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Toward Global Optimum of Part Ordering in a Flexible Manufacturing System

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FMS에서의 투입 부품의 최적 순서결정에 관한 연구

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Abstract

One of the important scheduling and control problems that must be solved for the efficient operation of FMS could be the "part ordering problem" which is finding optimal sequence of parts to be released into a manufacturing system. In this paper an approach which solves the problem using simulation-optimization technique will be presented. Currently available heuristic approaches for dispatching rules can only get the near optimum at the local level because of the complexities of the system and the dependencies of its components whereas the proposed approach will try to get the global optimum for a given criterion.

1. Introduction

It is well known that a proper return from a heavy investment for the installation of a highly automated manufacturing system, FMS, could be obtained only through efficient operations of the system, e.g. scheduling and control. Thus, a lot of research interests on these topics have been shown in last two decades since the system emerged[4]. One of the important problems that must be solved for scheduling and control of FMS is known to be "part ordering/release problem" which is finding optimal sequence of parts to be released into the manufacturing system(e.g. dispatching parts in AS/RS onto loading station of

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FMS)[1]. Methods currently used for handling this problem are through general dispatching rules which were originated from heuristics. For example, those rules are ones based on Random, FSFS (first stop, first served), SPT(shortest processing time first), Earliest due date, Slack etc.[2]. But heuristic approaches for scheduling and control of FMS can get only near optimum at the local level such as machining stations and queues because of the complexities of the system and the dependencies of its components[3].

Generally part release decision problem includes two basic elements : (a) which part to select next, i.e. sequence of parts be released, and (b) when should it be released. But, here it is assumed that a threshold value for inputing parts into the system because of limited number of pallets/fixtures allowed in the system is given so that whenever a mounted onto loading station with a pallet. We need, therefore, only to solve the sequencing problem in (a) with given production target which are part types, number of parts to be produced and required operations for each part type, to optimize the given performance criterion like makespan, tardiness, lateness etc..

In the manufacturing system under normal operation all parts are selected for being machined in the machine stations and for being moved by material handling systems using currently popular dispatching rule which is known to be one of the most effective ones for the given performance criterion[2, 3, 4, 9].

Each part among given production target could be through of as a node in the network where all the nodes should be gone through starting any node so as to minimize total distance/cost. That is, this ordering of parts could be modeled as a combinatorial problem like a kind of "Traveling Salesman Problem", but in which the nodes in any feasible sequences are not independent one another, i.e. distance(cost or time) between two adjacent nodes among sequence of nodes can have different value depending on the structure of sequence and therefore its cost matrix is not symmetric.

For evaluation of a given sequence of parts to be produced, simulation of the manufacturing system under normal operation will be conducted with currently popular dispatching rules. And for searching the feasible sequences of parts and finding optimal sequence of parts simulated annealing technique[7, 8] which has beeen recently much attracted in the engineering field, will be adopted with modifications for running efficiently using the results from simulation. This whole process is sometimes called simulation-optimization[5, 6].

2. Statement Of The Problem

The problem can be formulated as follows :

Minimize $c(X)$

subject to $X \in S$

where X is a vector $(x_1, x_2, \cdots, x_n)$ representing a configuration of part sequence and $c(X)$ is a performance value like a makespan for a given X which may be obtained only through simulation. And S is a feasible set of part sequences for production in the given manufacturing system. This constraint S may be caused by the assigned due-date and/or the required type of pallet/fixture for each part type.

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The characteristics for the given problem can be summarized as follow :

1) The objective function, $c(X)$ may not be calculated by the simple mathematical formula, but only through simulation with a given sequence, X, because of the complexities and dynamics of the manufacturing system,

2) X represents a sequence of parts, not variables which have usually real or integer values in optimization problem. Thus, the methods developed in simulation-optimization literature[5, 6] may not be used for solving this kind of problem,

3) Constraint, $X \in S$ could be checked only during simulation e.g. the violation of due-date by a specific part can only be known when the processing of part is finished during simulation of the manufacturing system with the given sequence of input parts,

4) Parts in any feasible sequences are not independent one another, i.e. costs or times between two adjacent parts among sequence of parts can have different values depending on the structure for the sequence of other parts and its cost matrix is, therefore, not symmetric. Hence, one of the developed heuristic methods like one in[12] for dealing with general traveling salesman problems cannot be adopted here.

5) The structure of cost function, $c(X)$ is usually irregular or flat with some dense holes because each part type has some amount of same parts and the manufacturing system may operate based on SPT/WINQ rule[2] for efficiency.

Considering the characteristics of the problem under study, as a search method simulated annealing technique which has already be proven to be as an effective tool for dealing with a type of traveling salesman problem of large size especially in areas of electronic circuit design, image processing, neural networks and graph partitioning etc. [7, 8, 10, 11, 15, 16, 18, 19, 20], was selected to handle the part ordering problem, which will be explained in the next section in detail.

It is generally agreed with effectiveness of dispatching rules which were developed in the literature. Thus, for evaluation of given sequence of parts to be produced, simulation of the manufacturing system under normal operation may be conducted with dispatching rules currently well known to be the most effective for the given performance criterion, e.g. SPT/WINQ rule[2] or EFTA rule [9] for a makespan criterion and rules in [4] for other criteria like tardiness, lateness etc..

3. Simulated Annealing For Part Ordering

Simulated annealing is a technique for combinatorial types of optimization problems. It was introduced by Kirkpatrick et al. in 1983[7], which was motivated by an analogy to the statistical mechanics of annealing in solids. Simulated annealing offers a strategy similar to iterative improvement method of optimization techniques, with one major difference : annealing allows perturbations to move uphill in a controlled fashion, which is referred as moves. Because each move can transform one configuration into a worse configuration, it is possible to jump out of local minima and potentially fall into a more promising downhill path. The procedure for simu-

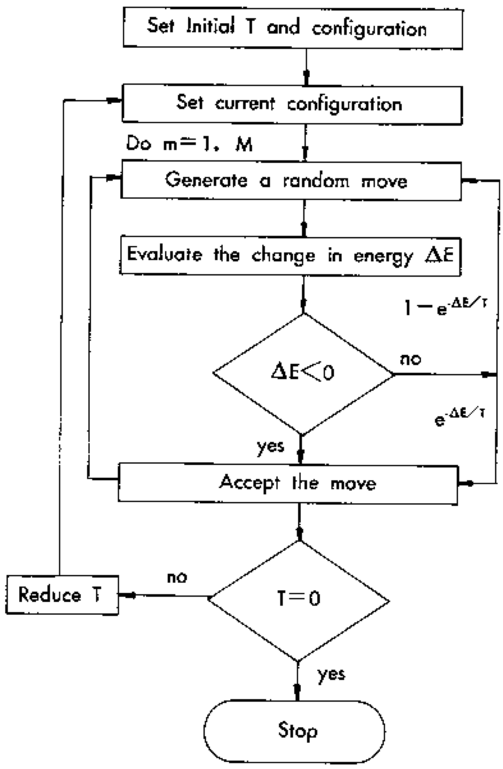

Fig 1. Procedure of Simulated Annealing.

lated annealing algorithm can be simply shown as in Fig. 1.

Annealing algorithm for solving the part ordering problem needs four basic components as follow :

1) Configuration :

A sequence of parts from the given production target to be released into the manufacturing system. Total $(n_1+n_2+\cdots+n_k)!/n_1!\,n_2!\cdots n_k!$ different configurations exist if part type 1 has n_1 parts, part type 2, n_2, and part type k, n_k. Thus, the number of all available configurations is very huge even for a small value for n_1, $n_2, \cdots$, n_k so that the evaluation of all possible sequences of parts is impossible.

2) Cost function :

It is assumed that total time to finish parts of the given production target(makespan) is given as a performance criterion by the management. Simulation is performed with given sequence of parts to get this finishing time. The configuration with the smallest cost so far obtained from simulation will be always kept through the whole process of annealing. Lower bound on the optimal solution can be obtained by summing all times required to process the scheduled parts on the machine of bottleneck which has the heaviest load among all the machines in the system.

3) Move set :

Configuration with two resources(parts) randomly selected from the current configuration and interchanged is usually used as a move. But this method creates a very big possible number of configurations as $N!/(N-2)!\,2! = N(N-1)/2$ where N is the number of resources. Thus, one resource is randomly selected among all the resources except the last one in the current configuration and the other is just taken as the last one in the current configuration, which makes the possible number of configurations as $N-1$ that is much smaller than the value of $N(N-1)/2$ obtained above. If the selected resources to be interchanged are of same type, another configuration is tried so that selecting the already evaluated configuation is avoided.

4) Cooling schedule :

Cooling schedule consists of initial hot temperature(or a heuristic for determining initial temperature) and rule to determine when the current temperature should be lowered (because equilibrium at given temperature has been reached), by how much the temperature should be lowered, and when annealing should be terminated(because global equilibrium has been reached). Temperature can be simply changed based on $T_{new}=\alpha\ T_{old}$, $0<\alpha<1$, where the initial temperature and cooling rate α are determined empirically to give good results. At each temperature, M moves can be tried as a deterministic length of trial or the length of trial could be determined dynamically based on means and variance of recently obtained outputs. One of the available policies for terminating the whole annealing process could be that when the cost improvement seen across a few successive temperatures is sufficiently small, e.g. less than 1 percent, or that when the current temperature is close to zero.

As a tool for finding optimal order of parts to be released into the manufacturing system, the interaction between simulated annealing and simulation model in the whole process in shown in Fig. 2.

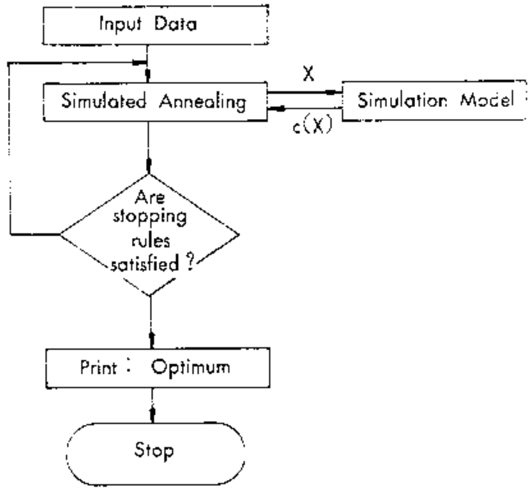

Fig. 2. Interaction Between Simulated Annealing and Simulation Model.

4. Development of Algorithm

Simulated annealing algorithm has its own drawbacks as follow :

1) Even though convergence of the algorithm with probability one has been proven theoretically, it may stop at one of the local optima before reaching the expected global optimum.

2) It usually requires heavy computation time to reach the satisfactory solution because it starts at high value of temperature, T and very slowly lowers the temperature down to reach the global optimum.

3) The developed algorithms for efficient execution of annealing are mostly problem dependent because of the structure of cost functions and the moving strategies.

4) When the cost function for configuration is "too irregular" or "very flat" with densely packed holes, it is hard to reach the global optimum.

To overcome the drawbacks above and get the high possibility for reaching the global optimum in a reasonable time the following things are inserted into the ordinary annealing algorithm :

4-1. Initial Configuration

It is recommended in [15, 19, 20] that starting at the appropriate temperature which is usually not high with a good configuration rather than random starting in annealing at very high temperature. Therefore, to find a good initial configuration for running the annealing algorithm, 2-phase controlled random search is conducted as follow :

Phase I :

i) Initially L configurations are selected randomly, evaluated and kept in the list.

ii) Select one configuration randomly and if it is better than the worst in the current list, replace it for the worst in the list. Do this procedure for the predefined finite times, K_1 or until the variation of costs for configurations in the list is less than some small value δ_1. (though the Phase I, good configurations over the search space are obtained. Refer to Fig. 3a).

Phase II :

i) Select one configuration randomly among current L configurations in the list and from this configuration, get the new configuration through a swap with two randomly selected parts.

ii) If the newly obtained configuration is better than the worst in the current list, replace it for the worst in the list. Do this procedure for the predefined finite times, K_2 or until the variation of costs for configurations in the list is less than some small value δ_2.

iii) Pick the best one among configurations in the last list as the initial configuration for the annealing algorithm(through the Phase II, a high possibility for starting the annealing algorithm from the area near the globally optimal configuration is obtained. Refer to Fig. 3b).

4-2. Initial Temperature

Instead of starting the annealing algorithm at very high temperature, the following procedure is used to get the appropriate initial temperature, T_0, for the initial configuration obtained above based on the method in [15].

i) At each equilibrium, cost function no longer changes, implying that the expected value of the change in cost function in zero, i.e. $E[\Delta c]=0$;

$$E[\Delta c]= \int \Delta c\ P(\Delta c)\ P_a(\Delta c) d\Delta c$$
$$\approx \Sigma\ \Delta c\ P(\Delta c)\ P_a(\Delta c)=0$$

where $P(\Delta c)$ be the probability for being Δc which is the difference between costs for arbitrarily successive configurations at the equilibrium state. And $P_a(\Delta c)$ is the acceptance probability for being Δc at the value of temperature, T such that

$$P_a(\Delta c)= e^{-\Delta C/T},\ \Delta c>0$$
$$=1 \quad ,\ \Delta c\leq 0.$$

It is assumed that currently the state is in some local equilibrium and $P_i(\Delta c)$ could be a good approximation for $P(\Delta c)$ where $P_i(\Delta c)$ is the probability for being Δc, where Δc is the difference between costs for the current configuration, i, and the arbitrary configuration swapped from the current configuration.

Then, $P_i(\Delta c)$ can be estimated by the following formula :

$$P(\Delta c_j)\approx P_i(\Delta c_j)=f_j/m \text{ for all possible values of } \Delta c_j$$

where f_j is a frequency for each Δc_j and m is the number of tried configurations from the current configuration, i.

ii) Let E_- and E_+ be the expected negative change of cost and the expected positive change of cost, respectively such that

$$E_-=\Sigma\ \Delta c\ P(\Delta c) \text{ for all } \Delta c<0$$
$$E_+=\Sigma\ \Delta c\ P(\Delta c)\ P_a(\Delta c) \text{ for all } \Delta c>0$$

Then an appropriate value for temperature, T, can be found such that $E_-=E_+$ through the binary search in which i-th iteration is conducted as follows :

if $E_-<E_+$, reduce the current value for T_i by $T_{i+1}=(T_i+T_{i-2})/2$ and

if $E_->E_+$, increase the current value for T_i by $T_{i+1}=(T_i+T_{i-1})/2$ and

if $E_-\approx E_+$, then stop

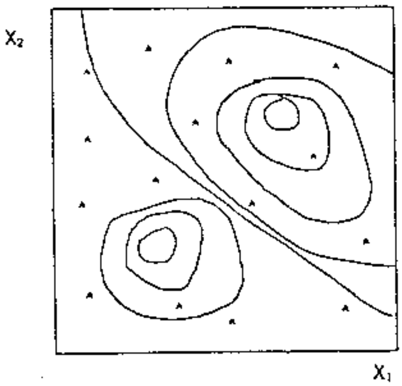

Fig. 3a. Results by Process I in 2 Dimensional Case.

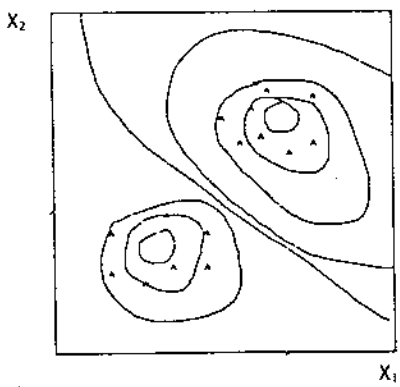

Fig. 3b. Results by Process II in 2 Dimensional Case.

where $T_{i-2} < T_i < T_{i-1}$.

4-3. Run Length At Each Temperature

The number of trial configurations is set to be $\beta^* N$, where N is the size of the problem, i.e. total number of parts to be processed in the planning horizon to be considered and β is the size factor which is an integer value greater than one and determined by the available time for execution.

4-4. Stopping Annealing

Unlike other problems dealt by simulated annealing, in our problem lower bound on the optimal solution can be obtained by summing all times for required to process scheduled parts on the machine of bottleneck which has the heaviest load among all the machines in the system. Annealing process will stop when a difference between local optimal cost and the lower bound is less than a predefined small value , γ, which is near zero, of the lower bound or when there is no improvement in local optimum in five consecutive temperatures.

5. Constrained Problem

The algorithm developed above considers only unconstrained problems in which any sequence of parts can be accepted as a feasible solution. To consider the constrained problem, it is assumed that a due-date has been assigned to each part type as the constraint. To deal with this constrained problem, the following two-stage algorithm based on the penalty function method is used.

5-1. Stage One

The annealing algorithm for unconstrained problems developed above is conducted to minimize the cost function, m(X) as follows :

$$m(X) = c(X) + \tau \sum_i \sum_j \sqrt{d_{ij}}$$

where c(X) is total finishing time for a given sequence of parts, X, $\tau(\tau > 0)$ is a violation factor which assigns a weight to total amount of violation for assigned due-date so as to make a cost function, m(X), smoothy and a delay for part j in part type i, d_{ij}, is calculated as follows :

$$d_{ij}=\begin{cases} a_{ij}-b_{ij}, & a_{ij}>b_{ij} \\ 0 & , a_{ij}<b_{ij} \end{cases}$$

where a_{ij} is the completion time for part j of part type i during simulation and b_{ij} is the assigned due-date for part j of part type i.

If the optimal solution founded by Stage One has the value of zero for $\tau \sum_i \sum_j \sqrt{d_{ij}}$, then stop here. Othewise, go to Stage Two, which may occur by the structure of cost function m(X).

5-2. Stage Two

With the optimal sequence obtained by Stage One as the initial sequence of configuration, the annealing algorithm for unconstrained problems is conducted with the cost function, g(X), as follows :

$$g(X)=\tau\sum_i\sum_j\sqrt{d_{ij}}$$

where as $\tau>0$ and $d_{ij}>0$, g(X) becomes to be positive. The optimal solution for minimizing g(X) to be obtained in this stage will be the value of zero if there exists. Once the configuration with the value of zero for g(X), which is usually located at near the optimum, has been found, then accepting the worse configuration with respect to c(X) as the next move is not permitted in the annealing algorithm. Therefore, the optimal solution obtained in this stage will be the optimal solution for the given constrained problem.

6. Case Study

To see if the proposed procedure works a case study was designed. It was pointed out in the literature that the size of the manufacturing system does not significantly affect the relative performa-

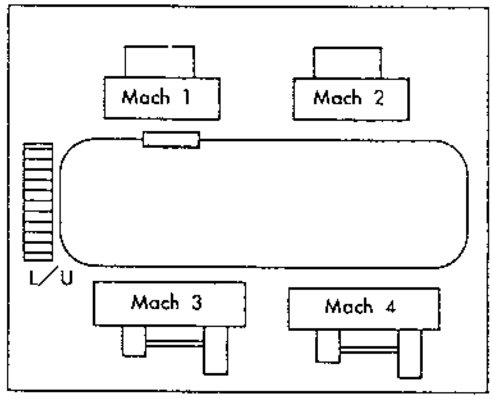

Fig. 4. Hypothesized Manufacturing System.

nce of the scheduling rules[4]. Thus, a manufacturing system of small size is hypothesized and shown in Fig. 4 which consists of 4 different machining centers, loading/unloading station and one AGV. Different types of part each of which has some number of part units are released from AS/RS. Required number of operations on the machines and their times are given in Uniform[3, 6] and Uniform[10., 100.] respectively. Time for loading and unloading a part onto a pallet is given to be 2 time units respectivley for all parts. Time for delivering a part from AS/RS is given to be 1 time unit and time for transfering parts between machines by AGV is assumed to be negligible.

Here it is assumed that a threshold value for inputing parts into the system because of limited number of pallets allowed in the system is given to be 12 for being appropriate traffic load which is about three times of number of machines based on the rule of thumb[13] so that whenever a pallet is available a part will be retrieved from AS/RS and mounted parts are selected for being machined

Here it is assumed that a threshold value for inputing parts into the system because of limited number of pallets allowed in the system is given to be 12 for being appropriate traffic load which is about three times of number of machines based on the rule of thumb[13] so that whenever a pallet is available a part will be retrieved from AS/RS and mounted parts are selected for being machined in the machine stations and for being moved by material handling systems using currently popular dispatching rule, SPT/WINQ rule[2] for a makespan criterion which is known to be one of the most effective ones for the given performance criterion.

To compare the results obtained by the proposed algorithm, a heuristic algorithm for releasing the parts into the system was designed as follows:

i) Initially parts are released onto loading station from AS/RS as many as the number of pallets to be allowed, according to the rule such that the part is alternately selected by each machine based on the shortest processing time rule, which must start to be processed by that machine except loading/unloading machine.

ii) Whenever a pallet/fixture is available, i.e. a part is completed its whole processing, another part is selected for being released onto loading station using the following rules:

a) The first operation for selected part must be conducted on the machine which has the least workload at that time.

b) When multiple types of part satisfying condition in a) exist select one among them based on the shortest processing time rule.

c) When none of part satisfying condition in a) exists, the machine which has the workload next to the least, and so on, is selected on which part to be released.

iii) Whenever a machine is free, the machine selectes a part from its queue based on the shortest processing time rule.

40 part types which has 5 part units respectively (total 200 part units) was simulated in SLAM II [14] based on heuristics above and a sequence of parts without mixturing part types which may be the upper bound on the optimal solution. Completion time for finishing all the production targets with the input sequence of parts without mixturing part types was 9660 time units and completion time based on the heuristic was 8078 time units.

The results are shown with the lower bound on optimal solution in Table 1.

The ordinary simulated annealing process was run with the initial temperature of 100 which was found by 100 initial trials to give a high probability for acceptance resulting in avoidence of local optimum and α in the formula $T_{new}=\alpha\ T_{old}$ was set to be 0.95 which showed usually good results[18] and $M=200(\beta=1,\ N=200)$ was given for the run length at each temperature. To terminate the whole process, one of the conditions should be satisfied, which are that a difference between the current local optimal cost and the lower bound on the global optimal solution is less than a predefined small value, $\gamma=0.0001$ of the lower bound or that

Table 1. Solutions by Heuristic, Without Maxturing and Lower Bound

Without Mixturing	Heuristic	Lower Bound on Optimum
9660	8078	7175

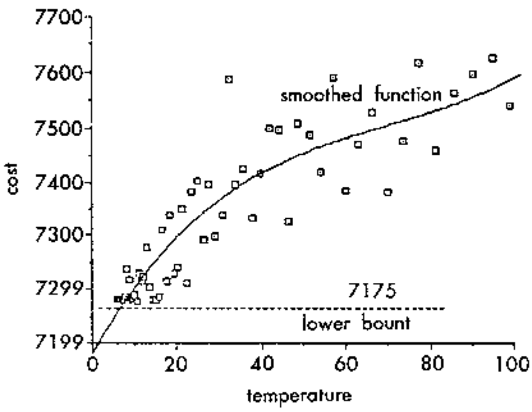

Fig. 5. Local Equilibrium Cost vs. Temperature Obtained by Ordinary Simulated Annealing.

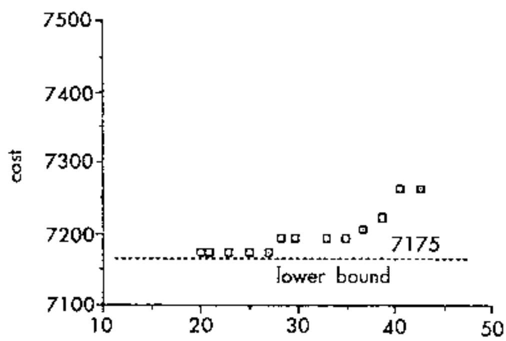

Fig. 6. Local Equilibrium Cost vs. Temperature Obtained by Proposed Annealing Algorithm.

there is no improvement in local optima in five consecutive temperatures. The obtained cost at each temperature of local equilibrium by the ordinary simulated annealing is shown in Fig. 5. To reach near the global optimum, 7181, total 11300 different configurations were evaluated using simulation.

The proposed algorithm for annealing described above was conducted with the same condition as the ordinary simulated annealing except that the value for parameters, L, K_1, K_2 for finding initial configuration is set to be 100 and number of trial configurations for finding $P(\Delta c)$ is set to be 100, which resulting in the global optimum with total 3000 evaluations of different configurations using simulation. The obtained cost for each temperature of 6local equilibrium by the proposed algorithm for annealing is shown in Fig. 6.

If the same number of configurations which is 3000 is allowed for two algorithm, the ordinary simulated annealing and the proposed algorithm, then the ordinary simulated annealing can only get 7509 time units whereas the proposed algorithm obtains the global optimum, 7175, which is summarized in Table 2.

For making the constrained problem, a due-date based on Uniform$[S_1, S_2]$ where $S_1=0.8Lb$, $S_2=$

Table 3. Solution Obtained for Constrained Problem

Solution	# of trials		
	stage one	stage two	total
7280	4600	2300	6900

Table 2. Solutions by Ordinary Annealing, Proposed Algorithm and Heuristic

Ordinary Annealing		Proposed Algorithm		Heuristic	
# of trials	solution	# of trials	solution	# of trials	solution
3000	7509	3000	7175	1	8087
11300	7181				

1.5Lb(Lb ; lower bound of optimal solution for unconstrained problem) is assigned to each part type and τ is set to be 0.5. The optimal solution for the constrained problem was obtained as 7280 with the trials of 4600 for Stage One and 2300 for Stage Two, which is summarized in Table 3.

7. Conclusion

In this paper the approach which solve the part ordering problem using simulation-optimization technique has been proposed. Currently available heuristic approaches for dispatching rules can only get the near optimum at the local level because of the complexities of the system and the dependencies of its components whereas the proposed approach have tried to get the global optimum in terms of given performance criterion. This approach could be more valuable when the size of batch for production is small and the number for types of part is large. When the stochastic nature is included in the simulation, e.g. machine failure with some stochastic distribution, some number of simulation runs for each sequence of configuration could be conducted and the results are averaged as a value for the cost function.

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