this system, there are five flexible machines with the ability to carry out various operations and the limited capacity of the tool magazine. Twenty parts, with an average of three different production processes, should be processed during a shift (450 minutes). For the production of these components, eight types of tools with different lifetimes and prices will be used. Each tool has a certain number of replacements in the system. Some tools and machines are capable of performing various operations. However, the time and cost of performing a particular process with different machines and tools can vary. The range of coefficients and data requirements are given in Tables 5 and 6.

This problem has been solved using the SA algorithm. The SA parameters are given in Table 7.

7.3. Results of the SA algorithm

The problem has been solved using the SA algorithm with different values of the initial temperature and probability function. Finally, the best values were considered for the problem. The algorithm has been run for 10,000 movements (about 30 minutes). Figure 3

Table 5. The values for the problem costs.

Idle cost ($/min)	Cost of transferring tool ($)	Replacement cost of the tool ($)	Tool price ($)	Part movement cost ($)	Part replacement cost ($)	Penalty cost for untimely delivery (min/$)		Machining cost (min/$)
						Earliness	Tardiness	
0.3–0.7	8	4	15–105	6–24	1.5–3	0.1–0.2	0.2–0.9	1–8

Table 6. The values for the problem inputs.

The number of spare parts of any type of tool	Useful life of the tool (min)	Machine tooling capacity	Replacement parts time (min)	Machining time (min)	Delivery times (min)
5–10	40–100	6–10	1–5	5–25	50–450

Table 7. SA parameters for solving the problem.

Initial temperature (C_0)	2000
Temperature reduction coefficient (α)	0.98
Neighborhood selection mechanism	Two-by-two displacement
Stop search criteria	10000 iteration

Table 8. Results of the SA algorithm.

Cost	The primary production plan	The final production plan	Percentage improvement
Total cost	38.1	4333.6	7000.7
Machining	33.0	2499.0	3729.0
Failure to deliver on time	75.3	200.9	811.7
Part replacement	27.1	215.5	295.5
Part movement	32.8	255.0	378.0
Tool consumption	14.8	667.0	782.9
Tool replacement	10.4	208.0	232.0
Tool movement	34.6	136.0	208.0
Machine idle	73.0	152.3	563.7

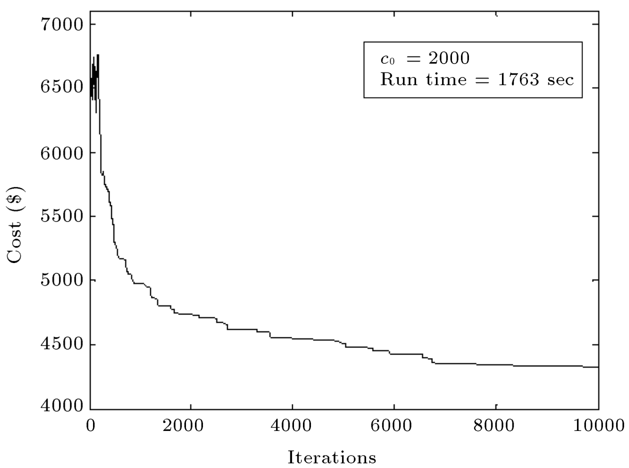

Figure 3. SA algorithm convergence in production planning.

shows the progress of this algorithm relative to the number of iterations. The objective function (total production costs) has decreased from 7,000 to 4333 units, which suggests a more than 38% improvement in production costs. The rate of convergence of the SA algorithm is also presented, in which the major part of the object's reduced function was achieved in the initial 2000 iteration (about 400 seconds) of the program.

As shown in Figure 3, the SA algorithm usually accepts worse responses at the beginning of the search due to high temperature. As the algorithm proceeds, only the improving answers will be accepted.

Table 8 shows the characteristics of the production plan for the best answer found during the search. For each cost component, the improvement in the final production plan relative to the original production plan is presented in this table. As outlined in this table, the SA algorithm has created the greatest improvement in the cost of failure of timely delivery, while the least improvement is related to the cost of replacement of the tool.

8. Conclusions

Nowadays, the diversity of products, the intensity of competition in the global market, and the industries' priority in responding quickly to customers' needs have all made production planning an important issue. The lack of a well-designed and optimized production plan increases the cost of production. In this research, a comprehensive model of the structure and effective factors of production planning in a flexible production system has been presented. The main objectives of the proposed model include the simultaneous allocation of equipment and operations and the determination of the route and timing of operations to minimize the total cost. The objective function involves important costs in a flexible production system, which reduces the total costs in the optimization process. The production planning problem has been solved by employing a Simulated Annealing (SA) algorithm, which ended in a 38% reduction in the total production costs. The computational results show that the proposed algorithm, as a method of optimization, has a high ability to solve these problems quickly and desirably, but for solving large and complex models, the SA algorithm, with regard to optimal response quality and higher convergence rate, performs better.

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