New meta-heuristic for dynamic scheduling in permutation flowshop with new order arrival

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Abstract

Permutation flowshop scheduling problem (PFSP) has attracted lots of attention from both academia and industry as it finds many applications especially for today’s mass customization. The PFSP is proved NP-hard, and the dynamic uncertainties such as stochastic new order arrivals significantly increase the problem complexity and difficulty. Many enterprises often struggle to make decisions on accepting new orders and setting due dates for them due to lack of effective scheduling methods. To fill in the knowledge gap, this paper is to propose a new meta-heuristic algorithm which is based on a new enhanced destruction and construction method and a novel repair method while adopting the architecture of the iterated greedy algorithm. Statistical tests were conducted and results show that the new algorithm outperforms existing ones.

Keywords Dynamic scheduling · New order · Permutation flowshop · Iterated greedy algorithm · Order mixing

1 Introduction

Customers nowadays demand more and more customized products at no extra cost comparing to that mass produced by dedicated production lines. Mass customization requires flow line production systems which can respond to the changing demand quickly and efficiently. A flow line, also known as a flowshop, refers to a production system in which machines are manufactured in a specified order, starting from the first to the last. Flow lines can be found in auto manufacturing [1], integrated circuit (IC) fabrication [2], photographic film production [3], and pharmaceutical and agro-food industries [4].

Flowshop scheduling is a challenging problem [5—9]. The flowshop scheduling problem has been proven to be non-deterministic polynomial-time hard (NP-hard) when the number of machines is larger than 2 [10]. Many studies [5, 11] focus on the static environment which simplifies the problem constraint. However, more attention should be paid to dynamic aspects that frequently occurred in reality such as new order arrival [12, 13], machine breakdown [14], and rush order [15]. It is typical in today’s mass customization that new orders frequently arrive into factories. The randomness of new orders often leads to sheer complexity in scheduling due to the dynamic changes given various constraints of resources. The uncertainties in terms of job types, job numbers, arrival times, due dates, etc. have created significant challenges [12, 16],

Notations

\( J_O \) Job set of the old order
\( J_N \) Job set of the new order
\( d_O \) Due date of the old order
\( J_T \) Tardy job set
\( J_E \) Early job set
\( m \) Number of machines
\( n_O \) Number of jobs belonging to the old order
\( n_N \) Number of jobs belonging to the new order
\( n \) Number of jobs from both orders, \( n = n_O + n_N \)
\( i \) Machine index, \( i \in [1,m] \)
\( j \) Job index for the old order, \( j \in [1,n_O] \)
\( k \) Job index for the new order, \( k \in [1,n_N] \)
\( t_{j,i} \) Processing time of job \( j \) on machine \( i \)
\( s \) Job sequence
\( T_{j,O}^{\max} \) The maximum tardiness of the old order
\( C_{j,N}^{\max} \) The maximum completion time of the new order

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which increases the complexity of the scheduling problem significantly. This happens in warehouses as well, and the problem is defined online order batching problems [17–20], in which new orders arrive frequently and stochastically, and scheduling or rescheduling should respond immediately upon their arrival. Three key questions should be considered concerning new orders: (1) if the new order can be accepted or not, given the due date constraint of the old order; (2) how to complete the new order as soon as possible; and (3) how to maximize the number of accepted orders in order to maximize revenue.

The problem is a constraint optimization problem. It is NP-hard in the strong sense especially when the due date of the old order is loose as it can be reduced to the PFSP by including all jobs from new orders [13]. In this paper, a new meta-heuristic is derived from the framework of the iterated greedy (IG) algorithm [21] under which a new enhanced destruction and construction method and a novel repair method are proposed. The paper is organized as follows. Literature review is presented in section 2, followed by the problem statement in section 3. Section 4 presents the new meta-heuristic algorithm named eIG_Rep. Section 5 introduces the experimental validation of the new algorithm. Section 6 concludes this paper.

2 Related work

The approaches to handling uncertainties can be classified into three categories [22, 23]: (1) reactive approach; (2) proactive approach; and (3) predictive-reactive approach. The reactive methods such as the shortest processing time (SPT) rule, the first come first serve (FCFS) rule, and the longest processing time (LPT) rule can be easily used to schedule jobs in real time. Right shifting (RS) strategy and real-time (RT) strategy are also reactive methods for coping with newly arrived orders [12]. RS and RT are two strategies which attach new orders to the end of the existing schedule. It has been confirmed that rescheduling the remaining jobs of the old order can provide a higher quality schedule [13, 16, 24]. However, no reactive methods can provide high-quality solutions with order mixing, therefore missing the opportunity of optimized schedule [25]. Proactive scheduling techniques are developed based on anticipated disturbances [26, 27]. It is widely used to deal with uncertainties that are easy to predict and simulate. By assuming probabilistic processing times, an improved genetic algorithm is developed in order to maximize the probability of completing orders before expected due dates [28]. A two-phase simulation-based algorithm is developed for flowshop scheduling with stochastic processing times [29]. Though the proactive approaches are robust to uncertainties, it cannot be applied to the problem studied in this paper, because new order arrivals are difficult to be predicted and simulated precisely due to many uncertain parameters in terms of job types, number of jobs, arrival times, and due dates.

The predictive-reactive approaches are commonly used scheduling methods under uncertainties [30, 31]. Two main steps are included: (1) a predictive schedule is generated over the time horizon and (2) the resulted schedule is then modified to respond to uncertainties. To handle newly arrived orders, a genetic algorithm with the non-reshuffle and reshuffle strategies is proposed for job scheduling, and a match-up strategy is applied to determine the time window for rescheduling of flexible manufacturing systems [32]. A hybrid algorithm by integrating genetic algorithm and tabu search algorithm is developed as a rescheduling technique to cope with new orders and machine breakdowns simultaneously in jobshops [33]. An assignment model is built for generating the baseline schedule and an improved genetic algorithm is developed for rescheduling of new orders in single-machine layout [34]. A refreshing variable neighborhood search (RVNS) approach is presented for job rescheduling to set common due dates for newly arrived orders in permutation flowshops [13]. In summary, the predictive-reactive method is the most popular one and it can provide high-quality schedules as order mixing can be achieved in job rescheduling. However, existing work focuses on jobshop or flexible manufacturing system [33, 34]. The PFSP coping with new orders of multiple jobs has not been well addressed.

Iterated greedy (IG) algorithm is a predicative-reactive approach. In the IG algorithm framework, a greedy construction heuristic including destruction and construction phases is iterated until the stopping criterion is satisfied, and a local search can be applied to further improve the performance. Depending on the solution feasibility, a repair method could also be used in order to enhance the algorithm’s effectiveness. IG has been employed to solve many scheduling problems [35–39], including the static permutation flowshop scheduling problems (PFSP) [40]. However, it tends to be trapped to local optimum. Many modifications have been developed for the IG algorithm [39–41]. For the destruction and construction phases, the majority of studies focus on the job insertion method. To avoid repeated job removing, tabu-based destruction methods are developed [39, 42]. Different heuristics or strategies are presented for choosing suitable jobs [43]. In [35], the prior and posterior jobs of the inserting job are reinserted in all possible positions in the construction phase. Some speed-up methods are presented for improving job insertion efficiency [38, 40]. Moreover, many studies concentrate on escaping from a local optimum with the destruction and construction phases [44, 45]. An insertion perturbation is designed to provide a different solution from the previous local optimum [44]. Some studies alter the number of perturbed jobs to change the strength of perturbation [36, 38]. Normally, it is a fixed and small value [45]. However, it has been confirmed that no single fixed value could ensure high-quality solutions [36]. It is difficult to escape from a local optimum if a small number of perturbed jobs is defined [35, 44, 46]. In [36], the number of perturbed
jobs is randomly selected within a defined range. In [38], a
differential evolution algorithm is modified and used to opti-
mize the number of perturbed jobs within IG algorithm for
node-permutation flowshop scheduling problems. However,
extra computation time is needed for the optimization process.

Many variants or modifications [41, 43] have been de-
veloped by modifying the local search method for improving IG
algorithm performance. A descent local search is added to the
IG algorithm for complex flowshop problems with sequence-
dependent setup times [41]. Three local search methods are
revised based on jump moves, swap moves, and variable
neighborhood descent approach for a scheduling problem
with unrelated parallel machines [43]. For no-wait flowshop
scheduling problems, a neighborhood search method based on
insert, swap, and double-insert moves is developed [39]. A
variant of the non-exhaustive descent algorithm is developed
by swapping any two positions in the sequence and the influ-
ence of ties is also investigated during the local search [37].
It can be concluded that different problems need different local
search methods. In this paper, a dedicated local search mech-
anism is proposed for skipping infeasible solutions which vi-
olate the due date constraints of old orders, in order to save
computation time.

For highly constrained optimization problems, e.g., new
order scheduling problem with due date constraints of old
orders, solution feasibility may not be guaranteed during
searching process, especially when using meta-heuristics
[47]. It is important to determine whether the infeasible solu-
tions are discarded or searched for finding feasible solutions.
A repair algorithm is developed in GA algorithms for solving
numerical optimization problems with nonlinear constraints
where two separate populations are kept, one for marking
“search points” which are to be repaired and evaluated, and
the other for keeping “reference points” which are used for
evaluation directly [47]. A repair algorithm for robot path
planning problems is presented through designed genetic op-
erators based on prior knowledge [48]. A genetic repair op-
erator is designed in parallel GA algorithms for the traveling
salesman problem and the graph partitioning problem by con-
structing a new feasible chromosome after identifying all gene
loci and alleles [49]. There are two techniques to deal with the
fixed infeasible solutions after repairing: returning it to popu-
lations or not. Some studies [50, 51] have taken the “never
replacing” approach, i.e., the repaired is never returned to
the population, while others [13] have taken the “always replac-
ing” approach. Orvosh and Davis [52] evaluate the perfor-
mance of both techniques in GA algorithms in terms of
returning the repaired or the original chromosome to popula-
tions. In summary, there are no standard heuristics for design-
ing a repair algorithm [53], and a repair method is usually
problem-dependent [54].

Various acceptance criteria are used for different problems.
A criterion “replace if better” (RB) is adopted for dynamic
parallel machine problems [55]. In solving blocking jobshop
problems, two acceptance criteria are developed, i.e., random
walk (RW) and simulated annealing-like (SA) [56]. When
using RW, each feasible solution is accepted after the con-
struction phase. While using SA, only the feasible solution
with a better performance is accepted, or the candidate solu-
tion is accepted with a probability. In [43], RB and RW criteria
are used for unrelated parallel machine problems. In [36], a
simulated annealing-like acceptance criterion is widely adopted
[35, 41]. However, for the constrained optimization problem
studied in this paper, e.g., new order scheduling problem with
due date constraint of old orders, solution feasibility may not
be guaranteed during searching process, especially in meta-
heuristics [47]. It is important to determine whether the infea-
sible solutions are discarded or searched for finding feasible
solutions. Three strategies are generally used to handle infea-
sible solutions: reject, penalize, and repair [57]. Reject stra-
tegy is a simple approach where only feasible solutions are
kept. It is reasonable to use this strategy when computation time is
to be saved. Penalizing strategy focuses on designing an ap-
propriate penalty function for the infeasible ones. It is difficult
to find a good compromise between the objective value and
the penalty. Repair method is a constraints handling strategy.
In many cases, the feasible region of the search space is very
small, and feasible solutions may be surrounded by the infea-
sible ones. So it is necessary to guide the search towards
feasible regions based on the infeasible solution information.
In this paper, the acceptance criteria take infeasible solutions
into consideration.

3 Problem statement

As shown in Fig. 1, the problem studied in this paper is a
constraint optimization problem in which \( n_O \) jobs of the old
order \( J_O \) have been scheduled but not fully completed yet
when \( n_N \) jobs of the new order \( J_N \) come into the production
system [16, 25]. All jobs of the old order have a common due
date \( d_O \) which cannot be violated. Mathematically, it can be
expressed as \( T^{J_O}_{\max} = 0 \). It is assumed that new orders will
arrive continuously and randomly but only one at a time. So
it is a dynamic problem but order selection is not considered
in this paper. In order to set a tight due date for \( J_N \) and accept
the maximum number of orders, the objective is defined as min-
imizing the maximum completion time of the new order \( C^{J_N}_{\max} \)
given the constraint of machine availability, \( a_k \), following the
convention of [24]. The problem can be denoted as \( Fm \)
\([prmu, d_O, a_k | C^{J_N}_{\max} / T^{J_N}_{\max} = 0] \) according to [58] where \( Fm \)
represents a flowshop with \( m \) machines, \( prmu \) stands for
permutation, $d_O$ indicates that all jobs of the old order have a common due date, $a_k$ represents the availability on machine $k$ and $C_{J_N}^{max}/T_{J_O}^{max} = 0$ is a constrained objective. Therefore, the objective function and due date constraint can be expressed as

$$
\text{Min} : F(s) = C_{J_N}^{max}, \tag{1}
$$

$$
T_{J_O}^{max} = 0, \tag{2}
$$

where $s$ represents a job sequence. The assumptions are defined as follows.

1. All jobs should start as soon as possible;
2. Processing times are known and deterministic;
3. Setup time is included in the processing time for each operation;
4. Machines are continuously available but cannot process two or more jobs simultaneously;
5. Job pre-emption is not permitted;
6. Buffers’ capacity between machines is infinite;
7. Only permutation schedules are allowed;
8. Each order arrives randomly;
9. Only one order arrives at a time;
10. Each order may contain one or multiple jobs;
11. Job information is known when the order arrives;
12. All jobs in an order should be finished before its due date;
13. Once a new order arrives, rescheduling is activated;
14. If all existing jobs are finished and no new jobs arrive, all machines stay idle and available;
15. No more than two orders can be mixed together, i.e., only the last old order can be rescheduled with the newly arrived order.

Note that when the new order arrives, the existing uncompleted jobs from the old order will be rescheduled with the new order. Old order jobs and partial jobs from the new order have to be scheduled before the due date. Therefore, the slack between the due date and its completion time of the old order has a direct impact on the resulted schedule. A relaxed due date of the old order can absorb more jobs from the new order and have a better chance to obtain a high-quality schedule. So, a reasonable and relaxed due date for the old order is assumed.

To solve the above problem, a new meta-heuristic is proposed based on the IG algorithm. Three types of problems including due date setting, order acceptance, and maximizing the number of accepted orders are studied.

4 New meta-heuristic: a modified iterated greedy algorithm (eIG_Rep)

In this section, a new meta-heuristic algorithm named the enhanced iterated greedy algorithm with repair method (eIG_Rep) is proposed. It is derived from the IG algorithm which is a single-point meta-heuristic that only one population is saved and searched in each iteration. It is fast but easy to be trapped in a local optimum even if an acceptance criterion is used. Therefore, an effective escape mechanism from a local optimum should be designed. Besides, the studied problem in this paper has a strong due date constraint that jobs from the old order should be completed by their due date. The best feasible solution may be surrounded by and evolved from infeasible solutions. So, an effective repair method is required to convert infeasible solutions into feasible ones.

During the searching process, the following two challenging issues should be solved: (1) how to escape from a local optimum and (2) how to repair infeasible solutions effectively. To address these issues, a new destruction and construction method and a new repair approach are proposed in this paper.

Figure 2 shows the flow chart of the new eIG_Rep algorithm. First, during initialization, the initial solution is generated, and the local search is applied to the initial solution. The initial parameters are given including $\delta$, $z$, $\delta^*$, and $\bar{t}$. In the main body of the algorithm, destruction and construction, local search, repair method, and acceptance criterion are run in an iterated manner until the stopping criterion is satisfied. Note that in the new enhanced destruction and construction method, the number of perturbed jobs, $\delta$, should be first decided before destruction and construction phases. The local search is then applied to the incumbent. If the solution resulted from the local search is infeasible, repair it. Otherwise, acceptance criterion is conducted directly. The details of the new algorithm are described below.
4.1 Initialization

An initial population is required for the eIG_Rep algorithm at the beginning. For this need, three initial solutions are generated: one is obtained by the NEH heuristic [59] that jobs from both the old and the new orders are mixed and scheduled without accounting for the due date constraint; the other two are generated by RS and RT strategies [12] respectively implemented with the NEH heuristic. Among these three solutions, the feasible one with the best objective value is chosen as the initial best solution $S_{\text{best}}$. So, a feasible solution is guaranteed in the initialization phase as a relaxed due date is assumed and determined by RT strategy implemented with the NEH heuristic. The local search method is then applied to $S_{\text{best}}$. If a solution $S$ obtained through the local search is feasible and better than $S_{\text{best}}$, then $S_{\text{best}}$ will be updated by $S$. Note that $S$ is defined as the incumbent solution in each iteration. The local search method will be detailed in section 4.3.

Four key parameters $\delta$, $z$, $\delta'$, and $T_i$ are set during initialization. $\delta$ represents the number of perturbed jobs, $\delta'$ is the enlarged number of perturbed jobs in the destruction and construction method, $z$ indicates the number of iterations allowing the performance of the incumbent to remain steady while not enlarging perturbation, and $T_i$ represents a control parameter for the acceptance criterion.

4.2 New destruction and construction method

In the herein paper, a new destruction and construction method with a steered variation approach for $\delta$ is designed in order to escape efficiently from a local optimum while maximizing the computational efficiency. The new method is presented as follows.

In the destruction phase, $\delta$ jobs are randomly selected, half from the old order and half from the new order. So $\delta$ is defined as an even number. When the incumbent is trapped in a local optimum or its objective value stays unchanged for $z$ iterations, the perturbation will be intensified by replacing $\delta$ with a larger value $\delta'$ ($\delta' > \delta$). The number of removed and reinserted jobs increases to $\delta'$, so as to diversify the population and escape from the local optimum. Once the objective value of the incumbent is improved, $\delta$ is changed back to maintain algorithm efficiency.

For example, 4 ($\delta = 4$) jobs are evenly selected from both the old and new orders in destruction phase. If the objective value does not improve after 2 ($z = 2$) iterations, 6 jobs ($\delta' = 6$) are then selected to enlarge the perturbation. If the objective value is improved, $\delta$ is changed back to maintain algorithm efficiency.

In the construction phase, for our problem, many infeasible solutions will be generated if all positions are
investigated when inserting jobs of the old order. The due date constraint will be violated if the jobs of the old order are reinserted after the due date. To avoid infeasible solutions, the idea of general local search [13] is used. If the job belongs to the new order, it is reinserted into each possible position. For the job from the old order, it is reinserted into each possible and feasible position given the due date constraint. That is, if the maximum completion time of the reinserted job exceeds the due date, the subsequent positions are then neglected. After construction, if a better and feasible solution is generated, then $S_{best}$ is updated.

4.3 Local search

In the IG algorithm, a local search can be applied after the construction phase to improve its performance [21]. In this paper, the general local search method [13] is modified to avoid infeasible solutions and save computational time.

Flow chart of the local search is shown in Fig. 3. For a given solution, choose one job and insert it into each possible and feasible position sequentially. When inserting jobs by using Taillard improvement [60], jobs from the old order are inserted given the due date constraint. That is, when the maximum completion time of the inserted job exceeds the due date, the subsequent positions are then neglected.
Identify all tardy jobs and early jobs in the infeasible solution

Yes

No early jobs?

No

Calculate the Euclidean distances between the tardy job and early jobs, and choose the pair with the least Euclidean distance

Swap the positions of the paired jobs

No

All tardy jobs reinserted?

Yes

End

Insert the tardy job before the last job of the old order randomly

Start

Fig. 4 Flow chart of new repair method

Fig. 5 ARPD values of different parameter combinations on small instances of VRF benchmark
Table 1 ARPD values of each algorithm on Taillard benchmark

| Problem | RS_NEH | RT_NEH | MR_WWD | RS_IG | RT_IG | RVNS | eIG_Rep |
|---------|--------|--------|--------|-------|-------|------|---------|
| 20 × 5  | 19.95  | 10.35  | 6.51   | 17.86 | 9.36  | 3.21 | 2.30    |
| 20 × 10 | 19.36  | 11.14  | 9.46   | 19.99 | 8.73  | 3.03 | 1.35    |
| 20 × 20 | 18.09  | 10.86  | 3.73   | 17.27 | 8.32  | 1.18 | 0.11    |
| 50 × 5  | 11.83  | 5.28   | 2.78   | 10.78 | 4.36  | 1.28 | 0.45    |
| 50 × 10 | 22.90  | 11.09  | 8.24   | 18.83 | 7.07  | 5.66 | 2.52    |
| 50 × 20 | 23.00  | 12.10  | 9.19   | 19.84 | 8.56  | 6.89 | 3.29    |
| 100 × 5 | 10.45  | 3.77   | 1.71   | 8.26  | 2.92  | 1.08 | 0.28    |
| 100 × 10| 15.30  | 7.25   | 4.61   | 12.66 | 5.36  | 3.90 | 1.58    |
| 100 × 20| 20.16  | 10.98  | 8.01   | 17.17 | 7.35  | 7.23 | 4.04    |
| 200 × 10| 12.43  | 4.11   | 3.05   | 10.80 | 3.04  | 2.55 | 1.16    |
| 200 × 20| 18.24  | 8.94   | 7.03   | 19.84 | 8.56  | 6.89 | 3.29    |
| 500 × 20| 12.83  | 4.94   | 4.60   | 11.66 | 4.30  | 4.00 | 3.37    |

Table 2 ARPD values of each algorithm on VRF benchmark

| Problems | RS_NEH | RT_NEH | MR_WWD | RS_IG | RT_IG | RVNS | eIG_Rep |
|----------|--------|--------|--------|-------|-------|------|---------|
| S        | L      | S      | L      | S     | L     |      |         |
| 10 × 5   | 19.32  | 14.52  | 11.26  | 6.79  | 4.29  | 3.03 | 18.44   |
| 10 × 10  | 14.25  | 20.82  | 8.09   | 10.75 | 2.06  | 5.63 | 12.84   |
| 10 × 15  | 19.16  | 16.20  | 10.49  | 8.07  | 4.12  | 4.02 | 16.24   |
| 30 × 5   | 14.82  | 15.30  | 5.16   | 8.01  | 1.64  | 3.98 | 9.69    |
| 30 × 10  | 22.82  | 13.34  | 12.33  | 5.77  | 5.26  | 2.48 | 19.77   |
| 30 × 15  | 25.97  | 14.76  | 14.67  | 7.20  | 5.73  | 3.54 | 23.33   |
| 40 × 5   | 19.73  | 14.51  | 11.67  | 7.12  | 5.41  | 3.62 | 17.74   |
| 40 × 10  | 50.40  | 16.20  | 10.49  | 8.07  | 4.12  | 4.02 | 16.24   |
| 60 × 5   | 22.64  | 14.03  | 12.13  | 6.88  | 6.08  | 3.28 | 17.98   |
| 60 × 10  | 21.88  | 10.97  | 13.13  | 4.27  | 5.16  | 1.72 | 18.14   |
| 60 × 15  | 24.89  | 14.76  | 14.67  | 7.20  | 5.73  | 3.54 | 23.33   |
| 80 × 10  | 20.09  | 12.99  | 10.40  | 6.43  | 4.45  | 2.88 | 16.20   |
| 80 × 15  | 22.77  | 10.39  | 12.52  | 4.09  | 6.38  | 1.38 | 18.68   |
| 80 × 20  | 21.56  | 12.81  | 11.97  | 5.96  | 5.91  | 2.71 | 18.86   |
| 100 × 5 | 12.35  | 12.78  | 3.59   | 6.19  | 1.51  | 2.71 | 9.78    |
| 100 × 10 | 18.74  | 9.49   | 10.25  | 3.79  | 3.81  | 1.29 | 16.54   |
| 100 × 15 | 22.73  | 11.93  | 12.12  | 5.32  | 5.97  | 2.60 | 18.84   |
| 120 × 5 | 20.52  | 12.13  | 12.06  | 5.76  | 6.44  | 2.71 | 18.33   |
| 200 × 5 | 18.54  | 14.28  | 9.76   | 6.92  | 3.87  | 3.31 | 15.92   |
| AVG     | 14.38  | 6.15   | 2.50   | 1.64  |

The italic number is the best ARPD value for each problem.
date, the subsequent positions are not examined. All jobs are selected and inserted one by one and the best solution is saved. After local search, if the generated solution is feasible and better than S\textsubscript{best}, then S\textsubscript{best} is updated. Otherwise, a repair method is applied.

### 4.4 New repair method

Although infeasible solutions whose completion times are beyond the due date constraint are largely avoided, many infeasible solutions with better objective values would be generated after the local search. Therefore, a repair method is required to convert these infeasible solutions into feasible ones during the search. In this paper, a novel repair mechanism is proposed.

Figure 4 shows the flow chart of the new repair method. The jobs of the old order J\textsubscript{T} which are completed beyond their due date are selected and defined as tardy jobs. The jobs of the new order J\textsubscript{E} which are scheduled before the due date are deemed as early jobs. In order to fix the infeasible solutions and keep their excellent performance, the tardy jobs and early jobs with similar processing times are paired and swapped one by one until all tardy jobs are scheduled before the due date. Herein, the least Euclidean distance is introduced as a measure of similarity of tardy and early jobs, in order to maintain the overall performance of the schedule after swapping. The Euclidean distance between two jobs is defined as

\[
Ed = \sqrt{\sum_{i=1}^{m} (t_{j_i} - t_{k_i})^2}, \quad i \in [1, m], \quad j \in [1, n_O], \quad k \in [1, n_N].
\]

If the number of tardy jobs J\textsubscript{T} is larger than that of J\textsubscript{E}, the rest jobs in J\textsubscript{T} after pairing will be randomly inserted before the last job position of the old order. After repairing, if a feasible and better solution is found, S\textsubscript{best} is then updated.

### 4.5 Acceptance criterion

In the IG algorithm, a simulated annealing-like acceptance criterion is normally used to improve population diversification and escape from a local optimum. During searching, the incumbent does not have to be feasible. If the solution S' resulted from the local search or the repair method has a better objective value, it is then used as the new incumbent S. If the solution S' is worse than previous incumbent, it can also be accepted as the new incumbent with a probability of

\[
e^{-\frac{(C_{\text{inc}}(S') - C_{\text{inc}}(S))}{\text{Temp}}},
\]

where Temp = \(T_i \times \frac{\sum \text{sumt}}{n_O \times n_N \times 10}\), where sumt is the sum of job processing times including the remaining jobs of the old order and the new order, n\textsubscript{1} is the number of the remaining jobs from the old order, n\textsubscript{2} is the number of jobs from the new order, and T\textsubscript{i} is a parameter to adjust the temperature which needs to be defined in the initialization. Otherwise, the current incumbent S is retained if the probability is not satisfied.

### 4.6 Calibration

In order to fully investigate algorithm potentials, parameter values should be decided carefully. In this paper, reference algorithms such as RS_NEH [12], RT_NEH [12], MR_WWD [25], RS_IG, RT_IG, and RVNS [13] are included. As few studies are involved with this topic, three existing heuristic algorithms, namely RS_NEH, RT_NEH, and MR_WWD are considered. No parameters need be tuned for them. IG is also adopted with RS and RT strategies, denoted by RS_IG and RT_IG for performance comparison. RVNS, as the existing study on this topic, is taken as the reference in this paper.

The parameters of IG algorithms in RS_IG and RT_IG algorithms should be carefully selected and kept same. Since the studied problem in this paper is similar to that of [13], \(\delta = 4\) and \(T_i = 0.4\) are selected as they have been confirmed robust in solving PFSPs and due date setting problems.
RVNS algorithm [13] focuses on setting tight due dates for new orders by minimizing makespan of the new order. It can be transformed into solving dynamic PFSPs with new order arrivals, and it is taken as a reference algorithm. In the RVNS algorithm, two parameters are required, i.e., \( k_{\text{max}} \) and \( q \). \( k_{\text{max}} \) is the maximum number of jobs in shaking method and \( q \) is the percentage of jobs in escape procedure. According to [13], \( k_{\text{max}} \) is set as 40 and \( q \) is randomly obtained between 75 and 95% of the number of jobs in either the old or the new order depending on the feasibility of the solution.

In the new algorithm, eIG_Rep, four parameters including \( \delta \), \( z \), \( \delta' \), and \( T_i \) need to be defined. The test ranges of each parameter are described as follows.

\[
\delta \in \{2, 4, 6, 8\}, \\
z \in \{1, 2, 4, 6\}, \\
\delta' \in \{4, 6, 8, 10\}, \\
T_i \in \{0.2, 0.3, 0.4, 0.5, 0.6\}.
\]

Due to \( \delta' > \delta \), \((4 + 3 + 2 + 1) \times 4 \times 5 = 200\) combinations in total can be generated for the eIG_Rep algorithm. To choose the most robust parameters for the eIG_Rep algorithm, all 200 combinations are tested.

Herein, the objective of setting a tight due date for the new order is taken for algorithm calibration since it can be validated on a large number of instances. The small instances of VRF benchmark [61] are used as samples. Each instance is evenly divided into two sets: the first half including the front part of the instance is taken as the old order while the second half is defined as the new order. Herein, the old order due date is set as a constant, \((1 + \alpha) \times C_{\text{JO}}^{\text{max}}, \) where \( \alpha \) is the relaxation factor and \( C_{\text{JO}}^{\text{max}} \) is the maximum completion time of the old order obtained by the NEH heuristic. \( \alpha \) is defined as 0.4. The computation time limit \( n \times (m/2) \times t \) milliseconds where \( t = 60 \) [21, 62] is defined as the stopping criterion. To avoid stagnation, all algorithms are run for 10 independent times and the best solution for each instance is retained. Note that the stopping criterion is also used in the following sections. All algorithms are coded in Matlab R2014b and run on a CPU E5520 computer with 6G memory.

To evaluate each algorithm, the performance measure of relative percentage deviation (RPD) is employed, and it is computed as follows:

\[
\text{RPD} = \frac{C_{\text{JO}}^{\text{max}} - UB}{UB} \times 100\%,
\]

where \( C_{\text{JO}}^{\text{max}} \) is the maximum completion time of the new order obtained on every instance, \( UB \) is the upper bound for each instance. The \( UB \) values provided by Vallada et al. [61] are used directly because the problem can be deemed as a static permutation flowshop scheduling problem if the slack between the completion time and due date of the old order is very loose and all jobs from the new order can be completed in the slack.

Figure 5 shows the results of each combination of the parameters on small instances of VRF benchmark. As shown in Fig. 5, the best three combinations \( \{\delta, z, \delta', T_i\} \) associated with

| Pair | Paired differences | \( t \) | \( p \) |
|------|--------------------|--------|--------|
| RS_NEH – eIG_Rep | 14.94651 | .45780 | 14.04001 | 15.85301 | 32.648 | .000 |
| RT_NEH – eIG_Rep | 6.30151 | .33727 | 5.63368 | 6.96934 | 18.684 | .000 |
| MR_WWD – eIG_Rep | 3.64559 | .23142 | 3.18736 | 4.10382 | 15.753 | .000 |
| RS_IG – eIG_Rep | 13.02019 | .47275 | 12.08409 | 13.95628 | 27.541 | .000 |
| RT_IG – eIG_Rep | 4.26178 | .30006 | 3.66764 | 4.85593 | 14.203 | .000 |
| RVNS – eIG_Rep | 1.81990 | .11024 | 1.60160 | 2.03819 | 16.508 | .000 |

| Pair | Paired differences | \( t \) | \( p \) |
|------|--------------------|--------|--------|
| RS_NEH – eIG_Rep | 14.76971 | .23650 | 14.30500 | 15.23442 | 62.451 | .000 |
| RT_NEH – eIG_Rep | 6.69939 | .16645 | 6.37233 | 7.02645 | 40.249 | .000 |
| MR_WWD – eIG_Rep | 1.94909 | .08031 | 1.79130 | 2.10689 | 24.271 | .000 |
| RS_IG – eIG_Rep | 12.74025 | .19755 | 12.35208 | 13.12841 | 64.492 | .000 |
| RT_IG – eIG_Rep | 4.51068 | .11758 | 4.27964 | 4.74172 | 38.362 | .000 |
| RVNS – eIG_Rep | .86038 | .04103 | .77976 | .94101 | 20.969 | .000 |
the lowest average RPD (ARPD) values on every instance are \(\{2, 1, 6, 0.5\}, \{4, 2, 6, 0.6\}, \) and \(\{6, 4, 6, 0.6\}\). To further check the performance of these parameter combinations, they are tested on VRF large instances and results show that the combination \(\{4, 2, 6, 0.6\}\) provides robust solutions on both small and large instances. So, the parameters of the new algorithm eIG_Rep are set as \(\{4, 2, 6, 0.6\}\).

5 Experimental validation

To validate the new algorithm, two evaluation schemes are conducted. One is to set the earliest due dates for new orders, and the second is to maximize the accepted number of orders whose due dates are given by a case study. The criterion of accepting an order is based on the due date. If the new order can be completed by its due date, it is accepted. Otherwise, it is rejected.

![Fig. 8 Convergence curve of eIG_Rep on TA052 Taillard instance](image)

![Fig. 9 Convergence curve of eIG_Rep on VRF 30_20_2 instance](image)

| Order no. | Arrival time | Due date | eIG_Rep |
|-----------|--------------|----------|---------|
| No. 1     | 0            | 1800     | 1743    |
| No. 2     | 8            | 2919     | 1743    |
| No. 3     | 10           | 2964     | 1743    |
| No. 4     | 9            | 2868     | 1743    |
| No. 5     | 7            | 6216     | 1743    |
5.1 Setting a tight due date

To fully evaluate the effectiveness of the new eIG_Rep algorithm, both Taillard [63] and VRF benchmarks are used, and the performance measure ARPD is adopted. As described in section 4, each instance is evenly divided into two sets representing old and new orders. The old order due date is set as $(1 + \alpha)\times C_{\text{max}}$, where $\alpha$ set as 0.4. The $UB$ values for Taillard benchmark are taken from [64]. Each meta-heuristic algorithm is run for ten times and the best one on each instance is retained.

Table 1 shows the test results of each algorithm on Taillard benchmark. The new eIG_Rep algorithm has an ARPD value of 2.10 which is much better than that of all the other references including RS_NEH, RT_NEH, MR_WWD, RT_IG, RS_IG, and RVNS algorithms. It performs best under most situations. Note that these algorithms, such as MR_WWD, RVNS, and eIG_Rep, allowing order mixing, show better performance than RS_NEH, RT_NEH, RS_IG, and RT_IG algorithms in which no order mixing is allowed.

Test results on VRF benchmark are shown in Table 2. The same conclusion can be obtained. The eIG_Rep algorithm provides the best result in terms of ARPD, followed by RVNS, MR_WWD, RT_IG, RT_NEH, RS_IG, and RS_NEH algorithms.

Figures 6 and 7 show the means plots and 95 confidence intervals of each algorithm on both benchmarks. No overlaps of ARPD means are observed between eIG_Rep and other algorithms, demonstrating that eIG_Rep shows significantly better performance.

In order to check if the differences of these ARPD values are statistically significant, the paired samples $t$ test is conducted with a confidence level of 95%. Results are shown in Table 3 and Table 4 for both Taillard and VRF benchmarks. The $p$ values for the comparison of the new algorithm are 0.000 on both test beds. Thus, it can be concluded that there are significant differences between the performances of the new algorithm eIG_Rep comparing to these reference algorithms.

Figures 8 and 9 show the convergence curve of the new algorithm on two instances, TA052 from Taillard and VRF 30_20_2 instance. The algorithm, eIG_Rep, is run for five times independently on each instance. It can be observed that the new algorithm generates stable solutions each time. The solution quality improves after several iterations as the size of the new destruction and construction method varies, escaping from a local optimum.

5.2 Case study on maximizing the number of accepted orders

To check the capability of each algorithm for the objective of maximizing the acceptance of new orders, a case study is conducted. It is assumed that ten orders with assigned individual due dates arrive continuously and randomly. Both the arrival times and due dates of each order are generated randomly. The ten orders are selected from Taillard benchmark [63], i.e., TA011-20 instances.

Table 5 shows the test results of order acceptance. No more than half of the new orders are completed by due dates if RS_IG and RT_IG algorithms are used. RVNS algorithm can accept seven new orders while the new eIG_Rep algorithm can complete nine new orders before their due dates. It can be seen that the algorithms with order mixing show a better chance of obtaining high-quality schedules against makespan. More orders can be absorbed and completed by their due dates. And eIG_Rep is more effective than RS_IG, RT_IG, and RVNS algorithms for this case.

6 Conclusions

This paper proposes a new algorithm for solving dynamic scheduling problems in permutation flowshops with new order arrivals. A new algorithm, named as eIG_Rep, is introduced based on a new destruction and construction method together with a novel effective repair method. The new destruction and construction method is developed by changing the strength of perturbation if the population performance remains unchanged for some iterations, in order to escape from a local optimum while maintaining high computational efficiency. The new repair method is developed for the first time by swapping tardy and early jobs. By using the new repair method, the infeasible solutions are converted into feasible ones while maintaining their solution quality as much as possible.

Statistical test results show that the new algorithm eIG_Rep is effective and outperforms the existing and reference algorithms including RS_NEH, RT_NEH, MR_WWD, RS_IG, RT_IG, and RVNS. This new eIG_Rep algorithm can be well applied to three types of problems, i.e., due date setting problem, order acceptance problem, and maximizing the number of accepted new orders. For the problem of setting tight due dates of orders, both the Taillard and VRF test beds are used for algorithm validation and the effectiveness of the new algorithm is demonstrated on both benchmarks. For the problems of order acceptance and revenue maximization, ten orders are assumed by assigning random arrival times and due dates when evaluating the new algorithm. Test results show that more orders can be completed by their due dates than existing algorithms by using the new algorithm eIG_Rep.
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