Coordinated Production and Delivery Operations With Parallel Machines and Multiple Vehicles

DUNHU LIU[1], **WEI WANG**[2], **LI HUANG**[3], **AND DAVID PROVERBS**[4]

[1]School of Management, Chengdu University of Information Technology, Chengdu 610225, China
[2]College of Harbour, Coastal and Offshore Engineering, Hohai University, Nanjing 210098, China
[3]School of Public Administration, Hohai University, Nanjing 210098, China
[4]Computing, Engineering and Built Environment, Birmingham City University, Birmingham B4 7XG, U.K.

Corresponding author: Wei Wang (13813826667@hhu.edu.cn)

ABSTRACT This paper investigated a coordinated optimization problem of production and delivery operations with parallel machines and multiple vehicles so that a more cost-effective and sustainable supply chain performance can be achieved. We propose an effective hybrid metaheuristic solution framework to deal with this problem, by which the investigated problem is decomposed into 3 sub-problems namely, vehicle assignment, parallel machine scheduling and traveling salesman sub-problem. This framework is established for handling the 3 sub-problems in a coordinated manner so as to simplify the optimization process and to reduce the computational complexity. To evaluate the effectiveness of the methodology, this paper integrates a genetic algorithm, the longest processing time heuristic and a tabu search under this framework to solve the investigated problem. Extensive numerical experiments have been conducted and experimental results show that the proposed solution framework can handle the investigated problem efficiently and effectively.

INDEX TERMS Production planning, parallel machines, distribution, genetic algorithm.

I. INTRODUCTION

Supply chain management is one of the most important research subjects in operation management. The increasing fierce competition forces enterprises to compete with other enterprises both on price and quality, and on the reliability and timeliness of delivery [1]. Due to the increasing market globalization, coordination between various stages of supply chain operations has received more and more attention from industry practitioners and academic researchers [2], [3]. One of critical aspects of the supply chain coordination is the integration of production and outbound logistics operations, which is important to reach a sustainable supply chain. To obtain an expected delivery performance at the minimum total cost, both production scheduling and logistics scheduling need to be considered in a coordinated and jointly manner [4]–[10], which is particularly important in some manufacturing companies producing time-sensitive products such as fast food and cement. In these companies, finished products usually need to be transported to customers shortly or immediately after the production process is finished. This

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paper deals with a coordinated optimization problem of production and delivery operations with parallel machines and multiple vehicles, called coordinated production and delivery optimization (CPDO) problem.

We first establish the mathematical model of the CPDO problem. To solve this problem, a novel solution framework is proposed based on hybrid metaheuristic, by which we decompose the investigated problem into 3 sub-problems, including an assignment sub-problem of orders to vehicles, a machine scheduling sub-problem with makespan minimization, and a travelling salesman sub-problem. This research contributes the literature by proposing the novel multi-level hybrid metaheuristic solution framework for complex CPDO problems. Comparing with other approaches, the proposed novel hybrid framework is able to simplify the optimization process and reduce the complexity of computation.

II. LITERATURE REVIEW
A. COORDINATED PRODUCTION AND DELIVERY OPTIMIZATION

The coordinated production and delivery optimization problem is also called as integrated production and delivery (or distribution) scheduling (CPDO) problem. Research on

CPDO has attracted more and more researchers' attention in recent years. Chang and Lee (2004) investigated a CPDO problem with one vehicle and single machine [2]. Boudia et al. (2008) researched into a single-product CPDO problem on a multi-period horizon [11]. They considered a production environment that both manufactures and customers could store the finished products. Toptal et al. (2013) investigated a CPDO problem with heterogeneous vehicles [12]. The manufacturer used two types of vehicles to deliver goods. Viergutz and Knust (2014) addressed a CPDO problem with lifespan constraints in single machine and single vehicle environment [1]. Seyedhosseini and Ghoreyshi (2014) presented a CPDO model for perishable products [13]. Chen (2010) has made a comprehensive review on CPDO problems and pointed out that the CPDO problems were more challenging than other CPDO problems and deserved more research due to their practicality [4]. However, CPDO problems with vehicle routing (i.e., CPDO) have been investigated seldom in the literature although vehicle routing widely exists in production and delivery operations in real world. Chen et al. (2009) examined CPDO problem of perishable food products in a single-machine environment [14]. Ullrich (2013) addressed a CPDO problem with the total tardiness [15]. Li et al. (2016) addressed a CPDO problem in a single-machine environment with the objective of minimizing vehicle delivery and total customer waiting time [10]. However, CPDO problems with parallel machines, heterogeneous vehicles and total cost minimization objective have not been reported so far. These problems widely exist in many make-to-order manufacturing environments, such as lumber and porcelain industry [16], which are the focus of this research.

B. TECHNIQUES FOR COORDINATED PRODUCTION AND DELIVERY OPTIMIZATION PROBLEM

Two types of approaches are usually adopted to handle CPDO problems, including exact methods, heuristics and metaheuristics. The exact methods are usually used to handle small-sized CPDO problems with a limited number of machines and vehicles. Li et al. (2005) addressed a CPDO problem in a single-machine environment and presented a dynamic programming model for handling a general case [17]. They pointed out that the model's computational complexity is very high when the number of machines was greater than 1. Mazdeh et al. (2007) addressed a single-machine scheduling problem with delivery by presenting a branch-and-bound scheme for this problem [18]. Due to the NP-hard nature of most CPDO problems [15], these problems have been solved usually by metaheuristic methods. Armentano et al. (2011) presented a tabu search method with a process of path relinking to deal with the CPDO problem in an environment with single plant and homogenous vehicles [19]. Chang et al. (2014) developed an ant colony optimization process for the CPDO problem with multiple unrelated machines and capacitated vehicles [20].

With the complexity increase of CPDO problems, traditional heuristics and metaheuristics have difficulties in finding effective solutions to these problems because even a very simple CPDO problem is NP-hard. Some researchers thus aim at converting the original problem into some simpler sub-problems so as to simplify the optimum-seeking process [21]. Geismar *et al.* [22] proposed a two-phase metaheuristics to handle a CPDO problem for short shelf life products. They used either genetic or memetic algorithm to choose firstly a locally optimal customer sequence, and then splitted the customer sequence and used the Gilmore-Gomory approach to sort the subsequences of customers and to form the coordinated schedule. Chen et al. (2009) presented a non-linear mathematical program model for CPDO problem with a single machine and perishable food products [14]. They decomposed the integrated problem into a production sub-problem handled by the constrained Nelder-Mead approach, and a vehicle routing sub-problem handled by a metaheuristic. Ullrich (2013) adopted a genetic algorithm-based approach for the CPDO problem [15], which decomposed the problem into a machine scheduling sub-problem as well as a vehicle routing sub-problem. This approach is easy to get trapped in local optimum because of the complexity of its genetic optimization mechanism with a complicated solution representation. Following these previous studies, this research develops a novel hybrid metaheuristic solution framework with simpler solution representation for the investigated CPDO problem by effective problem decomposition.

III. PROBLEM STATEMENT
A. PROBLEM DESCRIPTION

We investigate a coordinated production and delivery optimization problem with one manufacturing plant and multiple vehicles and many customers. The plant has multiple identical parallel machines to produce customer orders. Orders cannot be split and each order must be continuously produced on one machine. After production, orders are delivered to widely dispersed customers by heterogeneous capacitated vehicles. Finished orders should be delivered to specified customers before the specified delivery due dates, otherwise tardiness penalties are incurred. The manufacturing plant has to obtain a joint production and delivery plan, by deciding the optimal assignment of orders to machines, the optimal production sequence of customer orders, and the optimal vehicle routes of delivering finished orders to customers. The problem objective is to minimize the total cost of transport and delivery tardiness.

On the basis of real-world practices, we make the following reasonable settings in establishing the mathematical programming model of the investigated CPDO problem: (1) each customer has one order and one location; (2) each vehicle's departure time is the last completion time of all orders transported by this vehicle; (3) orders that are produced (delivered) on a same machine (vehicle) are processed consecutively on the same machine; (4) the product volumes of all orders are the same; and (5) the transport time among customers is equal to the transport distance among customers.
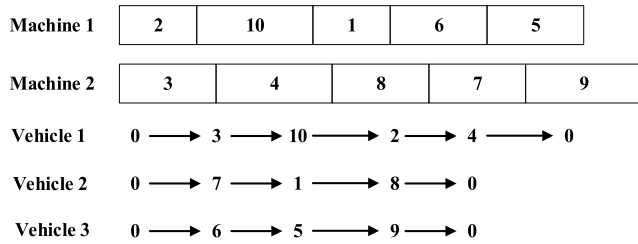
| Machine 1 | 2 | 10 | 1 | 6 | 5 |
| Machine 2 | 3 | 4 | 8 | 7 | 9 |

Vehicle 1 $0 \longrightarrow 3 \longrightarrow 10 \longrightarrow 2 \longrightarrow 4 \longrightarrow 0$

Vehicle 2 $0 \longrightarrow 7 \longrightarrow 1 \longrightarrow 8 \longrightarrow 0$

Vehicle 3 $0 \longrightarrow 6 \longrightarrow 5 \longrightarrow 9 \longrightarrow 0$

FIGURE 1. Illustration of a CPDO solution.

To facilitate the understanding of the investigated problem, we consider a CPDO example with ten orders (customers), two machines and three vehicles. FIGURE 1 depicts a feasible CPDO solution. Machine 1 produces orders 1, 2, 5, 6, 10 and production sequence is 2, 10, 1, 6 and 5 in turn. Machine 2 produces the remaining five orders and production sequence is 3, 4, 8, 7 and 9 in turn. Vehicle 1 delivers orders 2, 3, 4, 10 and the delivery route is 0→3→10→2→4→0 (0 is the depot). Vehicle 2 delivers orders 1, 7, 8 and the delivery route is 0→7→1→8→0. Vehicle 3 delivers orders 5, 6, 9 and the delivery route is 0→6→5→9→0.

B. NOTATIONS

Notations that are used in this paper are presented below.

Indices

i, customer/ order (alias $h, j, i = 1, \ldots, I$)

m, parallel machine ($m = 1, \ldots, M$)

k, vehicle ($k = 1, \ldots, K$)

Parameters

p_i, production processing time of order i

q_i, size of order i

l_i, delivery due date of customer i

c_{ij}, travel time between customer i and customer j

Q_k, vehicle k's capacity (maximal number of products vehicle k can transport)

μ, an infinite large number

α, transport cost per unit time

β, penalty cost per unit tardiness

Intermediate variables

CT_i, completion time of order i

a_i, arrival time at customer i

d_k, makespan of orders transported by vehicle k

Decision variables

o_{mi}, 1 if order i is produced on machine m; 0 otherwise

y_{ijm}, 1 if order i is the direct preceding of order j on machine m; 0 otherwise

t_{ki}, 1 if order i is delivered by vehicle k; 0 otherwise

x_{ijk}, 1 if the link (i, j) is a part routing of vehicle k; 0 otherwise.

C. MATHEMATICAL MODEL

$$\min F(o_{mi}, y_{ijm}, t_{ki}, x_{ijk}) = \alpha \sum_k \sum_i \sum_j c_{ij} \cdot x_{ijk}$$
$$+ \beta \sum_i \max(a_i - l_i, 0) \quad (1)$$

Subject to :
$$\sum_m \sum_i o_{mi} = I \quad (2)$$

$$\sum_m o_{mi} = 1, \quad \forall i \quad (3)$$

$$\sum_{i=1, i \neq j}^{I+1} y_{jim} = 1, \quad \forall j \in \{0, 1, \ldots, I\}; \ \forall m \quad (4)$$

$$\sum_{i=0, i \neq j}^{I} y_{ijm} = 1, \quad \forall j \in \{1, \ldots, I, I+1\}; \ \forall m \quad (5)$$

$$CT_0 = 0 \quad (6)$$

$$CT_i = \sum_{j, j \neq i} \sum_m (CT_j \cdot y_{jim}) + p_i$$
$$\forall i; \ \forall j \in \{0, 1, \ldots, I - 1\} \quad (7)$$

$$d_k = \max_i (CT_i \cdot t_{ki}), \quad \forall k \quad (8)$$

$$\sum_i \sum_k t_{ki} = I \quad (9)$$

$$\sum_k t_{ki} = 1, \quad \forall i \quad (10)$$

$$\sum_j \sum_k x_{ijk} = 1, \quad \forall i \in \{0, 1, \ldots, I\} \quad (11)$$

$$\sum_{i=0}^{I} x_{ijk} - \sum_{i'=0}^{I} x_{ji'k} = 0, \quad \forall j, k \quad (12)$$

$$\sum_j x_{0jk} = 1, \quad \forall k \quad (13)$$

$$\sum_i x_{i0k} = 1, \quad \forall k \quad (14)$$

$$\sum_i q_i \cdot t_{ki} \leq Q_k, \quad \forall k \quad (15)$$

$$a_i + c_{ij} - \mu (1 - x_{ijk}) \leq a_j, \quad \forall i, j, k \quad (16)$$

$$a_i \geq \sum_k (d_k \cdot t_{ki}) + c_{0i}, \quad \forall i \quad (17)$$

$$o_{mi}, t_{vi}, y_{ijm}, x_{ijk} \in \{0, 1\}, \quad \forall i, j, k, m \quad (18)$$

Objective (1) aims to minimize the total cost, including transport costs and tardiness penalty of all customer orders. Constraints (2)–(7) are machine scheduling constraints. Constraint (2) stipulates that all I orders should be allocated to machines I times while constraint (3) stipulates that each order must be exactly allocated to one machine. Constraint (4) ensures that order j either succeeds another order i or is the first order to be produced on machine m, where order 0 indicates the dummy first order processed on parallel machines m. Constraint (5) indicates that the order i is either the last to be produced on machine m or the immediate predecessor of order j, where $I + 1$ is the dummy last order processed on parallel machines. Constraints (6)-(7) calculates order i's completion time and the completion time CT_0 of the dummy first order is set to zero. Constraint (8) indicates that, for any vehicle k, the makespan d_k of orders delivered by this

vehicle is the maximal completion time of these orders. Constraints (9)-(10) guarantee that each order is allocated exactly to one vehicle. Constraints (11)–(17) are flow conservation constraints of traveling salesman problem. Constraints (11) and (12) enforce that vehicle k arrives at customer i once at most and each entering vehicle leaves customer i. Constraint (13) and Constraint(14) guarantee that each vehicle route starts and returns the same plant. Constraint (15) stipulates that the load delivered by vehicle k cannot exceed the vehicle capacity. Constraint (16) calculates the delivery time a_i of order i. Constraint (17) indicates that the delivery time a_i of order i is equal to or greater than the transport time from the customer to the plant plus the departure time of the vehicle transports this order. Constraint (18) stipulates the value ranges of four decision variables.

D. PROBLEM COMPLEXITY

The problem formulated above can be reduced easily to a vehicle routing problem if we set all orders' production times to zero. It is well-known that the vehicle routing problem is strongly NP-hard. The integrated problem is thus strongly NP-hard as well.

The investigated CPDO problem is very hard to solve because if its huge solution space. Consider the problem instance with M machines, K vehicles and I orders, the solution space of machine scheduling is $C_I^{M-1} \cdot I!$, the solution space of vehicle routing is $C_I^{K-1} \cdot I!$, and the solution space of investigated CPDO problem is $C_I^{M-1} \cdot I! \cdot C_I^{K-1} \cdot I!$. Take a simple CPDO problem with $M = 2, K = 2$, and $I = 10$ as an example. This problem has 8.7×10^9 candidate solutions. The real-world CPDO problems have the much larger solution space and are intractable since they usually need to deal with more machines, orders and vehicles.

IV. METHODOLOGY

A. PROBLEM DECOMPOSITION AND HYBRID METAHEURISTIC SOLUTION FRAMEWORK

We simplify the problem formulated above by effective problem decomposition and transformation. According to the actual characteristics of the CPDO, each order must be produced on one machine and transported by one vehicle, all orders are delivered by K vehicles and each vehicle leaves the plant immediately after the orders transported by the vehicle are finished. We can thus classify all orders into K groups, each of which consists of orders transported by a vehicle. Let N_k denote the number of orders transported by vehicle k. We have $N_1 + N_2 + ... + N_K = I$. As a result, we need to address a vehicle assignment sub-problem, which assign appropriate orders to each vehicle (determining the values of variable t_{ki}). Based on the vehicle assignment solution, we then need to address a parallel machine scheduling sub-problem, which decides these orders' production sequences on appropriate parallel machines (i.e., deciding the values of two variables - o_{mi} and y_{ijm}). Lastly, for each vehicle, a travelling salesman sub-problem is solved, which determines the

Line 1: Parameter initialization: Set $\rho, i, k, m, g_{\max}$;

Line 2: $g \leftarrow 0$;

Line 3: $M^g \leftarrow Initialization(\rho, i, k)$; / generate vehicle assignment (VA), population randomly /

Line 4: $M^g \leftarrow Evaluation(M^g, m)$; / evaluate each VA solution according to procedure 1 /

Line 5: repeat

Line 6: $I^g \leftarrow$ Generate new VA solution;

Line 7: $I^g \leftarrow Evaluation(M^g, m)$; / evaluate each VA solution according to procedure 1 /

Line 8: $M^{g+1} \leftarrow$ Generate new VA population; / M^{g+1} consisting of the best ρ VA solution in $\{M^g, I^g\}$ /

Line 9: $g \leftarrow g + 1$;

Line 10: until $g > g_{\max}$

Line 11: Select out the best solution I_{best} from M^g ;

Line 12: Return (I_{best}) ;

FIGURE 2. Pseudo-code of hybrid metaheuristic solution framework.

optimal travel routes of each vehicle (i.e., determining the values of x_{ijk}).

All the three sub-problems are classical optimization problems. The 1st sub-problem is equivalent to a generalized assignment problem, the 2nd sub-problem is a parallel machine scheduling sub-problem with makespan minimization, while the 3rd one is a travelling salesman problem. All these problems are NP-hard problems [23], [24], solution approaches for which range from exact techniques [25]–[32], heuristic techniques [33]–[43] to various metaheuristic techniques [44]–[48]. With the increase of problem scale and complexity of these problems, metaheuristic techniques usually exhibit superior performances to exact and heuristic techniques because the latter two have difficulty in finding effective solutions to complex NP-hard problems in a reasonable computation time.

Compared with the original CPDO problem, the 3 sub-problems are easier to handle. For example, the parallel machine scheduling sub-problem can be solved effectively by some heuristic rules [49], [27]. If so, the remaining solution space we need to search for is only the solution space size ($C_I^{k-1} \cdot I!$) of the vehicle assignment sub-problem times the solution space size ($I!$) of travelling salesman sub-problem, which is $C_N^{K-1} \cdot I! \cdot I!$.

On the basis of these 3 sub-problems, we propose a novel multi-level hybrid metaheuristic solution framework to solve the problem investigated. FIGURE 2 outlines the pseudo-code of the hybrid metaheuristic solution framework. First, we initialize algorithm parameters, including population size (ρ), the total number of orders (^{i}), the total number of vehicles (k), and the total number of parallel machines (m) as well as the maximal number of iterations ($g_{\max}$). We initialize the number of iterations in line 2. An Initialization procedure is utilized to generate randomly some initial vehicle assignment (VA) solutions $\{t_{ki}\}$ to the vehicle assignment sub-problem in line 3. Line 4 is utilized to access the performance (objective value) of candidate VA solution $\{t_{ki}\}$, which is performed according to Procedure 1. Then, a repeat-until-loop (from lines 5 to 10) is executed to generate the best solution I_{best}. From the parental VA solution at the gth iteration, the new VA solution is generated by performing genetic
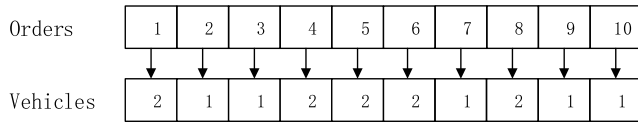
Orders	1	2	3	4	5	6	7	8	9	10
Vehicles	2	1	1	2	2	2	1	2	1	1

FIGURE 3. A representation example of assigning 10 orders to 2 vehicles.

operators in line 6. In line 7, the new VA solution is evaluated according to Procedure 1. Then, the new VA population M^{g+1} for the next generation I^{g+1} of VA solution is produced in line 8. M^{g+1} is composed of the best ρ VA solutions in the specified value range. After each iteration, the termination criteria of maximal iterations g_{max} is checked in the next line. If the number of maximum iteration is satisfied, the iterative process is ended. The resulting best solution is selected from M^g as the best one produced by our hybrid metaheuristic solution approach in line 11. Otherwise, the iterative process goes back to line 6 and continues generating new VA solution.

Procedure 1:

Step 1: obtain the values of $\{o_{mi}\}$ and $\{y_{ijm}\}$ by handling the machine scheduling sub-problem;

Step 2: obtain the values of $\{x_{ijk}\}$ by solving the traveling salesman sub-problem;

Step 3: calculate the objective function values according to formulation (1) based on the values of $\{t_{ki}\}$, $\{o_{mi}\}$, $\{y_{ijm}\}$ and $\{x_{ijk}\}$.

B. A GENETIC ALGORITHM-BASED HYBRID INTELLIGENT APPROACH

On the basis of the solution framework presented in the section A. PROBLEM DECOMPOSITION AND HYBRID METAHEURISTIC SOLUTION FRAMEWORK, a genetic algorithm-based hybrid intelligent (GAHI) approach is constructed to deal with the problem investigated [47], [50]. This research adopts the standard genetic algorithm, proposed by Goldberg (1989) [51], to handle the vehicle assignment sub-problem and obtain variable t_{ki}'s value. The LPT rule, proposed by Adams et al. (1988), is adopted to handle the parallel machine scheduling sub-problem and obtain variable o_{mi}'s value. The tabu search with intermediate-term and long-term memory, proposed by Fiechter (1994) [52], is utilized to handle the traveling salesman sub-problem and obtain variable x_{ijk}'s value. In the genetic algorithm, the chromosome representation incidates a candidate vehicle assignment solution $\{t_{ki}\}$, which is coded by a gene sequence, whose length is the number of orders to be produced. A gene indicates an order and the gene value implies the vehicle assigned to transport the order. A representation example of assigning 10 orders to 2 vehicles is shown in Fig. 3. The tournament selection (Goldberg 1989) [51] and the uniform-order crossover (Davis 1991) [52] are utilized as selection and crossover operations respectively. On the basis of the uniform mutation (Goldberg 1989) [51], a modified mutation operator is presented, which randomly changes the values of several randomly chosen genes.

The longest processing time (LPT) heuristic, developed by Adams et al. (1988) [54], has been proved to be very effective for the parallel machine scheduling problem with makespan objective and without preemptions [55], [56]. The tabu search, proposed by Fiechter (1994) [52], has been demonstrated that it can solve travelling salesman problems with up to 500 vertices very effectively. This method is able to find the optimal solutions to travelling salesman problems since the problem sizes of travelling salesman problem instances involved in this research are not more than 100.

V. EXPERIMENTS

This section validates the performance of proposed hybrid framework for the investigated CPDO problem based on extensive numerical experiments. We highlight 3 experiments next due to the page limit of the paper.

A. EXPERIMENT DATA AND SETTINGS

Extensive experiments have been performed to validate the effectiveness of the hybrid metaheuristic solution framework. Three representative experiments with different number of customers, vehicles and machines are shown as follows:

1) Experiment 1: 25 orders, 3 vehicles and 3 machines;
2) Experiment 2: 50 orders, 3 vehicles and 3 machines;
3) Experiment 3: 100 orders, 3 vehicles and 3 machines.

The capacities of vehicles in these experiments are 900, 1000, 1100 respectively. The data of customers and their orders are shown in Appendix. In the first 6 columns, the values show the customer number, geographical data in x-axis and y-axis, delivery due date, order size and processing time respectively. The processing time is set as the corresponding order size. The plant is located at coordinate (40, 50).

In our experiments, we set the population size to 100, the number of generations to 2000, the crossover probability to 0.7, and the mutation probability to 0.3 in GA [57], [47]. In tabu search [48], the tabu list length is set to 10, the number of neighboring solutions is set to 25, the maximum generation is 70, and ten best neighboring solutions are saved in each move. We set $\alpha = 1$, $\beta = 0.25$. The experiments were conducted on a laptop with Intel Core i5-3210M CPU @2.1 GHz and 3 GB RAM using MATLAB R2013a.

B. EXPERIMENTAL RESULTS AND PERFORMANCE COMPARISON

To evaluate the performance of the developed hybrid metaheuristic solution framework, we compared the performance of GAHI approach with that of the genetic algorithm, UGA, proposed by Ullrich (2013) [15].

In GAHI approach and UGA, if no better solution is found in several consecutive iterations or the maximum number of iterations is reached, the optimization process is stopped. To make a fair comparison, some algorithm parameters are set to the same. In GAHI approach and UGA, we set the population size to 100, the crossover probability to 0.7, the mutation probability is 0.3, the maximum number of iterations to 2000, and the number of consecutive iterations is 500.

Table 1 shows that the comparison results produced by the proposed GAHI approach and the UGA for the 3 CPDO

TABLE 1. Comparisons between GAHI approach and UGA.

Experiment		UGA	GAHI	gap (%)
Experiment 1	Mean	1.31E+03	9.17E+02	30.0
	Minimum	1.143E+03	0.861E+03	24.6
	Maximum	1.477E+03	0.973E+03	34.1
Experiment 2	Mean	3.78E+03	2.45E+03	35.2
	Minimum	3.057E+03	2.323E+03	24.0
	Maximum	4.510E+03	2.577E+03	42.8
Experiment 3	Mean	2.37E+04	1.21E+04	48.8
	Minimum	2.308E+04	1.116E+04	51.6
	Maximum	2.422 E+04	1.308 E+04	46.0

TABLE 2. Comparisons between GAHI and EM.

Mach ine	Ord er	Vehi cle	EM		GAHI		t_GAHI / t_EM
			Mean	Time(s)	Mean	Time (s)	
2	10	1	636.392	882.362	636.392	29.546	3.35%
		2	471.767	1344.487	471.767	54.767	4.07%
		3	422.001	6123.012	422.001	143.335	2.34%

experiments in 10 repetitive runs. In table 1, the rows of "Minimum" and "Maximum" mean the minimum and maximum of the objective functions, generated via GAHI and UGA in 10 repetitive runs. For each experiment, the relative gap between GAHI approach and UGA is calculated by the following formula (19).

$$gap = \frac{T^{UGA} - T^{GAHI}}{T^{UGA}} \times 100\% \qquad (19)$$

where T^{UGA} and T^{GAHI} denote the minimal total cost generated by the UGA and by the GAHI approach respectively.

The experimental results of table 1 show that:

1) The GAHI approach shows the better optimization performance than the UGA. The objective values of three experiments obtained by the GAHI approach are 861, 2323 and 11160 respectively, while the objective values obtained by the UGA are 1143, 3057 and 23080 respectively. These results show that the objective values obtained by the GAHI approach are much smaller than those obtained by UGA. The developed GAHI approach is capable of generating the better solutions to the CPDO problem compared to the UGA.

2) Compared to the UGA, the GAHI approach has a faster convergence rate and more difficult to trap in local optimum. Due to the difference of genetic code, the GAHI approach has a relative smaller searching space than the UGA, which leads to the UGA converges slower than GAHI approach. According to the results of experiment 1, the GAHI approach converged in the 85th generation, while the UGA converged in the 300th generation.

In summary, the proposed novel hybrid metaheuristic solution framework converts the CPDO into three sub-problems, which makes it possible to narrow down the search space of the CPDO. Compared with UGA, the GAHI approach under this framework could generate better solutions in terms of the examined experiments, and show a superior optimization performance.

C. OPTIMIZATION PERFORMANCE OF THE GAHI APPROACH

We further examine the optimum-seeking performance of the GAHI approach. The enumeration method (EM) is adopted

to find the optimal solutions to small-sized CPDO problems. The comparisons were conducted based on 3 small-sized problem instances with 10 orders, 3 vehicles and 2 machines. We perform 10 trials for the GAHI approach for each instance.

The comparison results between the GAHI approach and the EM are shown in table 2. The GAHI approach generated the optimal solutions to the three instances in each trial. The GAHI approach exhibits the good optimum-seeking performance for the CPDO problem investigated. For these instances, the computation time (denoted by t_GAHI) of GAHI approach is much shorter than that (t_EM) of the EM. Taking the instance with 2 machines, 10 orders and 3 vehicles as an example, the CPU time (denoted by t_EM) of the EM is 6123.012 s, while the GAHI approach only uses 143.335s, which is only 2.34% of the former. When the problem size increases, the gap in CPU time between the GAHI approach and the EM goes bigger.

Based on the comparison results described above, the GAHI approach and the proposed hybrid metaheuristic solution framework have the capability of handling the investigated CPDO problem effectively.

VI. CONCLUSION

This paper addressed a collaborated production and delivery optimization problem with parallel machines and multiple heterogeneous vehicles in manufacturing environments producing time-sensitive products. The mathematical programming model of the CPDO problem is established. A multi-level hybrid metaheuristic solution approach is developed to deal with this problem, by which the investigated problem is decomposed into 3 simple sub-problems including an assignment sub-problem of orders to vehicles, a machine scheduling sub-problem with makespan objective, and a travelling salesman sub-problem. By so doing, the candidate solution space searched by metaheuristics is reduced largely since the machine scheduling sub-problem can be solved determinedly by some classical heuristics.

To evaluate the performance of the hybrid metaheuristic solution framework, this research constructed a genetic algorithm-based hybrid intelligent approach by combining

TABLE 3. Original data of the 100 customers.

TABLE 3. *(Continued.)* Original data of the 100 customers.

Customer /Order No.	X-axis	Y-axis	Delivery due date	Order size	Processing time
1	25	85	803	20	20
2	22	75	282	30	30
3	22	85	601	10	10
4	20	80	774	40	40
5	20	85	203	20	20
6	18	75	518	20	20
7	15	75	430	20	20
8	15	80	497	10	10
9	10	35	501	20	20
10	10	40	649	30	30
11	8	40	325	40	40
12	8	45	353	20	20
13	5	35	783	10	10
14	5	45	165	10	10
15	2	40	304	20	20
16	0	40	385	20	20
17	0	45	833	20	20
18	44	5	465	20	20
19	42	10	384	40	40
20	42	15	667	10	10
21	40	5	345	10	10
22	40	15	505	40	40
23	38	5	331	30	30
24	38	15	811	10	10
25	35	5	914	20	20
26	95	30	659	30	30
27	95	35	276	20	20
28	92	30	279	10	10
29	90	35	324	10	10
30	88	30	376	10	10
31	88	35	295	20	20
32	87	30	751	10	10
33	85	25	210	10	10
34	85	35	617	30	30
35	67	85	787	20	20
36	65	85	173	40	40
37	65	82	687	10	10
38	62	80	408	30	30
39	60	80	194	10	10
40	60	85	459	30	30
41	58	75	506	20	20
42	55	80	163	10	10
43	55	85	704	20	20
44	55	82	347	10	10
45	20	82	167	10	10
46	18	80	619	10	10
47	2	45	235	10	10
48	42	5	862	10	10
49	42	12	570	10	10
50	72	35	637	30	30
51	55	20	456	19	19
52	25	30	305	3	3
53	20	50	505	5	5
54	55	60	731	16	16
55	30	60	729	16	16
56	50	35	687	19	19
57	30	25	527	23	23
58	15	10	912	20	20
59	10	20	172	19	19
60	15	60	824	17	17
61	45	65	388	9	9
62	65	35	297	3	3
63	65	20	169	6	6
64	45	30	321	17	17
65	35	40	141	16	16
66	41	37	696	16	16
67	64	42	398	9	9
68	40	60	742	21	21
69	31	52	287	27	27
70	35	69	940	23	23
71	65	55	371	14	14
72	63	65	190	8	8
73	2	60	416	5	5
74	20	20	775	8	8
75	5	5	362	16	16
76	60	12	398	31	31
77	23	3	894	7	7
78	8	56	495	27	27
79	6	68	482	30	30
80	47	47	952	13	13
81	49	58	485	10	10
82	27	43	282	9	9
83	37	31	235	14	14
84	57	29	525	18	18
85	63	23	474	2	2

TABLE 3. *(Continued.)* Original data of the 100 customers.

86	21	24	479	28	28
87	12	24	489	13	13
88	24	58	390	19	19
89	67	5	843	25	25
90	37	47	489	6	6
91	49	42	849	13	13
92	53	43	144	14	14
93	61	52	938	3	3
94	57	48	522	23	23
95	56	37	230	6	6
96	55	54	692	26	26
97	4	18	677	35	35
98	26	52	302	9	9
99	26	35	438	15	15
100	31	67	940	3	3

a genetic algorithm, a LPT rule and a tabu search under this framework. Extensive experiments have been performed to validate the effectiveness of the proposed framework by comparing the GAHI approach and two other approaches. For small-sized instances, the GAHI approach showed the ability of achieving the optimal solutions within a much shorter time than the enumeration method did. The GAHI approach generated much smaller objective values for the examined three problem instances, and showed a better optimization performance than the Ullrich's genetic algorithm did [15].

To sum up, this paper demonstrates that it is possible to handle effectively the CPDO problem based on the proposed hybrid metaheuristic solution framework. As a start, this paper presented the results of integrating several commonly used metaheuristics into this framework. We do not claim that the used techniques (e.g., GA, LPT heuristic) are the best under the solution framework, under which other metaheuristics can also be used. Future work can aim to integrate more advanced metaheuristics for each sub-problem into the proposed framework, and to compare their performances with those of the GAHI approach. Another future direction can consider the effects of vehicle departure time on integrated scheduling performances.

APPENDIX
See Table 3.

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DUNHU LIU was born in 1976. He received the Ph.D. degree from the Business School of Sichuan University, in 2010.

From 2010 to 2015, he was an Associate Professor with the Chengdu University of Information Technology, where he has been a Professor, since 2015. He has authored two books and more than 40 articles. He has completed more than 40 scientific research and engineering application projects in modern logistics. He has won three second prizes and two third prizes of provincial science and technological progress. His research interests include achievements transformation and data mining.

Prof. Liu was an Evaluation Expert for the National Natural Science Funds of China and for the Sichuan Provincial Science and Technology Funds.

WEI WANG was born in 1979. He received the M.S. degrees in traffic & transportation planning and management from Southwest Jiaotong University, in 2003, and the Ph.D. degree in management science and engineering from Hohai University, in 2009.

From 2003 to 2006, he was an Assistant Professor with Hohai University, where he was a Lecturer from 2006 to 2013. From 2013 to 2014, he was a Visiting Scholar with the University of Wisconsin–Madison. Since 2013, he has been an Associate Professor and a Master Tutor with the Water Transportation Planning and Logistics Engineering Department, Hohai University. He has authored two books, more than 60 articles, and more than 10 inventions. He has completed more than 80 scientific research and engineering application projects in modern logistics. He has won five second prizes and five third prizes for provincial and ministerial science and technological progress. His research interest is in modern logistics.

Dr. Wei Wang was an Evaluation Expert with the National Investment Project Evaluation Center of NDRC; a Key and Special Evaluation Expert for strategic and international scientific and technological innovation cooperation of the National Key Research and Development Programs of the Ministry of Science and Technology; a Member of the Association of Chinese–American Scientists and Engineers; the Executive Director and a Contract Research Fellow of the China Society of Logistics; Member of the Expert Database, Food Logistics Technology Division, Chinese Institute of Food Science and Technology; an expert of the Expert Database, China Water Transportation Construction Association; an expert of the Expert Database, National Technical Committee on Logistics Standardization, funded by Double Innovation, an initiative of the Jiangsu Province; a Member of the Freight and Logistics Expert Panel, Department of Transportation, Jiangsu; Member of Expert Committee, Jiangsu Communications and Transportation Association; Member of Jiangsu Cold Chain Association; an Appraisal and Review Expert for new high-tech enterprise in Jiangsu; and a Member of the Expert Committee, Wuxi Freight and Logistics Association. He serves as an expert in the evaluation and acceptance of investment and subsidy funds at all levels of the transportation and logistics industry for a long term, as adviser and a consultant to more than ten large-scale transportation and logistics enterprises, and as a Chairman of the technical committee of marine traffic engineering and water transportation infrastructure engineering of safety discipline for the Water Transportation Division of World Transport Convention, from 2017 to 2019.

LI HUANG was born in 1982. She received the M.S. degree in administrative management from Hohai University, in 2007, and the Ph.D. degree in management science and engineering from Hohai University, in 2009.

From 2010 to 2019, she was an Assistant Professor with Hohai University. From 2013 to 2014, she was a Visiting Scholar with the University of Wisconsin–Madison. She was an Evaluation Expert with the National Investment Project Evaluation Center of NDRC. Since 2019, she has been an Associate Professor with the School of Public Administration, Hohai University. She has authored three books, more than 40 articles, and more than 3 inventions. She has completed more than 40 scientific research and engineering application projects of modern logistics. Her research interest is in modern logistics. Dr. Huang has won a second prize and three third prizes of provincial and ministerial science and technological progress.

DAVID PROVERBS worked for 10 years in the construction sector as a Project Manager before joining academia as a Research Assistant in 1994, progressing quickly to become Head of Department and a Full Professor in 2004. He has led large built environment schools at two modern universities. He is currently responsible for establishing and growing a high-quality international portfolio of provision across the various disciplines in the faculty. He is currently a Professor of construction management and the Associate Dean International with the Faculty of Computing, Engineering and Built Environment, Birmingham City University.

Combining his expertise in building technology and flooding, he has pioneered the development of flood reinstatement and recovery to the benefit of many governments, agencies, charities, companies, and institutions worldwide. He has published extensively on topics linked to flood damage, flood adaptation, and resilience. He is a confident and adept communicator and has given many keynote presentations and guest lectures, and undertaken various media activities. He has excellent leadership skills, having led many teams, supervised numerous funded projects and provided mentoring to colleagues and students he has supported. He has published well over 200 refereed conference papers and journal articles, numerous consultancy reports and several leading textbooks on flood risk management. He is a Co-Editor to the *International Journal of Building Pathology and Adaptation*, a member of the RICS UK Education Standards Board, and a Trustee to the RICS Research Trust. He received research funding to the value of over 1.8 million sterling secured from a range of prestigious sources including EPSRC, NERC, World Bank, and DFID.

Dr. David, an Invited Eminent Fellow of the Royal Institution of Chartered Surveyors, in 2011, and a member of the RICS Education and Standards Boards, was a Chair of the Council for Heads of the Built Environment (CHOBE), from 2012 to 2016.

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