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Integrated Production and Distribution Problem of Perishable Products with a Minimum Total Order Weighted Delivery Time

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Abstract: In this paper, an integrated production and distribution problem for perishable products is presented, which is an NP hard problem where a single machine, multi-customers, and homogenous vehicles with capacity constraints are considered. The objective is to minimize the total order weighted delivery time to measure the customer service level, by making two interacted decisions, production scheduling and vehicle routing, simultaneously. An integrated mathematical model is built, and the validity is measured by the linear programming software CPLEX by solving the small-size instances. An improved large neighborhood search algorithm is designed to address the problem. Firstly, a two-stage algorithm is constructed to generate the initial solution, which determines the order production sequence according to the given vehicle routing. Secondly, several removal/insertion heuristics are applied to enlarge the search space of neighbor solutions. Then, a local search algorithm is designed to improve the neighbor solutions, which further generates more chances to find the optimal solution. For comparison purposes, a genetic algorithm developed in a related problem is employed to solve this problem. The computational results show that the proposed improved large neighborhood search algorithm can provide higher quality solutions than the genetic algorithm.

Keywords: integrated; production scheduling; distribution; large neighborhood search algorithm

1. Introduction

The usage of perishable products has a negative time sensitivity; that is, the usefulness or value of products decreases with time. The definition of perishable products was proposed by [1]. If at least one of the following conditions occurs during the planning period, goods that are raw materials, intermediate products, or final products can be called perishable products: "(1) its physical status deteriorates obvious, and/or (2) its value decreases in the customer's perception, and/or (3) some authorities believe that the future functions may be reduced". Therefore, perishable products have a wide range of definitions, including fresh fruits and vegetables, flowers, food, and other products with a short lifespan, such as blood, drugs, and concrete.

Perishable products should not be delivered long after production, so as to meet customer orders. In addition, companies with such products have employed make-to-order strategies, aiming to reduce the production and delivery lead time [2]. Obviously, for perishable products, it is insufficient to consider the production scheduling or logistics transportation optimization separately. For example, to reduce the value loss of perishable products in delivery, if we make the production start time of the orders as late as possible, it may be difficult to achieve a transportation scheduling of products that is optimal, and the scheduling may be infeasible. In contrast, if only the order transportation optimization is considered, it may lead to excessive production ahead of schedule, leading to a greater

value loss. Thus, production scheduling and distribution scheduling decisions should be made jointly at the operational level.

The integrated scheduling of production and distribution has received a lot of attention in recent years [3]. Various problems have been studied for industries such as fashion apparel and toys [4,5], consumer electronics [6], food catering industry [7,8], newspaper [9–11], home healthcare [12], and customized furniture [13]. For perishable products, there is less literature on optimizing production and transportation scheduling simultaneously [2,14–20]. Most of them consider one vehicle to serve all customers, simplifying routing decisions. Therefore, the integrated production and distribution problem for perishable products deserves further study.

In this paper, an integrated production and distribution problem for perishable products (IPDPPP) is presented. As shown in Figure 1, one machine and multi-customer are taken into account. Each customer has only one order, with a different weight according to the importance of each order. The produced products are transported by trucks to customers, without warehousing. In order to make full use of the vehicle capacity, different customers' orders can be loaded into the same vehicle. Obviously, the IPDPPP has to make two decisions—production scheduling and vehicle routing. Production scheduling means to determine the order production sequence. In addition, the orders must be batched first, and the orders in the same batch are produced in succession. Then, each batch is loaded onto a same vehicle. Vehicle routing aims to determine the optimized routing for each vehicle. While the collaborative scheduling problem usually takes customer response time as the first concern, trying to achieve better customer service with lower logistics costs under limited resource constraints [21], the objective of the IPDPPP is to minimize the total order weighted delivery time by making two decisions simultaneously.

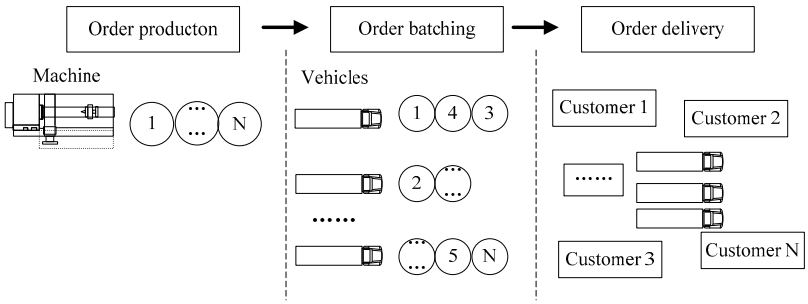


Figure 1. The integrated production and distribution scheduling procedure.

The main highlights are as follows. Firstly, the vehicle routing decision is considered, except for production scheduling, which is simplified in the majority of literature, with respect to the complexity of the problem. Secondly, the objective of this problem is to minimize the total order weighted delivery time, which is usually applied to measure the customer service level [21]. Thirdly, an improved large neighborhood search algorithm is proposed to address the problem. An initial solution is constructed by a two-stage algorithm. Then, the initial solution is improved by exploring a complex neighborhood, and a local search for improving the neighbor solution is developed. Finally, the experimental results show that the improved large neighborhood search algorithm is effective and efficient. Compared with the results of CPLEX and the published genetic algorithm for the related problem, the optimal or approximate optimal solution can be obtained by the improved large neighborhood search algorithm.

The paper is organized as follows. In Section 2, the relevant literature of the IPDPPP is reviewed. In Section 3, a mathematical model for the integrated problem is built. In Section 4, an improved large neighborhood search algorithm is described to solve the problem, and its performance is analysed in Section 5. Section 6 draws the main conclusions.

2. Literature Review

Recently, the IPDPPP has received considerable attention, but there is not much literature about it. In most of the cases, one customer or infinite vehicles are considered, thus vehicle routing is simplified or ignored [22].

For the IPDPPP without routing decisions, an integrated production–distribution model for a deteriorating inventory item was built [23], where one customer was considered. Thus, the routing of the delivery did not need to be decided. The objective was to minimize the total cost. Although considering multi-customers in [24–28], the vehicle routing problem was simplified by direct delivery, which means that each vehicle only served one customer in one trip. The objectives were to minimize the total cost or total transportation time. The IPDPPP considering items with a short lifetime were studied in [29–32]. They assumed that transportation is outsourced to third-party-logistics (3PL) providers, and the products are picked up at regular times. The routing decision was ignored by the manufactories, and only the order production scheduling was optimized. The objectives were to minimize the total profit or total cost. A food production and distribution was mentioned in [33], where infinite vehicles were considered for direct delivery. The objective was to minimize the total cost. A nuclear medicine production and delivery problem considering infinite vehicles was studied in [34]. The objective was to minimize the total cost. The infinite vehicles were also considered in [35], and the objective was to minimize the total cost. A chemotherapy production and delivery problem was addressed in [36]. There was one customer and one vehicle. The vehicle could make more than one trip between the pharmacy production unit and the patient location. The objective to minimize was the maximum tardiness of delivery. Different from the above articles, this paper considers multi-customer and finite vehicles simultaneously; both the order production scheduling and the vehicle routing are optimized. The objective is to minimize the total order weighted delivery time in this paper, which differs from these papers.

The IPDPPP becomes more complex when routing decisions are considered. The IPDPPP with time windows was addressed in [16]. They assumed that the demands of customers are stochastic. The aim was to maximize the expected total profit of the supplier. The IPDPPP considering the time windows and parallel production lines were studied in [18,37], the goals were to minimize the total cost. An integrated supply chain scheduling problem along with the batch delivery consideration was investigated in a series of multi-factory environments [38], while considering the due date of each order. The aims were to reduce the total cost of transportation and the total tardiness. The products with a short lifespan were considered in [2,14,15,17,19,20], as well as the order production sequence and delivery sequence were fixed. A truck that has enough capacity to deliver all of the orders in one trip was mentioned in [14,17]. The goal was to maximize the total demand without violating the production/distribution capacity, the product lifespan, and the delivery time window, by selecting a subset of customers from a given sequence to receive the deliveries. While one truck with a limited capacity for transportation was considered in [2,15], which could travel many trips. The goal was to minimize the maximum delivery time of the orders. Multi-trucks with a limited capacity for transportation was addressed in [19,20], which could travel many trips. Their objectives were to minimize the total cost and makespan, respectively. Comparatively, we relaxed the time windows constraint in this paper, which further increases the complexity of the problem due to an expansion in search space. The time windows constraint was also relaxed in [22], the scheduling of production and delivery were considered in a make-to-order environment considering a single machine, multi-customers, and multi-vehicles. The objective was to minimize the makespan and an improved genetic algorithm was proposed. In this paper, however, the objective is to minimize the total order weighted delivery time, which receives relatively less attention in existing literature.

As a result of the complexity in integrated production scheduling and transportation problems, they were solved, in general, via heuristic algorithms. Such as, the branch-and-bound algorithm [2,14], the genetic algorithm [15], the Nelder–Mead method with a heuristic algorithm [16], a new heuristic algorithm [17], the adaptive large neighborhood search [18], a heuristics algorithm based on evolutionary

algorithms [19], a greedy randomized adaptive search procedure with an evolutionary local search [20], a Benders decomposition-based heuristic [36], a novel three-phase methodology [37], and a Pareto approach [38]. What is more, in other areas of combinatorial optimization, new algorithms have emerged, such as multi-criteria optimization [39], and a biased-randomized iterated local search algorithm [40]. In this paper, an improved large neighborhood search algorithm is considered. By applying the proposed algorithm, the neighbors could be enlarged by their removal heuristics and insertion heuristics. Then, the solution space is enlarged, which generates more chances to find the optimal solution.

3. Problem and Model Definition

In this section, a mathematical model of the IPDPPP is developed. In the production phase, one machine is considered to produce products from all of the orders at a plant, with a constant production rate of η. The machine will not be able to produce a new order until the order being processed has been completed. $P = \{0, 1, 2, \ldots, n\}$ denotes the set of the plant and all of the customers, with 0 representing the plant and $N = \{1, 2, \ldots, n\}$ representing the customers. $A = \{(i, j); i, j \in P\}$ denotes the set of edges, with each edge having a travelling time of b_{ij} (from the plant to a customer or from a customer to another customer).

Customers are in different geographical locations. Each customer places an order to the plant, and $F = \{f_1, f_2, \ldots, f_n\}$ is the set of all orders. w_i denotes the weight of the order, f_i, which presents the importance of the order, f_i. Each order, f_i, has a definite demand, d_i, then the order processing time, t_i, can be calculated according to the formula $t_i = d_i/\eta$.

$U = \{1, \ldots, H\}$ is the set of multiple homogenous vehicles with a capacity of Q. Each vehicle can be used at the most once, starting and ending at the plant. The loaded order quantity of a vehicle cannot exceed the vehicle's capacity. Each customer's demands must be delivered at one time, not in batches. Orders belonging to different customers can be delivered by the same vehicle within one trip. We defined the departure time as the time when the vehicle leaves the plant. The objective is to minimize the total weighted delivery time of the orders, which is clearly influenced by the departure time and the transportation time of each vehicle.

The other notations are defined as follows:

Decision variables:

$$x_{ij}^h = \begin{cases} 1, \text{if vehicle } h \text{ visit the edge } (i,j) \\ 0, \text{otherwise} \end{cases} \quad y_i^h = \begin{cases} 1, \text{if vehicle } h \text{ is loaded with order } f_i \\ 0, \text{otherwise} \end{cases}$$

$$z_{ij} = \begin{cases} 1, \text{if order } f_i \text{ is produced prior to order } f_j \\ 0, \text{otherwise} \end{cases}$$

Variables:

V_i: the production completion time of order f_i D_i^h : the arrival time of vehicle h at customer i

Objective function:

$$Min \sum_{h=1}^{H} \sum_{j=1}^{n} w_j D_j^h \tag{1}$$

Constraints:

$$\sum_{h=1}^{H} \sum_{i=0}^{n} x_{ij}^h = 1 \; j = 1, 2, \ldots, n \tag{2}$$

$$\sum_{i=1}^{n} x_{i0}^h = 1 \; h = 1, 2, \ldots, H \tag{3}$$

$$\sum_{j=1}^{n} x_{0j}^{h} = 1 \; h = 1, 2, \ldots, H \tag{4}$$

$$\sum_{i=0}^{n} x_{ig}^{h} - \sum_{j=1}^{n} x_{gj}^{h} = 0 \; g = 1, 2, \ldots, n, \; h = 1, 2, \ldots, H \tag{5}$$

$$\sum_{i=0}^{n} \sum_{j=1}^{n} x_{ij}^{h} d_j <= Q \; h = 1, 2, \ldots, H \tag{6}$$

$$C_0 = 0 \tag{7}$$

$$V_i + t_j - V_j \leq (1 - z_{ij}) M \; i = 0, 1, 2, \ldots, n \; , \; j = 1, 2, \ldots n \tag{8}$$

$$\sum_{i=0}^{n} z_{ij} = 1 \; j = 1, 2, \ldots, n \tag{9}$$

$$\sum_{j=1}^{n+1} z_{ij} = 1 \; i = 1, 2, \ldots, n \tag{10}$$

$$D_i^h + b_{ij} - D_j^h \leq (1 - x_{ij}^h) M \; i = 0, 1, 2, \ldots, n, \; j = 1, 2, \ldots, n, \; h = 1, 2, \ldots, H \tag{11}$$

$$D_i^h \geq 0, \; i = 0, 1, 2, \ldots, n, \; h = 1, 2, \ldots, H \tag{12}$$

$$D_0^h \geq \max_{j \in N} (V_j y_j^h), \; h = 1, 2, \ldots, H \tag{13}$$

$$y_j^h = \sum_{i}^{n} x_{ij}^h \; j = 1, 2, \ldots, n, h = 1, 2, \ldots, H \tag{14}$$

$$x_{ij}^h \in \{0, 1\} \; y_j^h \in \{0, 1\} \; z_{ij} \in \{0, 1\} \; i = 0, 1, 2, \ldots, n, \; j = 1, 2, \ldots, n, \; h = 1, 2, \ldots, H \tag{15}$$

Objection Function (1) aims at minimizing the total weighted delivery time of the orders. Constraint (2) indicates that each customer's demands must be met at one time. Constraints (3) and (4) ensure that each vehicle can be used once, starting and ending at the plant. Constraint (5) represents that the entering vehicle of a customer must eventually leave that customer. Constraint (6) shows that the vehicle capacity cannot be exceeded. Constraint (7) represents the starting time of a machine. Constraints (8) to (10) ensure that each order has a single predecessor and a single successor in the production phase. Constraints (11) to (12) ensure that each customer has a single predecessor and a single successor in the delivery phase. Constraint (13) ensures that the departure time of each vehicle is greater than or equal to the latest production completion time among the orders onboard the vehicle. Constraint (14) indicates that each customer has to be served. Constraint (15) is the integer conditions.

The IPDPPP is an NP-hard problem, optimizing both production scheduling and vehicle routing [22]. Intelligent algorithms have made great achievements in solving production scheduling [41,42], and vehicle routing problems [43,44]. For the complexity of the integration of the production scheduling and distribution problem, metaheuristic can be an appropriate approach to solve it [38]. Therefore, a heuristic algorithm is developed.

4. An Improved Large Neighborhood Search Algorithm

The specialty of our problem is that production scheduling and vehicle routing are considered jointly, which interplay with each other. Production scheduling determines the production sequence of every order; the vehicle routing problem determines the delivery sequence of each order for every vehicle. It is remarkable that the vehicle routing problem is a weighted traveling repairman problem (TRP), not a traditional traveling salesman problem (TSP), as the aim of this research is to minimize the total order weighted delivery time in this research. The difference between them is that the TRP

aims at minimizing the sum of all the customers' delivery times by taking into account customers' satisfaction [45,46]; while the TSP aims at minimizing the total distances. For example, for a TRP problem or a weighted TRP, if the sequence of all of the customers in a route is reversed, the objective value would be changed; however, for a TSP problem, the objective value is not affected. Therefore, the heuristics to discuss the integration of production and transportation in the literature, with the goal of total cost or makespan, is not suitable to solve this problem.

With respect to the above special consideration, an improved large neighborhood search (ILNS) algorithm is proposed. The large neighborhood search (LNS) algorithm is a meta-heuristic algorithm, which finds better candidate solutions by exploring complex neighborhoods defined by destroy and repair methods. A destroy method destructs part of the current solution, while a repair method rebuilds the destroyed solution. By alternating between an infeasible solution and a feasible solution through destroy and repair methods, the LNS algorithm has been widely used in various combinatorial optimization problems, and has been proved effectively, such as for vehicle routing problems [47–49], machine scheduling problems [50,51], supply chain network design [52], satellites scheduling [53], and exam scheduling problems [54]. By applying the LNS algorithm to solve our problem, the neighbors could be enlarged, so as to solve the solution space. Compared with the traditional LNS algorithm, in addition to the above benefits, the improved large neighborhood search (ILNS) algorithm proposed in this paper uses a two-stage algorithm to construct the initial solution, and proposes a local search to improve the neighbor solution, which generates more chances to find the optimal solution. The ILNS algorithm includes the following five stages, and the major procedure of the ILNS algorithm is shown in Figure 2.

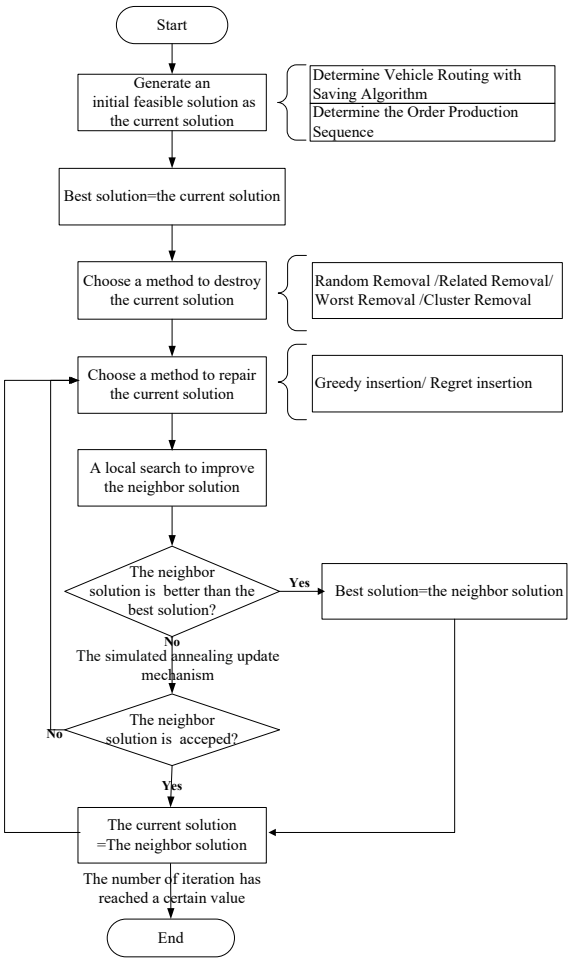


Figure 2. The major procedure of the improved large neighborhood search algorithm.

Stage 1: Initial solution generation. A two-stage algorithm is developed in the generation. The vehicle routing is determined with the savings algorithm first. Then, the order production sequence is determined by a certain rule, and the objective value of the solution is computed. The constructed initial solution is used as the current solution. The best solution is also equal to the initial solution at this stage.

Stage 2: Neighbor solution generation. A neighborhood is defined implicitly by a destroy and a repair method. In this paper, the destroy method consists of four removals, and the repair method consist of two insertion algorithms. Every time a neighbor solution is derived with the current solution, a certain removal and insertion algorithm is chosen with a certain rule. Each time the vehicle routing is generated, the order production sequence is determined, and the objective value of the neighbor solution is computed.

Stage 3: Local search. A local optimization algorithm is employed to improve the quality of the generated neighbor solutions.

Stage 4: Acceptance rule. If the newly derived neighbor solution is better than the best solution, we update the best solution and set it to be the new current solution; otherwise, the judgement criterion of the simulated annealing algorithm will be used to decide whether to accept the neighbor solution as the new current solution or not.

Stage 5: Stopping criterion. Such an iteration process (Stages 2 and 4) will be repeated until the defined number is reached.

4.1. Construction of an Initial Solution

A two-stage algorithm is proposed to construct the initial solution. First, the vehicle routing is determined with a savings algorithm. When the vehicle routing is given, the orders loaded on each vehicle are called a batch. Second, the production sequence of the orders in each batch is generated based on the vehicle routing. Finally, the objective value is calculated.

4.1.1. Determine Vehicle Routing with a Saving Algorithm

The saving algorithm for the vehicle routing problem is introduced in [55]. For the initial solution, each customer is assigned to a separate route. Then, for each customer i in route λ_1 and j in route λ_2, the savings are calculated as follows: $s_{ij} = b_{i0} + b_{0j} - b_{ij}$; 0 represents the depot and b_{ij} represents the cost of edge (i, j). Thus, the value of s_{ij} contains the savings of combining two routes λ_1 and λ_2, instead of serving two separate routes. A pseudo-code for the saving algorithm is presented in Algorithm 1.

Algorithm 1: Saving Algorithm

Set $X = 1$, $C = \{1,2, \ldots, n\}$, $S = \{s_{ij}: i,j \in C\}$
Insert n customers into n empty routes.
Calculate the savings s_{ij} between any two customers
Sequence s_{ij} in S in non-increasing order
While S is not empty do
Mark the largest savings s_{ij}
If the onboard quantity of vehicle X does not exceed its capacity when i and j are loaded, then
Append the arc (i,j) to the end of route X
Remove arc (i,j) and other arcs that contain point i or j from set S
else
$X = X + 1$
For each customer c in C, *do*
If customer c is not loaded to any route, then
Load the order of customer c into the route that has the largest remaining capacity
Return to the route of each vehicle

4.1.2. Determine the Order Production Sequence

As the vehicle routing decision has been made, the transportation time and the orders loaded on each vehicle are determined. The departure time of each vehicle should be reduced, because the objective is to minimize the total weighted delivery time of the orders. The departure time of a vehicle depends on the order production sequence, which is determined as follows.

The rule that the orders onboard the vehicle with the maximum sum of order weighted delivery times are produced first is employed. Assume that the departure times of all of the vehicles are 0. Then, calculate the sum of order weighted delivery times of each vehicle. Finally, arrange the production sequence of each vehicle as per the sum of the order delivery times of all vehicles, sorted in descending order. Assume that the orders that belong to the same order batch are produced successively, and that the production sequence of each order is the same as its delivery sequence; re-calculate the departure time of every vehicle and the sum of order weighted delivery times of each vehicle. Then, the total weighted delivery time of the orders is obtained. The pseudocode to determine the order production sequence is presented in Algorithm 2.

Algorithm 2: Determine the Order Production Sequence

(1) Set the departure time L_λ of each route λ to 0, $\lambda \subset \{1, 2, \ldots, H\}$;
(2) Calculate the sum of the order weighted delivery times S_λ of each route λ;
(3) Sort all routes in descending order of S_λ;
(4) Produce orders of each route in above turn;
(5) Re-calculate each L_λ and S_λ;
(6) $objective = sum(S_\lambda)$;

Return *objective*

4.2. Neighborhood Search

Given a current solution, s, several customers are removed and are then reinserted to generate neighbor solutions at each iteration. This is achieved by applying one of several removal and insertion heuristics. Each time a neighbor solution is generated, the objective value of the neighbor solution is calculated as the initial solution.

4.2.1. Four Removal Heuristics

The removal heuristic is to generate destroy neighborhoods by choosing m customers from a current solution, s, and putting them into a request bank, such as random removal, related removal, worst removal, and cluster removal, which can be seen in Figure 3. The black circles denote the removed customers and the dashed lines denote the new generated edges after moving (Figure 3).

(1) Random removal

The simplest removal heuristic randomly selects m customers and deletes them from the current solution, s, which is propitious to diversify the search.

(2) Related removal

The general idea of the related removal heuristic aims to delete somewhat similar customers, as it is considered fairly easy to create new and better solutions [47]. The similarity between two customers, i and j, is calculated by a correlation measure $R_{ij} = d_{ij}$ (the distance between two customers), where the lower value means the more similar customers. The related removal heuristic repeatedly chooses a new customer, i, randomly, and the customer i^r, having the smallest relatedness with i, removes them from the current solution, s, until m customers have been removed.

(3) Worst removal

This heuristic approach eliminates the customers with a high-cost in the current solution s. Let $Cost(s,i)^- = f(s,i) - f(s,i^-)$; $f(s,i)$ is the cost associated with customer i in the current solution s,

and $f(s, i^-)$ is the cost without customer i in s. The worst removal heuristic repeatedly selects a new customer i, with the highest $Cost(s, i)^-$, until m customers are deleted [56].

(4) Cluster removal

Some instances tested in the computational section contain clusters of customers; it needs to remove clusters of related customers from some routes. For each route, a modified version of Kruskal's algorithm is applied to divide its customers into two groups, it is stopped when two connected components are left [56]. Then, one of the groups is selected randomly and the customers of the group are removed so that they can be re-inserted appropriately. If more customers need to be removed, one of the removed customers is selected, and a customer is picked from a new route λ_{new} that is closer to the chosen customer. The new route, λ_{new}, is then divided into two clusters, and the process is repeated until m customers are deleted.

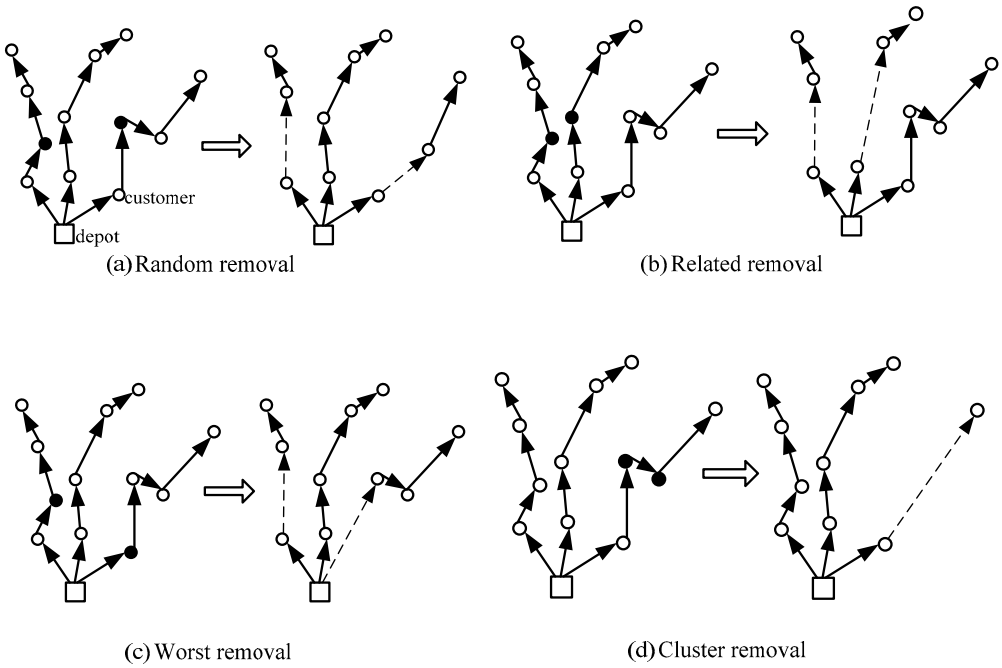


Figure 3. Four removal heuristics.

4.2.2. Two Insertion Heuristics

The insertion heuristic is used to rebuild the destroyed solution. When the removal heuristics remove customers from the existing routes into a request bank, to generate repair neighborhoods, the insertion heuristic choose m customers from the request bank, inserting them into one or more routes without violating the capacity constraint.

(1) Greedy insertion

Insert customer i into route k in the position that results in the lowest objective value. This process continues until m customers have been inserted. If customer i cannot be reinserted for the capacity constraint, leave it in the request bank. Finally, insert the customers remaining in the request bank into a route randomly, and let the objective value of the new solution be a very large number.

(2) Regret insertion

For each removed customer in the request bank, calculate its regret value, this is equal to the difference in cost between two solutions, in which i is inserted in its best route or in its second-best route [47].

Let $\Delta f(i^1)$ denote the change in the objective value by inserting customer i in the route λ_1, where customer i can be inserted at a minimum cost. Let $\Delta f(i^2)$ denote the change in the objective value by inserting customer i in route λ_2, where the customer i can be inserted at the second minimum cost. The regret value of customer i is equal to $\Delta f(i^2) - \Delta f(i^1)$.

Customer i with the highest regret value is chosen for insertion into the current solution, s, and customer i is deleted from the request bank. Customer i is inserted in its best route. The process is repeated until the request bank is empty.

4.3. A Local Search for Improving the Neighbor Solution

A multiple insertion (MI) algorithm was adapted for parallel machines scheduling [57]. The MI heuristic sorts the jobs in a non-increasing order of the modified processing times, then places each job in the position on the machine with the lowest makespan. In this paper, the MI algorithm is adopted to improve the quality of the neighbor solution. The vehicles can be treated as parallel machines, and the travelling time between customers can be the modified processing times. Thus, sort the customers in a non-increasing order of the travelling time, insert each customer one by one in every position of every route, and then place each customer in the position that results in the lowest objective value.

4.4. Acceptance Rule

The current solution update mechanism determines whether to replace the current solution s by the neighbor solution s'. The acceptance rule of the simulated annealing algorithm is used as the mechanism to accept neighbor solutions [58].

There are two situations that need to be considered. One is that if neighbor solution s' is superior to the current solution s—replace s with s'. Another is that if neighbor solution s' is inferior to the current solution s, the acceptance probability $\exp \frac{(v(s')-v(s))}{T}$ needs to be computed, with that, $v(s)$ and $v(s')$ are the objective values of the current solution and the neighbor solution, respectively. T is the current temperature, which starts at $0.005\times$ (the objective value of the initial solution). At every iteration, similar to [47], T decreases linearly to zero, according to a cooling rate fixed to 0.99975. If the acceptance probability is larger than a random number between $[0, 1]$, accept the neighbor solution s' and continue searching in the current neighborhood structure; otherwise, turn to the next neighborhood structure to search.

4.5. Stopping Criterion

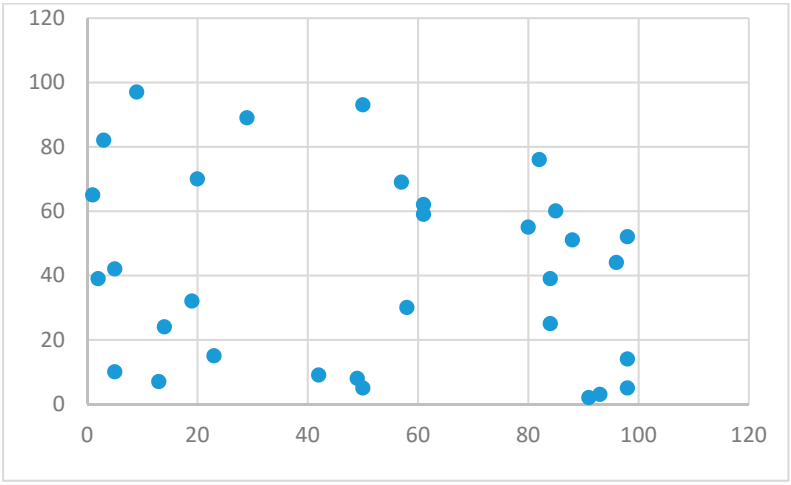
The removal and insertion heuristics are repeated until the number of iterations reaches 50,000 [47].

5. Computational Results

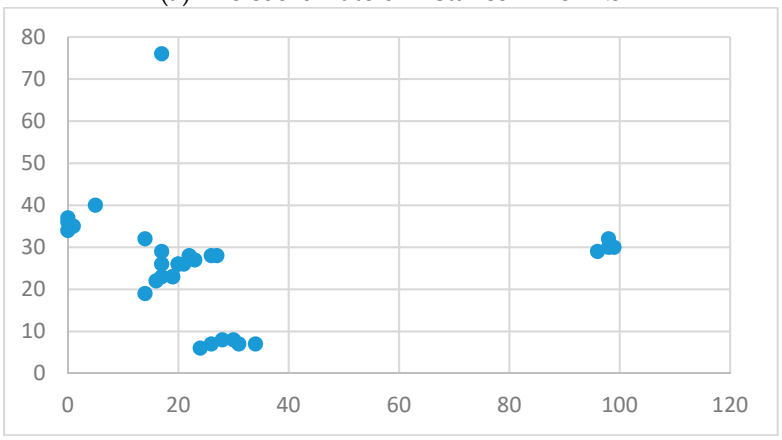
5.1. Instances Generation

There is no benchmark data for the IPDPPP, the test instances for the computational experiments should be generated according to certain rules. The first set of instances consists of small-sized instances including 5–10 customers and two vehicles. The vehicles are homogenous with a capacity of 20. The coordinates of each customer are randomly generated in [0, 50]. The demand of each customer/order is randomly generated in [1, 10], and the total demands of all of the customers does not exceed 40.

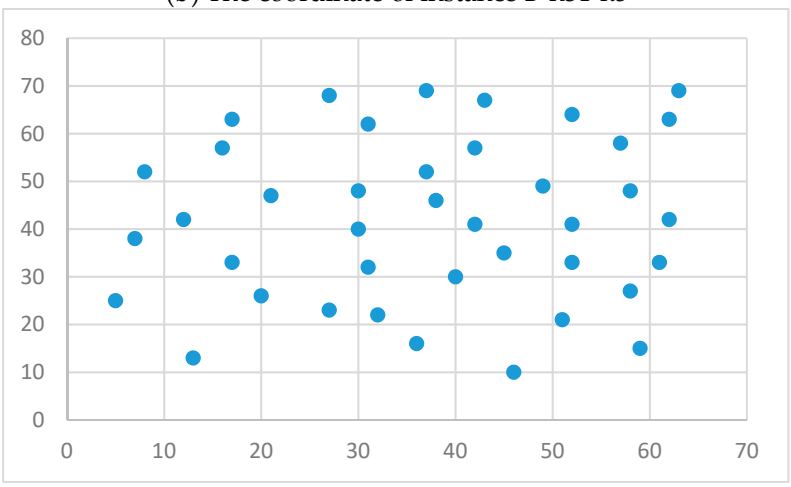
If the order production time is ignored, the problem IPDPPP is simplified to a capacitated vehicle routing problem (CVRP). Thus, the second set of instances consists of larger-sized instances generated from the well-known CVRP benchmarks (A, B, and P series), including 71 instances found on the website http://www.bernabe.dorronsoro.es/vrp/. The instances are composed of 15–100 customers and 2–15 vehicles. The number of customers, customer coordinates, and customers'/orders' requirements in the set of data are the same as the CVRP benchmark data. The characteristics of the customer coordinates of groups A, B, and P are different. Take the instances A-n32-k5, B-n31-k5, and P-n40-k5 as examples; the customer coordinates of Group A are generated randomly, while that of Group B are clustered and the customer coordinates of Froup C have an almost equal distance, which can be seen in Figure 4.



(**a**) The coordinate of instance A-n32-k5



(**b**) The coordinate of instance B-n31-k5



(**c**) The coordinate of instance P-n40-k5

Figure 4. Examples of the coordinates of instances in Groups A, B, and P.

For each instance, both in first and second set, the order weight is selected from the discrete uniform distribution U [1, 5], at random. For ease of calculation, similar to [15], the production rate is set to 1. In addition, similar to [44], the travel time between two customers or between the plant and a customer is equal to the distance between them.

5.2. Results for Small-Sized Instances

The mathematical model is validated by CPLEX. It should be noted that Constraint (13) in the mathematical model is non-linear; therefore, a new variable U_{jh} with $U_{jk} = C_j y_{jk}$ is defined to solve the problem. Then, the following linear Constraints (16) replace Constraint (13).

$$\begin{cases} D_0^h \geq \max\limits_{j \in C} U_{jh}, h = 1, 2, \ldots, H \\ 0 \leq U_{jh} + M y_{jh}, j = 1, 2, \ldots, n; h = 1, 2, \ldots, H \\ V_j \leq U_{jh} + M(1 - y_{jh}), j = 1, 2, \ldots, n; h = 1, 2, \ldots, H \end{cases} \tag{16}$$

Table 1 gives the solutions of CPLEX and the improved large neighborhood search (ILNS) algorithm for small-sized cases. The column "Instance" denotes the name of the instance, and "n" and "k" denote the number of customers and the number of vehicles, respectively. The results in Table 1 show that both CPLEX and the ILNS algorithm can get the optimal solution of small-sized test cases, while the running time of the ILNS algorithm is less than that of CPLEX for all of the test cases.

Table 1. Computational results of CPLEX and the improved large neighborhood search (ILNS) algorithm.

	CPLEX		ILNS		
INSTANCE CPLEX	**Objective**	**Time (s)**	**Objective**	**Time (s)**	**Optimal?**
Small-n5-k2	302	5	302	3	Yes
Small-n6-k2	349	5	349	3	Yes
Small-n7-k2	397	7	397	3	Yes
Small-n8-k2	720	9	720	3	Yes
Small-n9-k2	1116	210	1116	3	Yes
Small-n10-k2	1225	1381	1225	3	Yes

5.3. Results for Larger-Sized Instances

In order to evaluate the effect of the proposed improved ILNS algorithm for larger-sized instances, we compared it with the initial solution (IS) and a genetic algorithm (GA) [22]. Single machine, multi-customers, and multi-vehicles were considered in [22], while the objective was to minimize the makespan, and an improved genetic algorithm was proposed. For a fair comparison, the running time of GA was set to be equal to the ILNS algorithm for each instance. The ILNS algorithm and GA were coded in C++.

Tables 2–4 provide the results of the instance of Groups A, B, and P, obtained by algorithms IS, ILNS, and GA for the proposed problem. Column "Instance" denotes the instance name. Columns S1, S2, and S3 denote the results obtained by IS, ILNS algorithm, and GA, respectively. Columns T1 and T2 denote the running times of the IS and ILNS algorithms. The running time of GA is equal to the ILNS algorithm. Columns "Gap1" and "Gap2" denote the percentage gap between the IS and ILNS algorithm results, and the GA and ILNS algorithm results, respectively. They are calculated by $Gap1 = 100\% \times \frac{(S1-S2)}{S1}$ and $Gap2 = 100\% \times \frac{(S3-S2)}{S3}$.

Figure 5 provides the tendency in the results of IS, the ILNS algorithm, and GA for instances of Groups A, B and P. It shows that the results of the ILNS algorithm are better than those of IS and GA. Tables 2–4 show that the results of the ILNS algorithm are substantially improved based on IS. The average gaps between the IS and ILNS algorithms are 26.20%, 26.04%, and 22.94% for the three instance groups, respectively. At the same time, the computation time of the ILNS algorithm is short. The average running time of the IS is within 0.1 s, and the average running time of the ILNS algorithm is approximately 50 s. This indicates that the performance of the proposed ILNS algorithm is effective and efficient for not only random instances, but also cluster instances and related instances. It also suggests that the removal heuristics and insertion heuristics work well.

Table 2. Computational results of four algorithms for group A. IS—initial solution; GA—genetic algorithm.

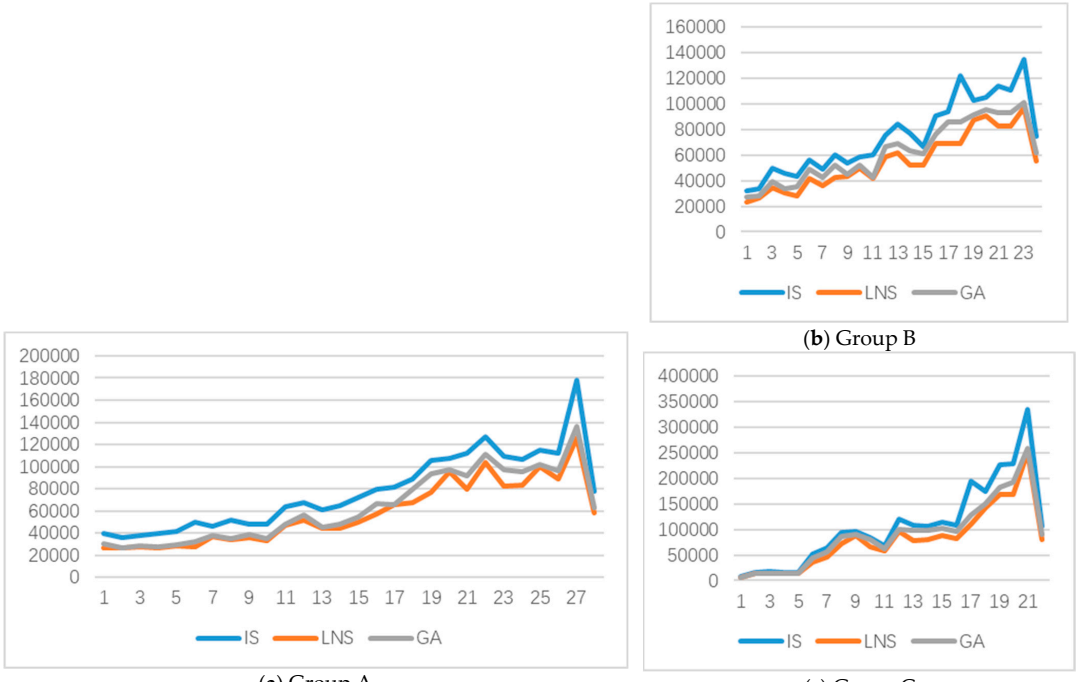
	IS		ILNS		GA	Gap1	Gap2
INSTANCE	**S1**	**T1 (s)**	**S2**	**T2 (s)**	**S3**	**(S1-S2)/S1 × 100%**	**(S3-S2)/S3 × 100%**
A-n32-k5	39,950	0.1	26,793	21	30,560	32.93%	12.33%
A-n33-k5	36,365	0.1	27,038	27	27,104	25.65%	0.24%
A-n33-k6	38,089	0.1	27,500	25	28,257	27.80%	2.68%
A-n34-k5	39,784	0.1	27,097	26	27,953	31.89%	3.06%
A-n36-k5	41,233	0.1	28,538	30	29,629	30.79%	3.68%
A-n37-k5	49,801	0.1	27,846	30	31,928	44.09%	12.79%
A-n37-k6	45,931	0.1	37,024	33	37,389	19.39%	0.98%
A-n38-k5	51,750	0.1	34,040	33	35,199	34.22%	3.29%
A-n39-k5	48,215	0.1	36,046	35	39,128	25.24%	7.88%
A-n39-k6	47,778	0.1	33,226	36	35,404	30.46%	6.15%
A-n44-k6	63,887	0.1	46,951	40	47,775	26.51%	1.72%
A-n45-k6	67,183	0.1	52,041	40	56,139	22.54%	7.30%
A-n45-k7	60,960	0.1	44,569	41	45,427	26.89%	1.89%
A-n46-k7	65,123	0.1	44,634	51	47,779	31.46%	6.58%
A-n48-k7	72,441	0.1	50,220	52	54,918	30.67%	8.55%
A-n53-k7	79,839	0.1	57,642	52	66,360	27.80%	13.14%
A-n54-k7	81,834	0.1	65,353	53	65,671	20.14%	0.48%
A-n55-k9	88,571	0.1	67,390	56	79,548	23.91%	15.28%
A-n60-k9	105,298	0.1	77,041	56	93,972	26.84%	18.02%
A-n61-k9	107,332	0.1	95,840	58	96,831	10.71%	1.02%
A-n62-k8	112,022	0.1	79,393	58	92,145	29.13%	13.84%
A-n63-k9	126,931	0.1	103,647	58	111,543	18.34%	7.08%
A-n63-k10	109,440	0.1	82,116	60	97,488	24.97%	15.77%
A-n64-k9	106,569	0.1	83,404	60	95,853	21.74%	12.99%
A-n65-k9	115,155	0.1	99,977	65	102,061	13.18%	2.04%
A-n69-k9	112,302	0.1	88,760	68	96,742	20.96%	8.25%
A-n80-k10	177,768	0.1	126,095	70	136,001	29.07%	7.28%
Average	77,465	0.1	58,156	46	63,289	26.20%	7.20%

Table 3. Computational results of four algorithms for Group B.

	IS		ILNS		GA	GA	Gap2
INSTANCE	**S1**	**T1 (s)**	**S2**	**T2 (s)**	**S3**	**(S1-S2)/S1 × 100%**	**(S3-S2)/S3 × 100%**
B-n31-k5	32,037	0.1	23,086	20	27,400	27.94%	15.74%
B-n34-k5	34,005	0.1	26,357	21	27,840	22.49%	5.33%
B-n35-k5	49,824	0.1	34,661	21	38,894	30.43%	10.88%
B-n38-k6	45,343	0.1	30,791	22	33,623	32.09%	8.42%
B-n39-k5	43,406	0.1	28,290	24	35,428	34.82%	20.15%
B-n41-k6	56,097	0.1	41,899	24	48,512	25.31%	13.63%
B-n43-k6	49,010	0.1	36,450	25	42,848	25.63%	14.93%
B-n44-k7	59,878	0.1	42,445	27	51,955	29.11%	18.30%
B-n45-k5	53,701	0.1	43,150	24	44,859	19.65%	3.81%
B-n45-k6	58,183	0.1	50,010	24	52,044	14.05%	3.91%
B-n50-k7	59,880	0.1	41,784	28	42,563	30.22%	1.83%
B-n50-k8	75,327	0.1	58,666	31	66,615	22.12%	11.93%
B-n51-k7	84,392	0.1	61,684	32	69,275	26.91%	10.96%
B-n52-k7	76,791	0.1	52,150	34	63,476	32.09%	17.84%
B-n56-k7	66,308	0.1	51,942	31	61,185	21.67%	15.11%
B-n57-k7	90,875	0.1	69,093	35	76,394	23.97%	9.56%
B-n57-k9	93,921	0.1	69,093	43	85,416	26.43%	19.11%
B-n63-k10	121,647	0.1	68,553	48	85,632	43.65%	19.94%
B-n64-k9	102,957	0.1	87,335	53	91,611	15.17%	4.67%
B-n66-k9	105,353	0.1	90,749	51	95,558	13.86%	5.03%
B-n67-k10	113,652	0.1	82,307	52	93,042	27.58%	11.54%
B-n68-k9	110,826	0.1	82,378	61	92,653	25.67%	11.09%
B-n78-k10	134,927	0.1	97,012	66	100,653	28.10%	3.62%
AVERAGE	74,710	0.1	55,212	35	62,064	26.04%	11.19%

Table 4. Computational results of four algorithms for Group C.

	IS		ILNS		GA	Gap1	Gap2
INSTANCE	**S1**	**T1 (s)**	**S1**	**T2 (s)**	**S3**	**(S1-S2)/S1 × 100%**	**(S3-S2)/S3 × 100%**
P-n16-k8	7375	0.1	5814	2	6673	21.17%	12.87%
P-n19-k2	15,717	0.1	13,190	2	13,679	16.08%	3.57%
P-n20-k2	17,867	0.1	13,616	2	14,814	23.79%	8.09%
P-n21-k2	16,059	0.1	13,420	3	14,113	16.43%	4.91%
P-n22-k2	16,968	0.1	13,272	3	14,427	21.78%	8.01%
P-n40-k5	52,858	0.1	36,417	26	44,662	31.10%	18.46%
P-n45-k5	63,627	0.1	46,808	25	55,816	26.43%	16.14%
P-n50-k7	93,494	0.1	71,981	31	86,726	23.01%	17.00%
P-n50-k8	95,320	0.1	87,236	34	89,506	8.48%	2.54%
P-n50-k10	83,723	0.1	65,187	45	79,185	22.14%	17.68%
P-n51-k10	68,048	0.1	58,944	47	62,206	13.38%	5.24%
P-n55-k7	119,836	0.1	95,366	52	100,486	20.42%	5.10%
P-n55-k8	108,155	0.1	78,880	56	97,682	27.07%	19.25%
P-n55-k10	105,705	0.1	79,318	56	97,313	24.96%	18.49%
P-n60-k10	114,276	0.1	87,847	51	102,735	23.13%	14.49%
P-n60-k15	107,808	0.1	82,345	52	95,938	23.62%	14.17%
P-n65-k10	194,119	0.1	111,145	55	128,938	42.74%	13.80%
P-n70-k10	174,502	0.1	143,062	55	151,189	18.02%	5.38%
P-n76-k4	227,017	0.1	167,543	60	182,731	26.20%	8.31%
P-n76-k5	228,876	0.1	168,409	62	192,277	26.42%	12.41%
P-n101-k4	334,428	0.1	249,633	91	258,090	25.36%	3.28%
AVERAGE	106,942	0.1	80,449	39	89,961	22.94%	10.91%



(**b**) Group B

(**a**) Group A

(**c**) Group C

Figure 5. The tendency in the results of three algorithms (IS, ILNS, and GA).

Moreover, the results of the ILNS algorithm are better than those of the GA. For the three instance groups, the average gaps between the ILNS algorithm and the GA are 7.20%, 11.19%, and 10.91%, respectively. The efficiency of the ILNS algorithm could be explained as follows. For the GA in [22], a method "MUS" which adopts some pre-designed rules to change the order of the customers in a route is defined as a local search algorithm. In their transportation phase, the goal is to minimize the maximum delivery time of the orders of each vehicle, "MUS" is employed to find more shortened routing for each vehicle. However, the objective of this paper is to minimize the sum of the order

weighted delivery time. In the transportation phase, the goal is to find a method to minimize the sum time of all of the customers receiving services. Obviously, the local search "MUS" is not suitable for solving this goal. For example, reversing all of the points in a TSP route does not affect the solution of the TSP (traveling salesman problem), but reversing all points in a path of this problem would change the solution. Thus, the local search "MI" applied in this paper is more effective than the "MUS" method for minimizing the sum of the order weighted delivery time.

6. Conclusions

This paper explores an integrated production and transportation scheduling problem for perishable products, which is an NP hard problem, aimed at minimizing the total of the order weight delivery time to improve customer service. In the production stage, a single machine is considered, and the order batching and the production sequence of the orders are determined. In the transportation stage, multiple vehicles and multiple customers are considered, and decisions on vehicle routing are made. An integrated mathematical model is built, and the validity is measured by the linear programming software CPLEX, by solving the small-size instances. An improved large neighborhood search (ILNS) algorithm is proposed to solve the larger-size instances. Firstly, a two-stage algorithm constructs an initial solution. The saving algorithm is developed to determine the vehicle routing, and then the optimal production sequence is decided by a certain rule, according to the given vehicle routing. Secondly, several removal and insertion heuristics are designed to destroy and repair the current solution, to generate extensive neighbor solutions to enlarge the solution space. Then, a local optimization algorithm is used to improve the quality of the generated neighbor solutions, which generates more chances to find the optimal solution. Finally, the acceptance rule of the simulated annealing algorithm is used to determine whether to accept the neighbor solution as the new current solution. To validate and evaluate the effectiveness of the proposed ILNS algorithm, the solutions are compared with the corresponding results obtained by the initial solution and the existing genetic algorithm in the literature. The computational results show that the proposed ILNS algorithm substantially improves the initial solution and is more effective than the genetic algorithm.

In the future, we will explore solving the perishable products' integrated production and distribution scheduling problem with exact algorithms, and explore the upper or lower bounds. Moreover, from a practical perspective, considering parallel machines and heterogeneous vehicles with time window constraints are also worthy of being addressed as well.

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