



# Integrating production scheduling and transportation procurement through combinatorial auctions

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## Abstract

This study uses the winner determination problem (WDP) to integrate auction transportation procurement with decisions related to production scheduling. The basic problem arises when a manufacturer has to clear a combinatorial auction to decide whether to cover transportation needs by using the in-house fleet or to procure transportation through auction. Thus, the manufacturer should include an additional decision level by integrating the WDP with production scheduling to gain efficiency and achieve savings in the logistics system. To the best of our knowledge, this is the first time production and transportation procurement problems are being solved simultaneously in an integrated manner. The study proposes a mathematical formulation and develops two heuristic approaches for solving the integrated problem. Extensive computational experiments and sensitivity analyses are reported to validate the model, assess the performance of the heuristics, and show the effect of integration on total cost.

## KEYWORDS

combinatorial auctions, integrated problem, production scheduling, transportation procurement, winner determination problem

## 1 | INTRODUCTION AND LITERATURE REVIEW

Production and transportation are foundational tasks in designing and operating logistics systems. The costs of these tasks represent a considerable share of any manufacturer's budget and have a direct effect on service level and competitiveness. Usually, companies choose from three transportation alternatives to deliver goods: either through in-house transportation or by outsourcing [9]. First, companies may decide to operate a private fleet of trucks, ensuring high-quality transportation service. Second, companies can outsource to external carriers by establishing bilateral forward contracts. Third, companies can use recent procurement paradigms, employing auctions to fulfill transportation needs. A combination of these three alternatives is a feasible solution and the most efficient method to reduce transportation costs. However, the company has the challenge of designing a transportation network. The appropriate alternative to meet transportation needs depends on several factors [56]. The problem becomes more challenging when transportation procurement must be coordinated with production scheduling to increase supply chain efficiency. Previous academic research and professional experiences have shown encouraging results (significant savings) of simultaneous planning of production and transportation activities [21]. Research studies focused on planning transportation in terms of freight distribution by solving either fleet management or vehicle routing problems [6]. Li et al. [39] analyzed different factors influencing outsourcing decisions within a production-transportation framework. Nagurney and Li [46] designed a supply chain that allows outsourcing for production and distribution in a competitive manufacturing context. However, to the best of our knowledge, no research has considered the integration of production scheduling with

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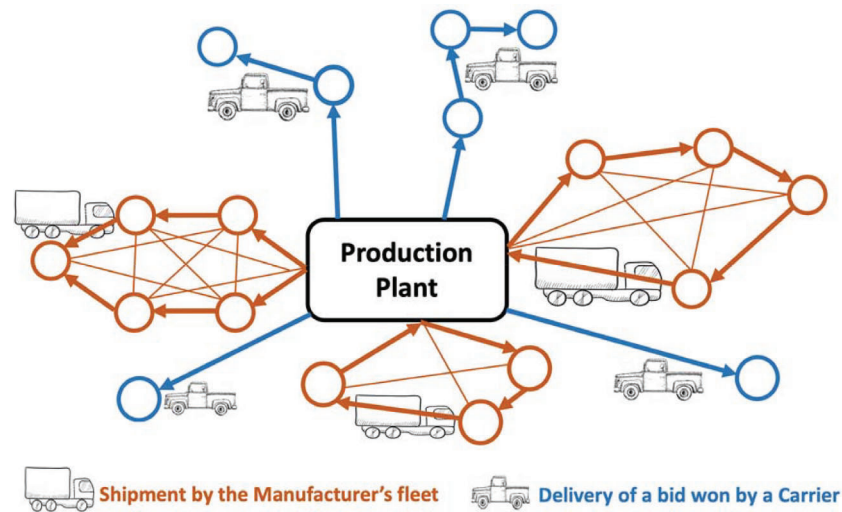


FIGURE 1 Problem description [Color figure can be viewed at wileyonlinelibrary.com]

transportation procurement while using the auction paradigm. The main contribution of this study fills this gap in the scientific literature.

Specifically, this study deals with extending the winner determination problem (WDP) to integrate production scheduling with transportation procurement and planning at the operational level (see Figure 1). We consider combinatorial auction (CA), in which carriers submit bids including a set of orders they are willing to serve and the corresponding price. The clearing process (i.e., the WDP) ensures that all orders submitted for each auction are allocated to the winning carrier; otherwise nothing at all. The winner is based on lowest price to serve the orders (first price). Carriers do not have access to competitors' bid information (sealed-bid) nor the chance to rectify submitted prices (single-round). Common in other studies, we assume a bidding language based on the "XOR" operator, so that a carrier can submit multiple bids but may be awarded only one. Therefore, the manufacturer diversifies transportation providers and does not rely on only a few carriers. The auction process gains efficiency and rapidity through Internet technology, which allows bi-weekly or even daily auctions to suit the timing of the production schedules, which is similar to what happens in the deregulated power systems market [8,45,59].

The problem being examined has its foundation in two research streams. The first is the use of auctions for transportation procurement, which have great potential for up to 15% savings for shippers [52]. This stream consists of solving three main optimization problems, as introduced by Caplice and Sheffi [11] (see Figure 2):

- LSP (*lane selection problem*): The manufacturer attempts to cover each transportation commitment (called a lane) by selecting the appropriate procurement alternative [27,61].
- BGP (*bid generation problem*): The company must decide which deliveries to include in bids submitted to the auction [4,10,14,35,37,49,55,58,60].
- WDP (*winner determination problem*): The auctioneer (manufacturer) clears the auction and identifies the winning carriers [11,30,42,50,51].

The WDP selects winners and assigns successful bids to carriers using cost minimization criteria. While this problem has been extensively investigated in different contexts, it has received limited attention in the transportation sector [19]. In deterministic settings, Caplice and Sheffi [11] proposed different optimization models for the WDP for truckload transportation auctions. Ignatius et al. [30] proposed three multi-objective optimization models for the WDP. This study considers cost, market fairness, and market confidence as criteria for deciding winning bids. Moreover, specialized models have been developed for real-life applications [22,36]. Research on the WDP has been directed toward stochastic and fuzzy settings. Ma et al. [42] suggested a recourse stochastic model that incorporates volumes of transported goods. Remli and Rezik [50] and Zhang et al. [66] used the recourse robust paradigm to incorporate the stochastic nature of shipment quantities into the auction clearing process. To solve the resulting stochastic WDP, Remli and Rezik [50] suggested a constraint generation algorithm, and Zhang et al. [66] used a data-driven approach. Sampling-based methods combined with Monte Carlo simulation have been used to solve the WDP in uncertainty [7,65]. Beyond shipping volumes, Ben Amor et al. [7] considered carriers' capacity and lead time stochasticity. Recently, Yan et al. [64] solved a WDP to ensure clearing price feedback from the shipper within the bi-level

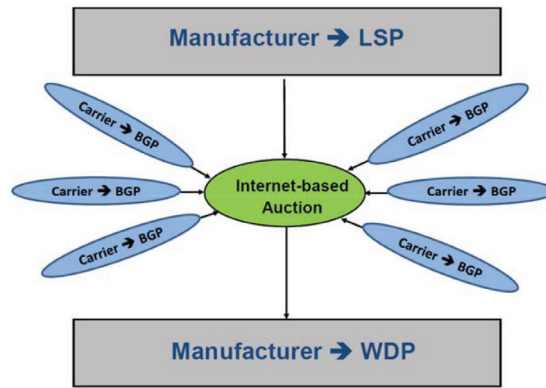


FIGURE 2 Bidding phases and problems in combinatorial auctions [Color figure can be viewed at wileyonlinelibrary.com]

procurement framework. They solve the problem from the carrier’s perspective, and their BGP uses fuzzy parameters to describe the random lane cost.

The second research stream related to this study is the production-transportation coordination in logistics systems. It defines detailed schedules for both production and distribution tasks, as surveyed by Chen [15], Ullrich [62], and Reimann et al. [48], and more recently, Moons et al. [44]. Ullrich categorized production-transportation coordination problems into two classes: transportation with direct deliveries and multidelivery consolidation. Given its complexity, the latter had limited attention in the literature, as it includes one of the routing problems variants. Our study belongs to this category of production-transportation problems and extends previous research to include the procurement aspect. Few studies belong to this category [28,34]. Some studies tackled different variants of the standard production-transportation problem with routing delivery [16,23,25,38,41,62]; some studies focused on developing approaches for its solution [2,5,32,33,43]; and some studies incorporated additional features within the problem, such as multi-objective optimization [31], uncertainty and robustness [17,53], and financial planning [3].

The above analysis highlights how the problem under examination has not been addressed in an integrated form in the literature. Our contribution attempts to merge two research streams that have flourished as different pathways separately without integration.

The remainder of this paper is organized as follows: Section 2 is devoted to formally describing the integrated problem, its advantage, and its corresponding mathematical formulation. Section 3 describes the approaches to solve this problem. Two methods are developed: one based on the memetic algorithm and one based on a decomposition iterative heuristic. The computational results and concluding remarks follow in Sections 4 and 5, respectively.

## 2 | PROBLEM DEFINITION AND MODELING

This section introduces characteristics and notations of the problem addressed in this study, and describes the optimization formulation proposed for the solution.

### 2.1 | Problem definition

Companies consider a set of orders  $N = \{1, \dots, n\}$  from customers that must be processed on one production line. A sequence-dependent setup time  $s_{ij}$  occurs when production changes from order  $i \in \{0\} \cup N$  to another order  $j \in N$ . We introduce a fictive order 0 and a corresponding customer 0. Let  $C_j$  denote the completion time of order  $j \in N$  and  $p_j$  denote processing time (with  $C_0 = p_0 = 0$ ).

Once order  $j \in N$  is processed, it must be delivered to the customer by due date  $d_j$ . We consider two transportation options for delivery: delivered by the manufacturer’s fleet  $V = \{1, \dots, v\}$  or outsourced to third-party carriers selected through auction. (The model extension to cover forward contracts for the transportation can be straightforward.) We assume the manufacturer has a homogenous fleet, with vehicle capacity  $Q$ . Each vehicle can be used iteratively, performing a new trip after the previous shipment is completed [13,40,47]. Let  $M = \{1, \dots, m\}$  represent shipments set for the manufacturer’s fleet and  $q_j$  represent units of fleet capacity needed to fulfill order  $j \in N$  by vehicle. Additionally, let  $c_{ij}$  represent the transportation cost of direct delivery from customer location of order  $i \in \{0\} \cup N$  to customer location of order  $j \in \{0\} \cup N$  and  $t_{ij}$  represent transportation time. The transportation times respect the triangle rule:  $t_{j_1j_2} + t_{j_2j_3} \geq t_{j_1j_3}, \forall j_1, j_2, j_3 \in \{0\} \cup N$ . Each vehicle needs a stopover

TABLE 1 Job profile

Order ( $i$ )	Processing time (time unit)	Quantity (unit)	Due date (time unit)
1	2	70	558
2	3	60	425
3	5	50	648

TABLE 2 Machine set up time with sequence dependent set-up

Job ( $j$ )	Job ( $i$ )			
	0	1	2	3
1	30	0	40	40
2	25	30	0	30
3	40	20	20	0

TABLE 3 Transportation distance

Job ( $j$ )	Job ( $i$ )			
	0	1	2	3
1	160	0	50	180
2	180	50	0	160
3	270	180	160	0

time  $S_j$  at the customer's location to serve order  $j \in N$ . The total transportation cost of each vehicle is the sum of all shipments performed, whereas transportation time of one shipment is the sum of each order's transportation time and service time at customer's location. When the delivery is outsourced to carriers, we assume a set of  $L$  carriers compete for the business. Each carrier  $l \in L$  submits a set of  $B_l$  bids to auction, but only a single carrier is successful (XOR bidding language). Let  $c'_{bl}$  denote the price suggested by carrier  $l$  to serve bid  $b$  (a bid typically includes several orders, and it is an all-or-nothing bid) and  $t'_j$  denote transportation time needed for the delivery of each order  $j$  included in bid  $b$ . Moreover, let  $R_{jbl}$  be a constant indicator equal to 1 if bid  $b$  by carrier  $l$  includes order  $j$ , and 0 otherwise. Let  $D_j$  represent actual delivery time of order  $j \in N$  by either manufacturer's fleet or external carrier. Then,  $T_j = \max\{0, D_j - d_j\}$  is the delivery tardiness of order  $j \in N$ . We consider a penalty cost  $w_j$  associated with each tardiness unit of order  $j \in N$ . Delivery tardiness can be caused by the chosen production schedule, the transportation alternative selected for each order, or the resulting production-transportation coordination. The production schedule is affected by the identified production sequence that can provoke additional costs of sequence-dependent set-up time. Consequently, the objective of the integrated production-distribution problem is to minimize routing costs, delivery auction costs, and delivery tardiness costs.

## 2.2 | Illustrative example: Effect of production-transportation integration

To illustrate the effect of integrated production scheduling and transportation problems, we consider the following example.

Number of jobs per customer: 3

Number of machines: 1

Number of vehicles: 2 (V1: manufacturer's fleet; V2: external carrier)

Vehicle capacity: Homogenous with loading capacity of 120 units each

Delivery tardiness cost: \$12/unit time

Transportation cost: \$17/unit distance (manufacturer's fleet) and \$21 (external carrier).

For the example, the job can be released at time zero and job preemption is not allowed. Of the available vehicles, one belongs to the manufacturer and the other is from the auction clearing. Additional details are shown in Tables 1 to 3.

In the example, we compare total production and transportation costs of the proposed method to two well-known methods. These two methods do not consider the integration of production and transportation delivery in the decision process.

TABLE 4 Cost components for the three methods

Method	Production sequence	Tardy time	Tardy cost	Delivery cost	Delivery sequence	Total cost
Method 1	O2-O1-O3	384	4608	17 536	Separately	22 144
Method 2	O1-O2-O3	729	8748	12 800	(O1-O3); O2	21 548
Method 3	O2-O1-O3	564	6768	12 800	(O1-O3); O2	19 568

- *Method 1*: Earliest due date (EDD) without integration: In the context of production planning and scheduling problems, EDD is widely used if minimizing tardiness is the objective [20]. Jobs are scheduled for production and delivery according to due dates.
- *Method 2*: Minimum tardy delivery (MTD) without integration: Jobs are scheduled for production based on production sequence. Delivery to customer is based on the delivery sequence, which minimizes transportation cost.
- *Method 3*: Our proposed method with integration: Our method integrates production function with delivery schedule. Jobs are schedule for production and delivery based on the minimum total cost, which consists of delivery tardiness cost and transportation cost.

Table 4 and Figure 3 show the results for the three methods. The tardy time and corresponding tardy costs are lowest for EDD; however, delivery cost is the highest. In EDD, jobs are delivered separately. Job 2 has the EDD and will be delivered first. The next delivery will be Job 1. Two jobs cannot be combined for delivery due to vehicle capacity constraint. Therefore, either Job 2 is delivered alone or Jobs 2 and 3 are combined for delivery; however, the tardy cost of Job 2 will be high, making individual job delivery better. Therefore, the manufacturer’s fleet (V1) must perform two trips for Jobs 2 and 3. Job 1 will be delivered by an external carrier.

For MTD, jobs are processed in the sequence O1-O2-O3. Job 1 and Job 3 will be delivered by vehicle 1 in the delivery sequence of O1-O3, and job 2 will be delivered by vehicle 2. The total cost of MTD is the highest among the three methods, because high tardiness delivery cost. As Figure 3B shows, all MTD jobs will be delivered tardy.

As shown in Figure 3C, the production sequence of the proposed method is similar to the EDD method: O2-O1-O3. The delivery planning and sequence are similar to MTD. Even though the tardy cost of the proposed method is higher than EDD, total cost of production and delivery is lower. Even for this small illustrative example, improvement in total cost by the proposed method is approximately 13% and 10% compared to EDD and MTD, respectively. Therefore, by integrating production planning and delivery scheduling in the decision process, the proposed method outperforms the other methods.

### 2.3 | Mathematical model

Besides the continuous variables  $D_j$  and  $T_j$  related to the actual delivery time of order  $j \in N$  and its tardiness, the mathematical formulation is based on introducing the following three sets of binary variables:

- Decision variables related to the production sequence:

$$X_{ij} = 1, \text{ if order } i \text{ is the direct predecessor of order } j \text{ on the production line } (i, j \in \{0\} \cup N, i \neq j) \\ = 0, \text{ otherwise}$$

- Variables related to transportation routing of the private manufacturer’s fleet:

$$Y_{ijv}^m = 1, \text{ if order } i \text{ is delivered just before order } j \text{ in the shipment } m \text{ with manufacturer’s vehicle } v \text{ } (i, j \in \{0\} \cup N, i \neq j, \\ v \in V, m \in M) \\ = 0, \text{ otherwise}$$

- Decision variables related to procurement of transportation needs through the auction:

$$Z_{bl} = 1, \text{ if carrier } l \text{ wins his bid } b \text{ through auction } (l \in L, b \in B_l) \\ = 0, \text{ otherwise}$$

Our formulation is a mixed-integer linear problem (MILP), expressed as:

$$\text{Minimize : } \sum_{i \in \{0\} \cup N} \sum_{j \in \{0\} \cup N, j \neq i} \sum_{v \in V} \sum_{m \in M} c_{ij} Y_{ijv}^m + \sum_{b \in B_l} \sum_{l \in L} c'_{bl} Z_{bl} + \sum_{j \in N} w_j T_j \tag{1}$$

Subject to:

$$\sum_{j \in \{0\} \cup N, j \neq i} X_{ij} = 1, \quad i \in \{0\} \cup N \tag{2}$$

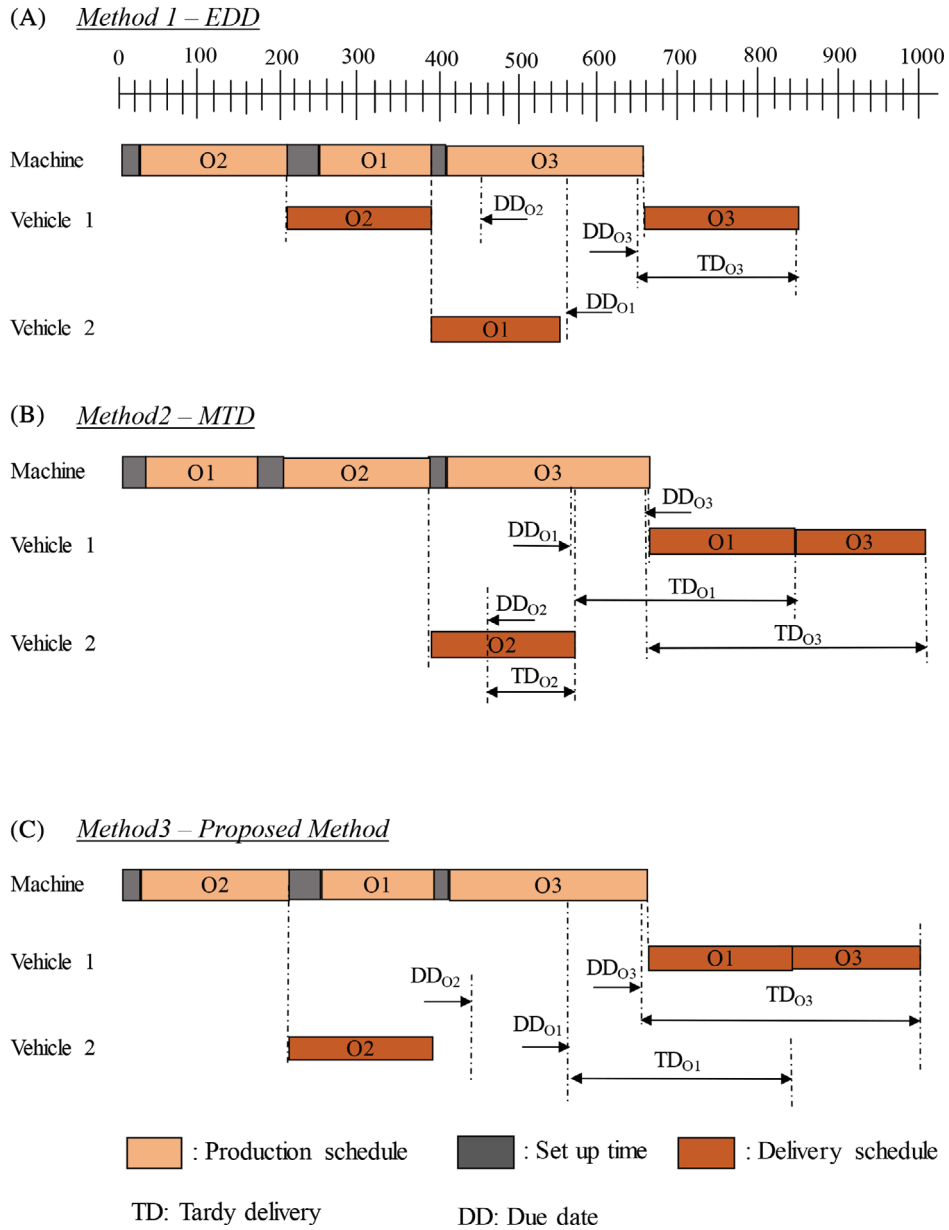


FIGURE 3 Production and delivery sequences generated by the three methods [Color figure can be viewed at wileyonlinelibrary.com]

$$\sum_{i \in \{0\} \cup N, i \neq j} X_{ij} = 1, \quad j \in N \tag{3}$$

$$C_i + s_{ij} + p_j - C_j \leq (1 - X_{ij})A_1, \quad i \in N, j \in N, i \neq j \tag{4}$$

$$\sum_{j \in \{0\} \cup N, j \neq i} \sum_{v \in V} \sum_{m \in M} Y_{ijv}^m = 1 - \sum_{b \in B_1, l \in L} R_{ibl} Z_{bl}, \quad i \in N \tag{5}$$

$$\sum_{i \in \{0\} \cup N, i \neq j} \sum_{v \in V} \sum_{m \in M} Y_{ijv}^m = 1 - \sum_{b \in B_1, l \in L} R_{jbl} Z_{bl}, \quad j \in N \tag{6}$$

$$\sum_{i \in \{0\} \cup N, i \neq j} Y_{ijv}^m - \sum_{h \in \{0\} \cup N, h \neq j} Y_{jlv}^m = 0, \quad j \in N, v \in V, m \in M \tag{7}$$

$$\sum_{j \in N} Y_{0jv}^m \leq 1, \quad v \in V, m \in M \tag{8}$$

$$D_i + S_i + t_{ij} - D_j \leq (1 - Y_{ijv}^m)A_2, \quad i \in N, j \in N, i \neq j, v \in V, m \in M \quad (9)$$

$$D_i + S_i + t_{i0} + t_{0j} - D_j \leq (2 - Y_{i0v}^{m-1} - Y_{0jv}^m)A_2, \quad i \in N, j \in N, i \neq j, v \in V, m \in M \setminus \{1\}$$

$$C_j + t_{0j} \left( 1 - \sum_{b \in B_1} \sum_{l \in L} R_{ibl} Z_{bl} \right) + t'_j \sum_{b \in B_1} \sum_{l \in L} R_{ibl} Z_{bl} \leq D_j, \quad j \in N \quad (10)$$

$$C_j + t_{0i} + \left( \sum_{k \in N} Y_{ikv}^m + \sum_{k \in N} Y_{kjv}^m - 2 \right) A_3 \leq D_i, \quad i \in N, j \in N, v \in V, m \in M \quad (11)$$

$$\sum_{i \in \{0\} \cup N, j \in N, j \neq i} \sum q_j Y_{ijv}^m \leq Q, \quad v \in V, m \in M \quad (12)$$

$$\sum_{b \in B_1} Z_{bl} \leq 1, \quad l \in L. \quad (13)$$

$$0 \leq T_j, \quad j \in N \quad (14)$$

$$D_j - d_j \leq T_j, \quad j \in N \quad (15)$$

$$X_{ij} \in \{0, 1\}, \quad i, j \in \{0\} \cup N, i \neq j \quad (16)$$

$$Y_{ijv}^m \in \{0, 1\}, \quad i, j \in \{0\} \cup N, i \neq j, v \in V, m \in M \quad (17)$$

$$Z_{bl} \in \{0, 1\}, \quad b \in B, l \in L \quad (18)$$

The objective function (1) minimizes total cost of producing and delivering all orders. It consists of transportation costs, either by the manufacturer's fleet or by the winning carrier, and the possible delivery-tardiness costs. Constraint (2) ensures that each order  $i$  has only one successor on the production line. Similarly, constraint (3) ensures that each order  $j$  has only one predecessor on the production line. Constraint (4) establishes the relationship between completion time of order  $i$  and order  $j$  whenever order  $i$  is the direct predecessor of order  $j$  on the production line (if  $X_{ij} = 1$ ). In Equation (4),  $A_1$  represents a large enough number. Constraints (5) and (6) ensure that each order is served once, either by the manufacturer's fleet or by a third-party carrier through auction. Constraint (7) ensures the flow balance at each customer location. Constraint (8) prohibits any vehicle to depart more than once with the same shipment  $m$ . Constraint (9) establishes the delivery time restriction between order  $i$  and order  $j$  when order  $j$  is delivered directly after order  $i$  with vehicle  $v$  on shipment  $m$  (if  $Y_{ijv}^m = 1$ ). Conversely, constraint (10) establishes the delivery time restriction between order  $i$  and order  $j$  when order  $j$  is delivered directly after order  $i$  with vehicle  $v$  but on different consecutive shipments  $m - 1$  and  $m$ . In this case, both variables  $Y_{i0v}^{m-1}$  and  $Y_{0jv}^m$  assume value 1 and the right side of each constraint (10) will be zero. The resulting constraint  $D_i + S_i + t_{i0} + t_{0j} \leq D_j$  ensures that vehicle  $v$  has enough time, before serving order  $j$ , to stop at customer's  $i$  location, return to the depot, and begin shipment  $m$  toward order  $j$ 's location. However, if  $Y_{i0v}^{m-1}$  or  $Y_{0jv}^m$  is zero, then the large number  $A_2$  prevails, and the corresponding constraint (10) becomes redundant. In Equations (9) and (10),  $A_2$  is a large enough number. Constraint (11) establishes the relationship between completion time and delivery time for order  $j$ , irrespective of whether the order is shipped by manufacturer fleet or external carrier. If the manufacturer fleet is used ( $Z_{bl} = 0$ ) and order  $j$  is served directly from the depot,  $C_j + t_{0j} \leq D_j$  is active. If order  $j$  is not served directly from the depot, the relationship is still valid, as the transportation time respects the triangle rule. However, if an external carrier is used ( $Z_{bl} = 1$ ),  $C_j + t'_j \leq D_j$  is also active. Constraint (12) ensures that the vehicle departs only after completion of all orders for the assigned shipment. Each constraint is active only if  $i$  and  $j$  belong to the same shipment  $m$  with vehicle  $v$ . Otherwise, one or both summations (over index  $k$ ) are equal to zero, and the resulting negative value multiplied by the large number  $A_3$  makes the constraint redundant. Constraint (13) imposes a capacity constraint on each manufacturer's vehicle  $v$ . Constraint (14)

expresses the XOR bidding language chosen during the auction design. Constraints (15) and (16) define delivery tardiness  $T_j$  and, constraints (17) to (19) define the binary nature of other decision variables.

In the above model, the WDP is embedded within the production-transportation model to be solved by the manufacturer. The WDP is known to be NP-complete in combinatorial auction mechanisms. Its complexity is due to not being able to identify the price of serving a single job, because carriers bid on delivering bundles of jobs rather than on a single job (because of the combinatorial nature of the auction). Moreover, the price  $c'_{bl}$  is not the sum of prices for serving single jobs combined in a bundle because of the synergy effect [58]. Synergy plays a crucial role in the transportation industry and cannot be ignored in framework optimization. In combinatorial auction context, the all-or-nothing bundling mechanism, together with the single pricing technique associated with each bundle, ensures synergy in the carrier's network and protects against the so-called "exposure problem" [18].

### 3 | SOLUTION APPROACHES

The mathematical model above is a mixed-integer linear program whose complexity increases quickly with number of shipments, vehicles, carriers, bids, and orders. The problem is NP-hard, because it is an extended variant of the problem proposed by Fu et al. [23], which is NP-hard (see also [24]). Moreover, the complexity is exacerbated by inclusion of an additional decision level related to transportation auction clearing. Solving the problem using the mathematical model is not compatible with real-life application requirements. The results reported in Section 5 show that the MILP exact method (coded with MATLAB) succeeded in solving instances with limited size. Therefore, heuristic algorithms are proposed in the sequel to overcome difficulties and solve large-scale instances of the problem.

#### 3.1 | Memetic algorithm

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##### Algorithm 1: Memetic algorithm

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Generate initial population of size  $\alpha$ ;
Educate best solution;
while ending criterion do
    Select a pair of parent chromosomes to generate offspring;
    educate offspring with probability;
    Add offspring into the population;
    if the size attends  $2\alpha$ , then
        Apply surviving operator to reduce population size to  $\alpha$ ;
    if the non-improved iterations satisfy limit, then
        Diversify population by adding  $\alpha$  new individuals and apply the surviving operator;

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Memetic algorithms (MA) are evolutionary optimization approaches that utilize a population of solutions identify the optimal solution. Since MA can adapt to different situations, it is used extensively to solve combinatorial optimization problems in several scientific disciplines. This study takes advantage of MAs to address the complexity characterizing the problem under consideration. Insights are from algorithmic frameworks proposed by Vidal et al. [63] and Cattaruzza et al. [12].

##### 3.1.1 | Chromosome representation

Memetic algorithms require genetic representation of the studied problem [26,29]. Rather than binary representation, permutation representation is used in this study. The individual chromosome consists of three sequences. The first sequence represents the production schedule with sequence of orders. The second sequence represents the bidding result, which is characterized by the winning bid index for each carrier. The third sequence represents the distribution schedule of the manufacturer's fleet, which is characterized by a set of trips  $A_1, \dots, A_k$ , where  $A_i = ai_1, \dots, aim$  denotes the trip  $i$  of the manufacturer's fleet, and  $aij$  is the  $j^{\text{th}}$  order delivered in the trip. The chromosome representations are shown in Figure 4.

As shown in Figure 4A, order 3 has the first priority in the production schedule, and order 4 has the last priority. The bidding chromosome shows that there are two bidders or carriers. Assume that carrier 1 bids to deliver orders (6) and (6, 2). Carrier 2 bids to deliver orders (5) and (5, 7). In the bidding chromosome, index 1 represents that carrier 1 wins the bid for order 6. Index 2 represents that carrier 2 wins the bid for orders (5, 7). The delivery chromosome shows that the manufacturer's fleet will deliver orders (1, 2, 3, 4) in two trips. In the first trip, the fleet will deliver orders (2, 4) in the delivery sequence of 4-2, and in the second trip, it will deliver orders (1, 3) in the sequence of 1-3.



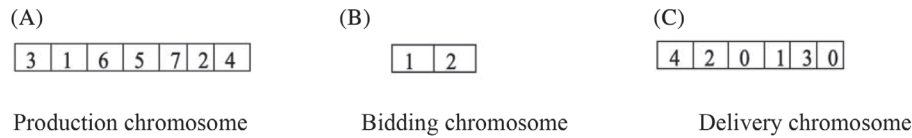


FIGURE 4 An illustration of production, bidding, and delivery chromosomes

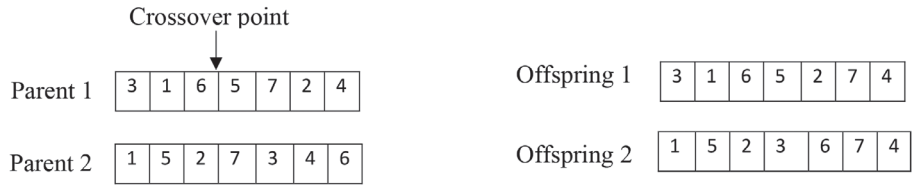


FIGURE 5 Offspring generation for production chromosome

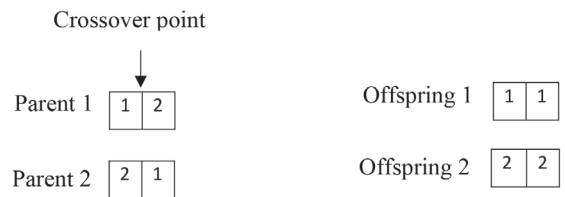


FIGURE 6 Offspring generation for production chromosome

### 3.1.2 | Initial population generation

The initial population is typically generated randomly or by a construction heuristic. In the proposed MA, the random method is applied to generate the initial population. In each generated individual, a random sequence of orders is assigned to the production schedule, as shown in Figure 4. Further, some orders are randomly assigned as winning bids to carriers who participate in the bidding process. During order assignment to the carrier, we ensure that winning bids of two different carriers do not contain identical orders. The remaining orders are delivered by randomly generated trips with the manufacturer’s fleet. In this step, if the total shipped orders exceed vehicle capacity, 0 must be inserted in the subsequence; otherwise, 0 can be inserted with probability. In the generated individual, production schedule and bidding results are feasible, and vehicle capacity constraint ensures feasibility of the distribution schedule.

### 3.1.3 | Crossover operator

The classic roulette wheel technique is used to select a pair of parent chromosomes to generate offspring. In this technique, the election is based on the selection probability, which is the ratio of individual fitness to summation of the fitness function of all chromosomes in the current generation. We propose a crossover method as follows (Figure 5):

*Step 1:* Offspring generation for the production sequence

A crossover point is generated randomly in the production schedule. The offspring inherits the subsequence of the first parent chromosome production schedule before the crossover point and the remaining orders according to occurrence in the second parent chromosome production schedule.

*Step 2:* Offspring generation for bidding by carrier.

A crossover point is generated randomly in the bidding result. The offspring inherits the bidding result of the first parent chromosome before the crossover point and of the second parent chromosome after the crossover point. According to Figure 6 and based on the example in Section 3.1.3, offspring 1 shows that carrier 1 and carrier 2 win the delivery for order 6 and order 5, respectively. Additionally, offspring 2 shows that carrier 1 and carrier 2 win the delivery for order (6,2) and order (5,7), respectively. The bidding result of the offspring is adjusted to ensure that winning bids of different carriers do not contain identical orders.

*Step 3:* Offspring generation for delivery by the manufacturer’s fleet

A crossover point is generated randomly in the distribution schedule of the manufacturer’s fleet. The offspring inherits the subsequence of the distribution schedule of the first parent chromosome before the crossover point, and the remaining schedule

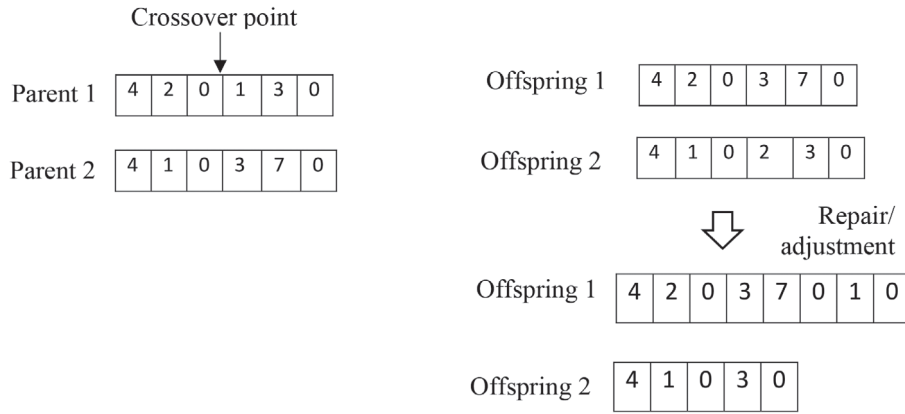


FIGURE 7 Offspring generation for the delivery schedule

according to occurrence in the distribution schedule of the second parent chromosome. The orders delivered by carriers are eliminated and remaining orders are added at the end of the distribution schedule.

As shown in Figure 7, in the chromosome of offspring 1, order 1 is inserted at the end of delivery sequence in the repair phase, because this order is eliminated during crossover and is not available in the bidding phase in Step 2. Similarly, in the chromosome of offspring 2, order 2 is eliminated, as it is included in the bidding result in Step 2.

As discussed, the production schedule, bidding result, and delivery sequence are feasible in the generated offspring. Further, the vehicle capacity constraint ensures the feasibility of the manufacturer’s distribution schedule.

### 3.1.4 | Education

We apply the following three neighborhood search methods to educate and improve the generated initial individuals and offspring.

- *Insertion*: In this mutation, two positions in the chromosome sequence are chosen randomly. The order in one position is inserted after the other position.
- *Swapping*: In this mutation, two positions in the chromosome sequence are chosen randomly. The order corresponding to these positions are swapped.
- *Inversion*: In this mutation, two positions in the chromosome sequence are chosen randomly, which determines a substring. This substring is inverted, and the original is replaced with inverted substrings.

The pseudocode for the education phase is shown below (Algorithm 2).

---

Algorithm 2: Education

---

while ending criterion  
do

    for a subset of pairs of orders do

        Consider three neighborhoods of the production schedule by inserting one order after another, swapping them, or inverting the subsequence between these orders;

    for each carrier do

        Consider another winning bid:

    for a subset of pairs of orders do

        Consider three neighborhoods of the distribution schedule of the manufacturer’s fleet by inserting one order after another, swapping them, or inverting the subsequence between these orders;

---

### 3.1.5 | Surviving and diversification

When the size of population is  $2\alpha$ , the surviving operator is applied by selecting the best  $\alpha$  survivors. If the nonimproved iteration attends the limit, the population is diversified by adding new individuals and applying the surviving operator.

### 3.2 | Two-phase iterative heuristic

Decomposition methods are powerful tools for solving complex integrated problems by reducing complexity [57]. A two-phase iterative heuristic (2-PIH) method was first proposed by Absi et al. [1] to solve an integrated production planning and vehicle routing problem. The problem they considered did not have the option of delivery by external carriers selected through the auction mechanism. This study proposes a 2-PIH method by decomposing the integrated problem into production and WDP distribution phases. The production phase determines production sequence, which affects order completion time. This will further impact delivery tardiness. The machine setup time is sequence dependent. The distribution phase determines whether the delivery will be by the manufacturer's fleet or by the external carrier. This phase determines the distribution sequence of the orders delivered by the manufacturer's fleet. These two phases are solved iteratively to ensure adequate integration between production and transportation solutions.

---

**Algorithm:** Two-phase iterative heuristic (2-PIH)

---

Initialize a Production Schedule (PS) with the earliest due date rule:

Distribution phase: solve the distribution scheduling problem subject to the production schedule PS, record the best solution identified;

**while ending criterion do**

Production phase: generate a neighborhood production schedule PS' of the production schedule PS by using neighbor search methods;

Distribution phase: solve distribution scheduling problem subject to the production schedule PS', record the best solution identified;

Update PS by PS';

---

Initially, the heuristic generates a production schedule characterized by the earliest due date (EDD) sequence. Using the EDD method helps minimize total tardiness, which is an objective of the optimization problem. Thereafter, using the result of this phase as an input, the transportation procurement problem is solved by a purposely developed MA method (a similar but simplified version of the one discussed in Section 4.1). The 2-PIH heuristic generates, at each iteration, a neighborhood production schedule by randomly using three methods (insertion, swapping, and inversion) and determines a distribution schedule using the ad-hoc MA. The algorithm stops when a specified maximum number of iterations is reached.

## 4 | COMPUTATIONAL ANALYSIS

The computational analysis aims to validate the optimization model and to ascertain the efficiency of the proposed heuristic algorithms and the advantage of integration. Additionally, a sensitivity analysis is conducted to check the effect of various problem parameters on the proposed heuristic algorithms. Both the MILP model and the heuristic algorithms are coded in MATLAB R2015b and executed on a DELL 2.50 GHz personal computer with 8 GB RAM.

For order deliveries, the instances developed by Solomon [54] are suitably modified for the problem under study. The customer location coordinates and the fleet size and capacities are maintained as originally defined in the Solomon instances. The number of customers for any given instance is randomly selected with the demand information and due dates unaltered. The manufacturer's location is positioned as a depot, located at the origin of the axes with coordinates (0, 0). The Euclidean distances between each pair of locations are rounded to the nearest integer. Since Solomon instances consider only distribution parameters, production parameters such as order processing time, sequence-dependent setup time, and delivery penalty are generated randomly in the interval [0,10]. Furthermore, the order transportation time  $j$  is selected as  $t'_j = 0.8t_{0j}$  and bidding costs for procuring transportation through auction  $c'_{bl}$  belong to the range  $[\sum_j 0.8c_{0j}, \sum_j 1.2c_{0j}]$ , where  $j$  represents orders composing bids  $b$  by carrier  $l$ . Parameter values for the heuristic algorithms considered in the computational analysis are listed in Table 5. Parameter selection is based mainly on complexity of space (e.g., population size) and time (e.g., maximum number of iterations, education probability) and is based on preliminary computational experiments conducted to ensure an efficient tuning phase of the governing parameters.

Apart from the maximum number of iterations, if the solution does not improve in 20 consecutive iterations, the population will diversify. The stopping criterion for diversification is fixed at 20 iterations if the solution does not improve.

**TABLE 5** Parameter values considered in our heuristic algorithms

Parameter	Value
Population size in each iteration	20
Maximum number of iterations	500
Education probability	0.2

**TABLE 6** Performance of the heuristics with respect to the exact solution

	Exact method		MA			2-PIH		
	Cost	CPU time (s)	Cost	Gap (%)	CPU time (s)	Cost	Gap (%)	CPU time (s)
5	885.25	1.27	895.61	1.17	6.57	897.45	1.38	13.25
6	984.92	6.00	1005.34	2.07	11.65	1004.87	2.03	24.47
7	1110.15	207.12	1161.15	4.59	15.54	1152.52	3.82	34.63
8	1285.67	1007.4	1370.63	6.61	18.85	1357.72	5.60	45.74

#### 4.1 | Exact method vs heuristic algorithms comparison

First, the problem is analyzed using the exact MILP method compared to the heuristic algorithms while considering a limited number of orders and a single vehicle for manufacturer's deliveries. The objective the analysis is 2-fold: (a) to understand the extent to which the exact method can find an optimal solution to the problem, and (b) to assess the performance of heuristic algorithms with respect to the exact solution. Table 6 reports the results obtained for four problem instances with an increasing number of customer orders  $n \in \{5, 6, 7, 8\}$ . The table shows computational results of the exact method, the MA, and the 2-PIH in terms of average cost, optimality gap, and average CPU time (averaged over 56 runs in the case of the heuristics). The gap is measured as the percentage difference of cost between the considered heuristics and the exact method.

Table 6 illustrates that the average gap in the solution cost of both heuristics with respect to the exact method range from 1.17% to 6.61%. These small gap values show that both the MA and 2-PIH succeed in finding near-optimal solutions in the case of limited-sized instances. Only in the case of five-order instance, the MA finds better solutions with respect to 2-PIH, where the 2-PIH outperforms the MA in all other cases. As expected, the average CPU time of the exact algorithm increases exponentially with the number of orders and reaches nearly 22 minutes when  $n = 8$ . However, the average CPU times of MA and 2-PIH vary slightly for different instances. The average CPU timing of the MA is approximately half that of 2-PIH. Therefore, the results confirm that the proposed heuristic approaches can find near-optimal solutions within an acceptable amount of time for all small instances. When the number of orders exceeds eight, the exact algorithm cannot find an optimal solution within a reasonable time.

#### 4.2 | MA vs 2-PIH comparison

Tables 7 to 9 show computational results of the proposed heuristic algorithms for the cases when the instances are characterized by a high number of orders (i.e.,  $n \in \{50, 100, 200\}$ ). The performance of the MA and 2-PIH algorithms are evaluated in terms of average cost and CPU time for six different Solomon instances C1, C2, R1, R2, RC1, and RC2. To obtain maximum insights from the experiment in this study, six instances are categorized to include different characteristics:

- In instances R1 and R2, customer positions are selected randomly in the geographical area.
- In instances C1 and C2, customers are positioned in groups (clusters of customers spread over the geographical area).
- In instances RC1 and RC2, some customers are placed randomly, and others are clustered.
- Instances R1, C1, and RC1 have orders with shorter due dates and low vehicle capacity.
- Instances R2, C2, and RC2 have orders with longer due dates and high vehicle capacity.

Therefore, R2, C2, and RC2 can serve more customers per shipment compared to the problems R1, C1, and RC1.

For the objective function, Tables 7 to 9 show that MA performs better than 2-PIH for all instances and problem sizes. Specifically, when  $n = 200$ , MA obtains better solutions at roughly half the 2-PIH solution cost. For large-sized problems ( $n = 100, 200$ ), the execution time of 2-PIH is high. Therefore, the expectation is that the 2-PIH algorithm cannot compete with the MA for large-scale problems characterized by a high number of orders (i.e.,  $n > 200$ ).

TABLE 7 Results when  $n = 50$ 

Problem	MA cost	2-PIH cost	MA time	2-PIH time
C1	8023.46	10013.29	148.78	617.85
C2	6560.69	7034.71	155.93	608.14
R1	19743.12	34151.44	148.70	605.82
R2	8885.61	9787.51	158.45	628.97
RC1	24199.39	35972.75	155.34	596.61
RC2	12207.10	13646.44	142.39	572.66

TABLE 8 Results when  $n = 100$ 

Problem	MA cost	2-PIH cost	MA time	2-PIH time
C1	22622.91	26915.72	745.41	3387.50
C2	16294.56	17075.12	707.19	3310.56
R1	76174.76	112485.39	633.92	2368.94
R2	17202.86	20550.99	629.70	3026.59
RC1	85107.01	107051.89	603.17	2226.61
RC2	21738.89	27828.35	705.08	3351.64

TABLE 9 Results when  $n = 200$ 

Problem	MA cost	2-PIH cost	MA time	2-PIH time
C1	117270.37	256793.35	1844.75	7807.37
C2	62635.51	90690.13	2876.44	11169.13
R1	245588.82	411772.74	1829.41	5480.58
R2	66205.75	145296.91	2336.52	10031.03
RC1	291549.33	483345.16	2995.68	5666.35
RC2	70476.70	104313.83	2598.91	10629.65

### 4.3 | Comparison of MA with available methods

As a further experiment for validating the performance of our MA algorithm, we compared its results with the algorithm proposed by Johar et al. [32] in terms of total cost (we will refer to their algorithm as JNP, following the authors' abbreviated names). The problem addressed by Johar et al. [32] is not exactly the same as the one we addressed, but it is the closest we could find in the literature. Moreover, Johar et al. [32] have solved their production-distribution problem by considering the same Solomon instances (only for  $n = 100$ ) but by using different cost parameters. For this reason, performing this comparison required slight adaptation of the input parameters in order to ensure, up to some extent, homogeneity of the costs to be compared. The results reported in Table 10 show that MA performs remarkably better than JNP for most of the instances. For the problem instances C2, R2 and RC2, the cost of MA is less than half the cost of Johar's et al. [32] algorithm. However, MA does not perform well for R1 and RC1 and its cost is almost double that of JNP. Thus, even though our MA has good performance for most of the problems, it is not perfectly suitable to solve a specific class of problems: those characterized by unclustered customers having short due dates and served by low manufacturer's vehicle capacity.

Finally, it is to be noted that despite our efforts to make the results comparable, a remarkable difference between the two solved problems still persists. While Johar et al. [32] have considered the pure production-distribution problem, our MA was designed to solve the problem involving the additional variables/constraints related to the procurement through auctions. We shall expect that our MA performs even better and gain more advantage with respect to JNP whenever the two problems are made completely homogeneous.

### 4.4 | Integrated vs nonintegrated methods comparison

To demonstrate the effect of integrating production planning and delivery decisions, the results of MA are compared with the solution obtained without integrating the two decision problems. The results of the nonintegrated method are obtained by solving the two problems separately, as follows:

**TABLE 10** Cost comparison of MA and JNP algorithms (for  $n = 100$ )

Problem	MA	JNP	MA/JNP
C1	22 622.91	40 855.50	0.55
C2	16 294.56	42 032.00	0.39
R1	76 174.76	47 527.00	1.60
R2	17 202.86	46 866.50	0.37
RC1	85 107.01	44 359.50	1.92
RC2	21 738.89	45 167.00	0.48

**TABLE 11** Cost comparison between integrated and nonintegrated methods

Prob.	$n = 50$		$n = 100$		$n = 200$		Average cost		% age diff
	MA	NI	MA	NI	MA	NI	MA	NI	
C1	8023.46	11 442.59	22 622.91	31 105.66	117 270.37	278 026.00	49 305.58	106 858.08	116.73
C2	6560.69	7283.90	16 294.56	19 322.00	62 635.51	97 021.74	28 496.92	41 209.21	44.61
R1	19 743.12	44 667.60	76 174.76	142 545.90	245 588.82	346 458.92	113 835.56	177 890.81	56.27
R2	8885.61	12 170.45	17 202.86	25 975.13	66 205.75	156 082.58	30 764.74	64 742.72	110.44
RC1	24 199.39	57 331.26	85 107.01	115 917.56	291 549.33	516 952.98	133 618.58	230 067.26	72.18
RC2	12 207.10	17 522.03	21 738.89	32 083.58	70 476.70	121 062.26	34 807.56	56 889.29	63.44

**TABLE 12** Effect of clustering customers on total cost

Problem	Manufacturer fleet cost	Carriers auction cost	Penalty cost	Total cost
C1	4597.71	3765.17	2.58	8365.45
C2	3719.19	3206.20	0.00	6925.38
R1	6844.14	5125.01	6920.59	18 889.74
R2	3990.31	5303.73	0.00	9294.04
RC1	7856.17	7730.39	9841.64	25 428.20
RC2	4289.88	8237.86	17.78	12 545.52

**Step 1:** Generate the production schedule using the EDD rule.

**Step 2:** Apply a simplified version of MA subject to the previous fixed production schedule.

Table 11 shows the comparison results between MA and the nonintegrated (NI) method in terms of total cost for different values of  $n$ . The MA production-delivery costs are lower for all instances compared to when the two decision problems are carried out separately. On average, total cost of the NI method is from 44.61% to 116.73% higher than that of MA.

## 4.5 | Sensitivity analysis

As observed in Section 4.2, the MA performs better than the 2-PIH in terms of cost and execution time in all instances. Therefore, the MA approach is examined, and a sensitivity analysis is performed for the same test problems with  $n = 50$ . The effect of varying the delivery due dates, vehicle capacity, and customer distribution on the MA solution is emphasized.

### 4.5.1 | Effect of customer clustering

First, the effect of customer clustering on the total cost while considering different problem instances is checked. Each problem instance has its own characteristic, as discussed in Section 4.2. Table 12 illustrates the different cost components, as defined in the problem's objective function. The results point to important conclusions: the case characterized by fully clustered customers (i.e., C1 and C2) exhibit smaller total costs compared to the nonclustered cases (R1 and R2) and the partially clustered cases (RC1 and RC2). By clustering customers, batch delivery is possible by consolidating several orders within a shipment, resulting in significant transportation cost savings.

TABLE 13 Effect of due date and vehicle capacity on total cost

Due date	Capacity	Manufacturer fleet cost	Carriers auction cost	Penalty cost	Total cost
PRES due	0.8 × PRES cap	5482.59	5206.01	3023.38	13 711.97
	PRES cap	5306.06	5513.92	3038.24	13 858.22
	1.2 × PRES cap	5243.20	5799.88	3082.32	14 125.40
0.8 × PRES due	0.8 × PRES cap	5715.98	5287.32	4484.45	15 487.74
	PRES cap	5411.62	5821.44	4603.96	15 837.03
	1.2 × PRES cap	5445.29	5918.04	4427.45	15 790.77
1.2 × PRES due	0.8 × PRES cap	5263.10	4786.07	2091.20	12 140.37
	PRES cap	5001.79	5575.29	1925.56	12 502.63
	1.2 × PRES cap	4953.16	5729.21	1963.94	12 646.32

#### 4.5.2 | Effect of due date and vehicle capacity

The second set of analyses consists of checking the effect of varying the due date and fleet capacity (*PRES due* and *PRES cap*, respectively) with respect to the originally considered values.

Table 13 shows cost components averaged for 56 runs, including all problem instances when  $n = 50$ . For problems characterized by orders with longer due dates and large vehicle capacities, the manufacturer's fleet can serve more orders in the same shipment. However, it does not guarantee a cheaper total cost. At a constant due date, the total cost is lowest when the manufacturer's fleet capacity is lower. However, the lowest cost occurs when the due date is the longest and the manufacturer's fleet capacity is 80% of the capacity originally considered. Further, at constant capacity with a decrease in the flexibility of the due date (i.e., shorter due dates), all cost components increase. Therefore, the total cost is higher when the due date is shorter than that of the counterpart.

## 5 | CONCLUSIONS

Researchers and practitioners worldwide are oriented toward integrating several aspects of the logistics system within a common solution framework to increase savings and competitiveness. However, the problem of integrating production scheduling with transportation procurement, while using the auction paradigm, has not been solved in the literature. This study's main contribution fills this gap by extending the WDP to include an additional decision level related to the production scheduling. This study uses a mixed-integer mathematical formulation, incorporating production and transportation procurement components. We suggest two heuristic approaches, one based on the memetic algorithm and the other based on the decomposition technique. The performance of our approaches was evaluated with respect to the exact solution as well as the closest production-routing method available in the literature. The results collected and the sensitivity analysis study performed confirm the efficiency of both methods and elect the memetic-based algorithm to achieve better performance in solving large-scale instances. The advantage of integration is assessed with respect to solving production and transportation procurement problems separately.

For further developments, this work can be extended along several directions. It would be interesting to develop exact methods and bounds not only on Solomon's instances but even to solve problems related to real-life applications. Moreover, it may be useful for some manufacturers to extend the planning horizon to include a multi-period environment. Finally, future investigation could consider the stochasticity related to the volume of shipment in each order by using the chance-constrained paradigm.

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