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A Hybridization of Simulated Annealing and Electromagnetic Algorithms for Flowshop Problems with Skipping Probability

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Abstract: This study considers a specific case of flowshop problems in which some jobs might not visit all the production stages. To tackle the problem, a hybrid metaheuristic which is a combination of electromagnetic algorithm and simulated annealing, called EMSA is presented. The optimization criterion is makespan. To evaluate the proposed hybrid metaheuristic, the study carries out a benchmark by which EMSA is compared against some dispatching rules as well as pure simulated annealing and electromagnetic algorithms in a fixed given computational time. All the results and analysis, obtained through the benchmark, show that EMSA is an effective algorithm for the problem.

Key words: Scheduling, flowshops, electromagnetic algorithm, simulated annealing, hybrid metaheuristic, skipping probability

INTRODUCTION

Production scheduling is defined as determining the process sequence by which the working parts are processed on a certain machine or on some manufacturing equipments to satisfy some performance measures under the constraints of production. Through scheduling, all parts in a manufacturing system can be worked and fPinished by passing through each piece of equipment according to a pre-determined process sequence. In flowshops, each job has a set of m operations $\{O_{i1}, O_{i2},..,O_{im}\}$ and each operation j can be done by one machine j. All the jobs have the same processing route, starting from machine 1 until finishing at machine m. Each job i has a non-negative, known and fixed processing time for each operation j. P_{ij} denotes the processing time of job i on machine j. By removing the restriction that all jobs need to be processed at all machines, regular flowshops convert to flowshops with skipping probability (so-called flexible) which is more realistic than regular flowshops. The objective is to find jobs sequence, so that an established criterion is optimized. The common used criterion is makespan or C_{max} which is equivalent to minimizing the maximum completion time for all the jobs.

A detailed survey for the flowshop with skipping probability has been given by Linn and Zhang (1999) and Wang (2005). Moursli and Pochet (2000) presented a branch-and-bound algorithm to minimize makespan in the hybrid flowshop with skipping probability. Iranpoor *et al.* (2006) considered flexible flowshops under finite planning horizon. The optimization criterion was earliness tardiness. Since, flowshop problem belongs to special case of combinatorial optimization, known to be NP-hard, presentation of effective metaheuristics is inevitable. This study introduces an efficient metaheuristic which is a hybridization of Simulated Annealing (SA) and Electromagnetic Metaheuristic Algorithm (EMA). The purpose is to make simultaneous use of diversification capability of EMA and intensification capability of SA. The effectiveness of the hybridization is evaluated by a set of instances.

PROPOSED ALGORITHM

Here, it is intended to present present hybrid algorithm. In order to do so, it is necessary to present the encoding scheme which makes a solution recognizable for algorithms. Then electromagnetic algorithm and simulated annealing are separately reviewed. Finally, the hybridization way of these two algorithms are explained.

Encoding scheme: The most frequently used encoding for the flow shop is a simple permutation of the jobs. The relative order of the jobs in the permutation indicates the

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processing order of the jobs on the first machine in the shop. It is necessary to be addressed that a drawback of algorithms proposed in flow shop with skipping probability problems is that they just order jobs according to earliest ready time of jobs at the beginning of each stage. But in FS with skipping probability problems, it is very likely to have some jobs with the same ready time at the beginning of each stage. For example, all the jobs which skip the first stage would have the ready time of zero at the beginning of the second stage. So, it is needed to establish a clear criterion to order these jobs. In this study, if some jobs have the same ready time at the beginning of stage t (t = 2, 3, ..., g), they are arranged the same as their order at stage t-1. We adapt all the compared algorithms to this criterion.

Simulated annealing: Simulated Annealing (SA) got its existence from the physical annealing of solid metal. In SA, solutions are randomly generated from a set of feasible solutions. This process accepts not only those solutions, which improved the objective function, but also those solutions, which do not improve objective function on the basics of Transition Probability (TP). The fundamental idea is to generate a new job sequence s by a random rule from the neighborhood of present sequences. This new sequence is accepted or rejected by another random rule. A parameter t, called the temperature, controls the acceptance rule. The variation between objective values of two candidate solutions is computed $\Delta C = C_{max}(s)-C_{max}(x)$. If $\Delta C \leq 0$, sequence s is accepted. Otherwise, sequence s is accepted with probability equal to $(-\Delta C/t_i)$. The algorithm proceeds by trying a fixed number of neighborhood moves (max) at temperature t_i, while temperature is gradually decreased. The procedure is repeated until a stopping criterion is met. Moves resulting in solutions of worse quality (uphill move) than the current solution may be accepted to escape from local optima. SA starts at a high temperature (T_0), so most of the moves are accepted at first steps of the procedure. The probability of doing such a move is decreased during the search. Figure 1 shows the general outline of SA. Simulated annealing starts from an initial solution and a series of moves are made according to a user-defined annealing schedule. In this research, the initial solution is obtained using SPT (Shortest Processing Time). The algorithm checks 100 neighbors at temperature t_i (max = 100). Moving operator generates a neighbor solution from current candidate solution by making a slight change in it. These operators must work in such a way that avoids infeasible solutions. In this research, the following moves are considered:

```
Procedure Simulated_annealing
t = T0
x = initialization
xbest = x
while stopping criterion is not met do
      for iter = 1 to max do
            s = move x by an operator
            if f(s)<f(x) then
                  x = s
                  If f(s) < f(xbest) then
                        xbest = s
                  endif
            else
                  if random < exp{-(f(s)-f(x))/t} then
                        x = s
                  endif
            endif
      endfor
      t = α . t
endwhile
```

Fig. 1: General outline of simulated annealing

- Swap Operator (SO): The random keys (RKs) of two randomly selected jobs are swapped
- Single Point Operator (SPO): The RK of one randomly selected job is randomly regenerated

As mentioned earlier, to avoid local optima, the solutions with worse objective values are probably accepted depending on the value of temperature. When the procedure proceeds, the temperature is slightly lowered under a certain mechanism which is called cooling schedule. Here, exponential cooling schedule is utilized, $T_i = \alpha \cdot T_{i-1}$ (where, $\alpha \in (0, 1)$ is temperature decrease rate), which is often believed to be an excellent cooling recipe (Naderi *et al*., 2008).

Electromagnetic algorithm: Electromagnetic Metaheuristic Algorithm (EMA) is a population-based metaheuristic which has been proposed to solve continuous problems effectively. This method originates from the electromagnetism theory of physics by considering potential solutions as electrically charged particles spread around the solution space. Birbil and Fang (2003) proposed EMA which is a flexible and effective population-based algorithm to search for the optimal solution of global optimization problems. This metaheuristic utilizes an attraction-repulsion mechanism to move the particles towards optimality. EMA is useable for particular set of optimization problems with bounded variables in the form of:

$$\text{Min } f(x)$$
$$\text{st: } x \in [l, u]$$

Where:
$[l, u] := \{x \in R^n \mid l_k \le x_k \le u_k ; k = 1,2,...,n\}$

Traditionally, in an EMA, the initial population is generated randomly. However, it is known that the initial solutions can influence quality of the results obtained by the algorithms. The initialization procedure in such a hard combinatorial problem has to be made with great care, to ensure convergence to desirable and better objective functions in a reasonable amount of time. Because of this, initial solutions for proposed EMA are generated by Shortest Processing Times (SPT).The objective values of solutions are calculated and the best one is recorded as x_{best}.

Each candidate solution is regarded as a charged particle. The charge of each candidate solution is related to makespan. The size of attraction or repulsion over candidate solutions in the population is calculated by this charge. The direction of this charge for candidate solution i is determined by adding vectorally the forces from each of other solutions on candidate solution i. In this mechanism, a candidate solution with good objective function value attracts the other ones, candidate solutions with worse objective function repel the other population members and better the objective function value result in the higher the size of attraction.

As shown in Fig. 2, EMA has four phases including initialization of algorithm, computation of total force exerted on each particle, movement along the direction of the force and local search.

Initialization: The first procedure, initialization, is used for sampling m points from the feasible region and assigning them their initial function values. The initialization procedure in such a hard combinatorial problem has to be made with great care, to ensure convergence to desirable, better objective functions in a reasonable amount of time. Because of this, initial solutions for proposed EMA are generated by SPT. The remaining population (popsize-2) is randomly generated. The objective values of solutions are calculated and the best one is recorded as x_{best}.

Local search: Proposed EMA is hybridized with a local search in order to increase the performance of the algorithm. The procedure of this local search can be described as follows. The random key of the first job (x_{i1}) in the sequence of candidate solution i (x_i) is randomly regenerated (i.e., the first job is relocated to a new random position in sequence). If this new sequence (v) results in better total completion times, the current solution (x_i) is replaced by the new sequence (v). This procedure iterates at most for all the subsequent jobs in sequence. If we

```
Procedure Electromagnetism_algorithm

Initialization
While termination criterion are not satisfied do
    Local search
    Computation total forces
    Movement by total forces
Endwhile
```

Fig. 2: Pseudo code of an EMA

```
Procedure Local_search
   k = 1
   while k < n+1 do
          v = x_ik is randomly regenerated
          if f(v)<f(x_i) then
                x_i = v
              k = n
          endif
          k = k + 1
endwhile
```

Fig. 3: Procedure of the local search

have improvement in kth<g, the local search for the current solution terminates. After all, the best solution is updated. Procedure of the local search is shown in Fig. 3.

Computation of total forces: In order to compute the force between two points, a charge-like value q_i, is assigned to each point. The charge of the point is calculated according to the relative efficiency of the objective function values in the current population i.e.,

$$q_i = \exp\left(-n.\frac{f(x_i) - f(x_{best})}{\sum_{j=1}^{popsize}(f(x_j) - f(x_{best}))}\right) \quad \forall i \;\; i = 1, 2, ..., popsize \tag{1}$$

where, x_{best} represents the point that has the best objective function value among the points at the current iteration. In this way the points that have better objective function values possess higher charges. Note that, unlike electrical charges, no signs are attached to the charge of an individual point in the Eq. 1 instead, the direction of a particular force between two points will be determined after comparing their objective function values. The total force F_i exerted on candidate solution i is also calculated by following formula:

$$F_i = \begin{cases} \sum_{j \ne i}^{p} (x_j - x_i)\dfrac{q_i . q_j}{\| x_j - x_i \|^2}; & f(x_j) < f(x_i) \\ \sum_{j \ne i}^{p} (x_i - x_j)\dfrac{q_i . q_j}{\| x_j - x_i \|^2}; & f(x_i) < f(x_j) \end{cases} \tag{2}$$

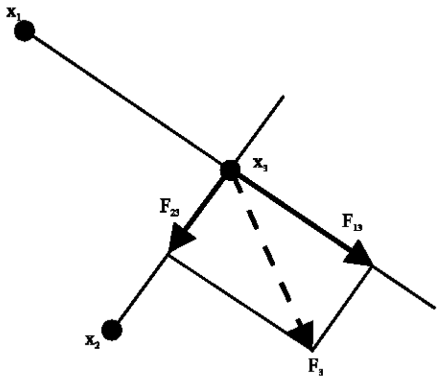

Fig. 4: Example of exertion of forces

```
Procedure computation_of_total_forces

for i = 1 to popsize do
        calculate (q_i)
        F_i = 0
endfor
for i = 1 to popsize do
     for j = 1 to popsize do
          if f(x_j) <f(x_i) then
               F_i = F_i + (x_j - x_i) (q_i.q_j)/(|| x_j - x_i ||^2)
          else
               F_i = F_i + (x_j - x_i) (q_i.q_j)/(|| x_j - x_i ||^2)      0
          endif
     endfor
```

Fig. 5: The procedure of the computation of total forces

Two-dimensional example total force vector F_i exerted on candidate solutions is shown in Fig. 5. The force exerted by x_1 on x_3 is F_{13} (repulsion: the objective function of x_1 is worse than that of x_3) and the force exerted by x_2 on x_3 is F_{23} (attraction: the objective function of x_2 is better than that of x_3). F_3 is the total force exerted on x_3 by x_1 and x_2. The procedure of the computation of total forces is shown in Fig. 4.

Movement by total forces: The total force exerted on each point by all other points is calculated in the CalcF( ) procedure which has been shown in Fig. 6. All the candidate solutions are moved with the exception of the current best solution. The move for each candidate solution is in direction of total force exerted on it by a random step length. This length is generated from uniform distribution between (0, 1). It can be guaranteed that candidate solutions have a nonzero probability to move to the unvisited solution along this direction by selecting random length. Moreover, by normalizing total force exerted on each candidate solution, production of infeasible solutions is avoided.

```
Procedure Movement_by_ total_forces

for i = 1 to popsize do
    if i ≠ best then

        □□ = random [0, 1]

           F^i = F_i / || F_i ||

        for k = 1 to n do
           if F_ik>0  then
                x_ik = x_ik + β . F_ik (1-x_ik)
           else
                x_ik = x_ik + β . F_ik (x_ik)
           endif
        endfor
    endif
endfor
```

Fig. 6: Movement procedure by total forces

The hybridization of simulated annealing/ electromagnetic algorithm: The idea of the hybrid approach for flow shop problems has been widely exploited before, for example, Zhang *et al.* (2008), Heinonen and Pettersson (2007) and Huang and Liao (2006). The hybridization is usually done to fulfill some drawbacks of algorithms.

In some other fields of research, it is shown that hybridization of EMA with another metaheuristic can provide convincing results. Moreover, initial instances showed us that the performance of EMA strongly depends on the initial solution. The greater choice of initial solution, the better result obtained by the algorithm. Therefore, the hybridization of EMA with another algorithm is motivated. Several metaheuristics are examined, it finally turned out that hybridization with local search based metaheuristics can yield interesting results. On the other hand, simulated annealing is known to be almost independent on the initial solution. However, due to lack of the memory function, the searching may return to old solutions and become oscillation in local optimum surrounding. Therefore, utilization of simulated annealing in initialization phase of EMA is explained. The combination of the flexible and effective population-based algorithm to search for the optimal solution and the convergent characteristics of simulated annealing provides the rationale for developing a hybrid algorithm (EMSA) strategy to solve flexible flowshop to minimize makespan.

In sum, this proposed hybrid metaheuristic consists of two phases, initialization and improvement. In initialization phase, SA commences from SPT. SA quickly improves the SPT solution. Then EMA can start its process from a relatively good initial solution produced

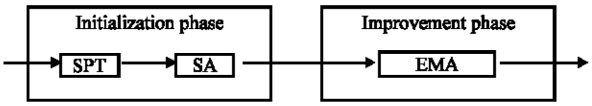

Fig. 7: General outline of EMSA

by SA. The remaining initial solutions are randomly generated. The general outline of the hybrid algorithm is shown in Fig. 7.

EXPERIMENTAL EVALUATION

Here, a benchmark is applied to evaluate the performance of the three proposed algorithms (i.e., EMA, SA and EMSA). These algorithms were coded and implemented in MATLAB 7.0 running on a Pentium IV PC with an Intel processor running at 3 GHz and 1 GB of RAM memory. Relative Percentage Deviation (RPD) is used for the total completion time as common performance measure to compare the methods (Ruiz and Stützle, 2008). The best solutions obtained for each instance (which is named Min_{sol}) were calculated by any of all algorithms. RPD was obtained by the following equation:

$$RPD = \frac{Alg_{sol} - Min_{sol}}{Min_{sol}} \times 100 \quad (3)$$

where, Alg_{sol} is the makespan obtained for a given algorithm and instance. RPD takes value between 0 and 100. Clearly, lower values of RPD are preferred.

Data generation: Data required for a problem consists of the number of jobs (n), number of machines (m), range of processing times (p) and skipping probability. The instances are generated based on Taillard benchmark values. There are n = {20, 50, 100, 200, 500} and m = {5, 10, 20} which resulted in 15 combinations of n×m. The processing time in Taillard's instances were generated from a uniform distribution over the range (1, 99). Flexible flow shop was considered by allowing some jobs to skip some stages. The probability of skipping a stage was set at 0.1 or 0.4. There are 10 instances for each scenario, similar to Taillard benchmark.

Parameter tuning: It is well known that the quality of algorithms is significantly influenced by the values of parameters.

Simulated annealing: The proposed SA has two parameters: cooling schedule, (initial temperature T_0, cooling rate α) and move operator. The combination of

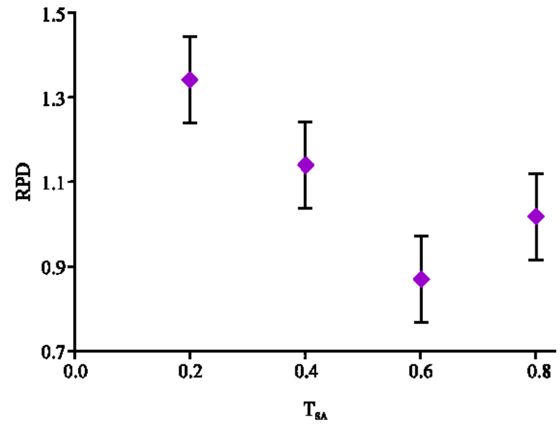

Fig. 8: Mean values plot and LSD intervals for total time assigned to SA in EMSA

T_0 = 50 and α = 0.98 results in statistically better output than the either of two other sets. As the results of analysis, the parameters are set to as MO = SPO and (T_0, α) = (50, 0.98).

Electromagnetism algorithm: One of the advantages of EMA is that it has only one parameter, popsize (number of population). In present case, popsize of 4 provides statistically better results than the other values of popsize = 2, 6, 8.

Hybrid algorithm (EMSA): After tuning the parameters of SA and EMA, there remains only one parameter of EMSA to be set. As earlier indicated, the stopping criterion is a fixed computational time. The remaining parameter of EMSA is the proportion of total time assigned (T_{SA}, T_{EM}|$T_{SA}+T_{EM} = 1$) to each of the two phases, initialization and improvement. The following 4 levels are considered for T_{SA}: 0.2, 0.4, 0.6 and 0.8. The results are shown in Fig. 8. T_{SA} = 0.6 is statistically better than 0.2 and 0.4. However, T_{SA} = 0.6 and 0.8 are statistically the same. Based on average RPD, T_{SA} = 0.6 is chosen.

Experimental results: Here, we compares the proposed EMSA with dispatching rules like Longest Processing Time (LPT) and Shortest Processing Time (SPT) as well as SA and EMA. The stopping criterion is n.m. 0.2 sec computation time. RPD measure is used to compare the algorithm.

The results of the experiments, averaged for each combination of n and m are shown in Table 1. EMSA provides the best results among the algorithms with RPD of 0.37. SA with RPD of 1.41 is better than EMA with RPD of 2.48. The worst performing algorithm is LPT with RPD

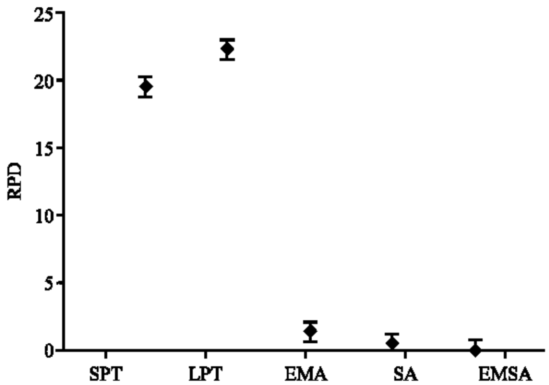

Fig. 9: Mean values plot and Tukey intervals (at the 95% confidence level) for the type of algorithm factor

Table 1: Average relative percentage index (RPD) for the algorithms grouped by n and m

Instance	SPT	LPT	EMA	SA	EMSA
20×5	20.71	35.81	1.15	1.05	0.11
20×10	21.66	27.41	1.67	1.01	0.10
20×20	13.12	16.60	1.90	1.09	0.02
50×5	19.04	32.23	3.87	1.28	0.01
50×10	18.07	24.56	3.21	2.19	0.04
50×20	15.58	20.15	3.77	2.01	0.00
100×5	12.92	34.07	1.96	1.79	0.01
100×10	15.40	22.63	3.35	2.08	0.01
100×20	12.41	14.90	3.16	0.99	0.01
200×5	12.44	27.53	1.65	1.95	0.29
200×10	12.60	20.84	1.36	0.85	0.03
200×20	11.60	16.84	1.89	0.68	0.04
500×5	10.44	35.22	2.27	1.99	1.45
500×10	10.30	19.32	2.61	3.09	1.67
500×20	12.13	16.19	3.39	2.09	1.80
Average	14.56	24.29	2.48	1.41	0.37

of 24.29. In order to verify the statistical validity of the results shown in Table 1 and to find which the best algorithm is, a design of experiments and an analysis of variance (ANOVA) has been conducted where the algorithm type is considered as a factor and RPD as the response variable. Figure 9 shows the means plot and Tukey intervals for the type of algorithm. Figure 9 demonstrates that EMSA statistically supersedes all the algorithms including SA, EMA and dispatching rules.

To analyze the interaction between quality of the algorithms and different levels of number of jobs, the average RPDs obtained by each algorithm in different problem sizes are shown in Fig. 10. As could be seen, EMSA keeps its robust performance all ranges of number of jobs. The first impressive conclusion of these analyses is that although SA and EMA are both effective for the problem, the hybridization

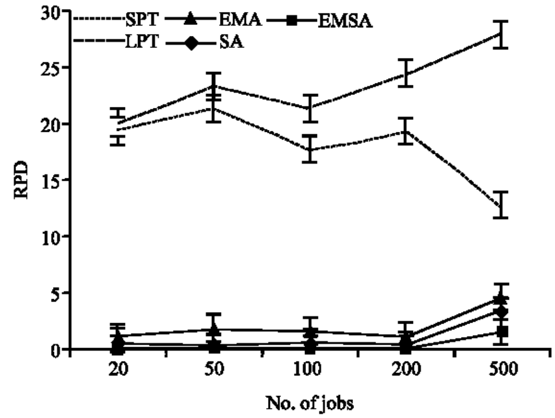

Fig. 10: Mean values plot for the interaction between the type of algorithm and the number of jobs

of SA and EMA even is superior to the both when they are given a fixed computational time.

CONCLUSION

In this study we presented a hybrid approach for flow shop scheduling with skipping probability. This hybrid approach, (EMSA), is the combination of simulated annealing and electromagnetic algorithms to overcome some drawbacks of them. To evaluate the proposed hybrid algorithm, we compared it with some existing algorithms, SA and EMA in a fixed given computational time. The computational results exhibit the suitable performance of the EMSA in extracting acceptable scheduling solutions within the same given time. As a result, the proposed algorithm generates acceptable and better solutions than other methods. This study examines the behaviors of the algorithm as regards the number of jobs and the results have shown that EMSA keeps its robust performance in different levels of number of jobs. It is possible to extend the EMSA to other scheduling problems or to the problems considered in this study with other objectives, such as total tardiness and number of tardy jobs.

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