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Study on Multi-Objective Optimization of Logistics Distribution Paths in Smart Manufacturing Workshops Based on Time Tolerance and Low Carbon Emissions

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Abstract: In the Industry 4.0 environment, an ideal smart factory should be intelligent, green, and humanized, and the logistics transportation from raw materials to final products in the factory should be completed by smart logistics. In order to address the problems of low efficiency, poor workstation service satisfaction, high distribution costs, and non-greening during the logistics distribution processes in discrete smart manufacturing workshops are required. A mathematical model of optimized multi-objective green logistics distribution paths in a smart manufacturing workshop has been constructed in this study, with low costs, high efficiency, and workstation service satisfaction taken into consideration. Then, this mathematical model was solved with an improved ant colony optimization algorithm. A "time window span" was introduced in the basic ant colony optimization algorithm to prioritize the services to workstations with a relatively high urgency in material demand, with the aim of improving workstation service satisfaction. Lastly, in order to verify the effectiveness of the model and algorithm proposed in this study, a simulation experiment has been conducted on the workstation logistics distribution system in a smart manufacturing workshop to provide convincing evidence for optimizing workstation logistics distribution paths in workshops of discrete manufacturing enterprises.

Keywords: time tolerance; low carbon emission; smart manufacturing; workshop logistics distribution; path optimization

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1. Introduction

Many researchers abroad and at home have investigated the problem of path optimization for logistics distribution. For example, Zhao Z X and Li X M have investigated the path optimization problem of electric vehicles for fresh food delivery in traffic varying with time [1]. With customer satisfaction on cold chain distribution taken into consideration, Rent T, Xiang Y C, et al. constructed an optimized model with minimum carbon emissions [2]. With customer satisfaction defined with a time-window fuzzy method, Yin Y and Zhang H Z established a multi-objective model for optimal-path selection [3]. Hu Z A, Jia Y Z, and Li B W et al. have used customers' feedback on service time and good integrity as indicators to measure customer satisfaction [4]. Although the studies mentioned above have emphasized customer satisfaction, only a few of them have analyzed the time-sensitivity of customers, and the majority of these studies have still taken the costs of logistics enterprises as their starting points. To address the problem of intelligent production logistics systems in manufacturing enterprises, Lu Z Y, Zhuang Z L, and Huang Z Z et al. proposed a system framework of multi-agent-based production logistics.

With a real-time, intelligent, decision-making capability, this system can thereby resolve the problems of order scheduling and AGV path selection in the production processes [5]. Several scholars have used multiple system simulation software, including Flexsim, Arena, and Witness to construct models to simulate various links in production logistics and seek their bottlenecks. By adjusting parameters to optimize the system, they wanted to achieve the objectives of the highest efficiency, lowest costs, and optimized services in the system [6,7]. Existing studies on path optimization of logistics distribution have applied such algorithms such as the pigeon flock-intelligent water droplet complementarily improved optimization algorithm [8], and ant colony optimization algorithm [9], which have many parameters and a low solution efficiency. Several studies have revealed that the plant growth simulation algorithm has fewer parameters, and has been successfully used in multi-level planning, combinatorial optimization, and integer programming [10]. However, although this algorithm has been successfully used in solving multi-objective questions [11], its search is extremely random with a relatively slow convergence. Thus, it still needs to be improved to solve multi-objective problems.

To this day, the vehicle routing problem is a popular research topic not only in China but also abroad in the field of logistics research. The problem model is mainly studied in terms of four main pairs of considerations: vehicle capacity, time constraint, and vehicle class. For the vehicle path problem with capacity constraints, Ahmed (2018) proposed an efficient particle swarm optimization algorithm based on a two-layer local search and found that the proposed algorithm out-performs other particle swarm optimization algorithms [12]. Reihaneh and Ghoniem (2018) developed a branch-and-cut algorithm for solving [13]. Altabeeb et al. (2019) proposed a hybrid firefly algorithm to improve the quality and convergence speed of the solution and assessed it to be significantly better than other firefly algorithms by example [14]. Smiti et al. (2020) addressed the cumulative capacity constrained vehicle path problem through developing a mathematical model with the shortest arrival time to the customer as the optimization objective, and two optimization models were proposed to solve it [15]. For the vehicle path problem with time windows, Molina et al. (2020) proposed a hybrid ant colony algorithm with local search, and verified experimentally that the method has a good performance [16]. Bogue et al. (2020) proposed a column generation algorithm and a post-optimization heuristic algorithm for solving [17]. Jalilvand et al. (2021) developed a two-stage stochastic model and proposed a recursive hedging algorithm for a vehicle path problem with a two-level time window allocation and stochastic service times [18]. Tilk et al. (2021) designed a branch pricing cut algorithm to solve the model [19]. Hoogeboom et al. (2021) solved the model using a branch-and-cut approach with the objective of minimizing the travel time and the risk of violating the time window [20]. For the problem of multiple paths for pairs of vehicles, Gholami et al. (2019) used a genetic algorithm to solve a mixed-integer nonlinear model with cost minimization as an objective when studying a multi-vehicle path problem considering product transfer between vehicles in a dynamic situation [21]. Wang et al. (2019) developed a mathematical model with the optimization objective of minimizing total carbon emissions when considering an integrated single-vehicle scheduling and multi-vehicle path problem, and then proposed a forbidden search hybrid algorithm to solve it [22]. Behnke et al. (2021) proposed a column generation method for solving the vehicle path problem with heterogeneous vehicles and heterogeneous roads [23]. Intelligent logistics is one of the five core industries of intelligent manufacturing, and workshop logistics and distribution are the key par. Logistics distribution in the workshop belongs to the distribution problem of discrete task-driven automated guided vehicle AGV, whose task orders arrive in real time, and the transportation environment has dynamic uncertainty [24]. The research of intelligent manufacturing logistics distribution paths based on multi-objective optimization is as follows. For example, multi-AGV obstacle avoidance path planning based on initial time window detection [25,26], improved ant colony algorithm, and corresponding conflict resolution strategies are designed to obtain the optimal solution of the multi-AGV global path [27], Dijkstra algorithm and time window arrangement are used for multi-AGV path planning, with AGV collisions and conflicts avoided according to priority [28], production process optimization [29], equipment scheduling optimization [30], and equipment fault prediction and health maintenance [31], etc. Lee C et al. established a physical information system model of an intelligent robot warehouse to predict AGV movement through workflow data collection and process monitoring and used a variety of strategies to implement collaborative decisions to avoid AGV conflicts [32]. Cai et al. proposed that the digital twin model of machine tools can be constructed through the acquisition and processing of real-time data [33].

It is known from the research of foreign scholars that most of the current research in this field are based on vehicle path problems that consider both the vehicle capacity and time window, or based on vehicle path problems that consider both the vehicle capacity and vehicle type, while relatively few studies consider vehicle capacity, service attitude, carbon emission, time window, and vehicle type simultaneously.

The logistics distribution in the workshop belongs to the problem of discrete task-driven multi-automated guided vehicle (AGV) distribution, whose task orders arrive in real time, and the transportation environment has a dynamic uncertainty. According to the actual operation status of the logistics distribution in the workshop, the logistics distribution encompasses the characteristics of the continuous and uninterrupted work of the AGV equipment, dynamic path planning, and simultaneous operation of multiple AGVs, thus optimizing the efficiency of logistics distribution under the premise of avoiding conflicts. However, even disturbance events are the key to the problem, and the optimization effect of the traditional path planning methods is still far from the demand of intelligent logistics. The research on AGV path planning algorithms has been relatively mature, but for the multi-AGV dynamic path planning problem, the existing methods still have the problems of the weak handling of perturbation events, and high difficulty in obtaining the global optimal solution. With the development of physical simulation technology, and the accumulation of workshop environment data, it is therefore worthwhile to study the direction of integrating the appropriate model, data, and algorithms to optimize the multi-AGV path planning problem. The current workshop AGV logistics system has the following upgrade requirements: (1) the path planning method needs to quickly plan a conflict-free distribution path when the distribution task is issued and reduce the cost of the distribution time; (2) the path planning method needs to be in a dynamic environment, according to the detailed conditions of the unexpected events. The planned path of the AGVs is adjusted in real time to avoid conflicts with a small cost of conflict adjustment time by establishing the workshop digital twin environment model, realizing the workshop state update and information synchronization, adjusting the path planning algorithm parameters using the model optimization, realizing the optimization of the workshop AGV path planning problem, realizing on-time delivery, and realizing the high satisfaction of the work station of the delivery service; and (3) the promotion of low-carbon actions in society, logistics and transportation equipment usually consumes a lot of energy and has a high carbon emission, while the energy saving and emission reduction in transportation is the general trend to reduce energy consumption and emissions in transportation. In order to respond to the national advocacy of a "low-carbon economy", the current internal material transportation link of the workshop must therefore be optimized.

In summary, in an Industry 4.0 environment, an ideal smart factory is intelligent, green, and humanized. In such a factory, the logistics transportation from the raw materials to the final products is completed by smart logistics. In order to address the problems of low efficiency, poor workstation service satisfaction, high distribution costs, and non-greening during the logistics distribution processes in discrete smart manufacturing workshops, a mathematical model of multi-objective optimized workshop green logistics distribution paths has been constructed in this study, with low costs, high efficiency, and workstation service satisfaction taken into consideration. Then, with an improved ant colony optimization algorithm, the mathematical model constructed was solved. A "time window span" was introduced in the basic ant colony optimization algorithm to prioritize the services into workstations with a high level of urgency in material demand to improve the workstation service satisfaction. Finally, in order to verify the effectiveness of the model and algorithm proposed in this study, a simulation experiment with the Solomon's VRPTW standard problem set used with its test instances was performed to provide convincing evidence for optimizing the workstation logistics distribution paths in the workshops of discrete manufacturing enterprises.

This article is structured as follows: Section 2 provides the problem description and prerequisite assumptions. Section 3 presents the notation description and mathematical model. Section 4 presents the algorithm design. Lastly, the paper ends with Section 5 that concludes the research outcomes.

2. Problem Description and Prerequisite Assumptions

2.1. Problem Description

The path optimization problem of workshop logistics distribution is essentially a vehicle routing problem (VRP), which was first introduced by the scholars Danting and Ramser in 1959 [34]. From the perspective of theoretical research, the path optimization problem of logistics distribution has been proven to be an NP-hard problem [35], with a high solution complexity and a large computational amount. The initial studies on this problem primarily focused on optimizing a single objective such as the shortest driving path, the lowest consumption cost, and the shortest time used. With the progress of science and technology, the focus of these studies have gradually shifted to multi-objective optimization, with more diversified factors taken into consideration. Therefore, these studies can reflect the actual workshop logistics distribution processes to a greater extent. On the basis of a soft time window, Muller decomposed the multi-objective optimization problem and solved it with a heuristic algorithm [36]. At the current stage, the studies on vehicle path problems are primarily focused on model construction and solution algorithm selection. In terms of model construction, these studies have primarily used optimization objectives and constraint conditions to improve their models.

With comprehensive reference to the existing literature and analyzes of the path optimization problem of workshop logistics distribution, this study has found that in some workshops, distribution carts cannot deliver the required materials to the workstations within the time windows specified by these workstations, thus incurring high-time penalty costs, and leading to low workstation service satisfaction. Furthermore, unreasonable route planning increases the number of carts used in the distribution process and the distribution distance and drives up the costs of distribution as a result. On the basis of each workstation's demand for production materials, this study has constructed an optimization model for multi-objective workshop logistics distribution paths with low costs, high efficiency, and workstation service satisfaction taken into consideration. In a case where there are K distribution carts with a capacity of Q in a discrete manufacturing workshop, there are N workstations to which the materials should be delivered to, and the location of each workstation and the number of materials required by each workstation are known. Thus, the delivery of these workshop materials with the objective of achieving workstation service satisfaction can be described as a task to use each distribution cart to deliver the required materials from the workshop distribution center to each workstation within the time window specified by each workstation. During the distribution process, each distribution cart delivers its materials along with the planned route and adjusts its delivery service order to the workstations according to the size of the time-window span specified by each workstation to ensure that workstations with a higher level of urgency in material demand can receive their required materials in priority. Therefore, the distribution efficiency of workshop materials can be enhanced, and a minimum quantity of carts used in the whole distribution process, as well as the shortest distribution distance and highest workstation service satisfaction, can be achieved. With the materials delivered to each workstation and distribution carts returned back to the workshop distribution center, the delivery task would therefore be accomplished.

2.2. Prerequisite Assumptions

In this study, the following basic assumptions have been made:

(1) Constraint on the carrying capacity. The material quantity q_i required by workstation i is known, and the sum of material quantities of workstations along each specified delivery path of each distribution cart should not exceed the maximum carrying capacity Q of that distribution cart.
(2) Constraints on the distribution carts. The stopping, starting, loading, and unloading times of each distribution cart as well as its breakdown, is negligible. All distribution carts start from the distribution center and return back to the distribution center after completing their delivery tasks. A single distribution cart can serve multiple workstations in one task. However, each workstation can be served by only one distribution cart each time. During its whole distribution process, the driving speed of each distribution cart is constant and known.
(3) Constraint on the distribution center. In each workshop, there is only one material distribution center. The location of this distribution center is known, and its materials are sufficient and can meet the requirements of all workstations.
(4) Constraint on the time window. For workstation i, the distribution cart must provide its service within the time window of $[e_i, l_i]$. If the distribution cart arrives earlier than the moment of e_i, then it must wait at the workstation, and if the distribution cart arrives later than the moment of l_i, then its service must be delayed.

3. Notation Description and Mathematical Model

3.1. Notation Description

Many notations and variables are used in this paper. Therefore, for the convenience of analysis, explanations, and descriptions are provided here for these notations.

G denotes a distribution network.

In n = (N, E), N represents a set of n workstation nodes ($N = \{n_0, n_1, n_2, \ldots, n_n\}$), and E represents a set of edges ($E = \{e_1, e_2, \ldots, e_m\}$), indicating there are m edges linking every two nodes.

n_0: material distribution center
n_i: distribution node of each workstation
d_{ij}: distance between node i and node j
q_i: material quantity required by workstation i
Q: maximum carrying capacity of each distribution cart
k: a set of distribution carts
T_i: time moment for a distribution cart to arrive at workstation i
E_i: the earliest time moment when a distribution cart is allowed to arrive at workstation i, the latest time moment when a distribution cart is allowed to arrive at workstation i
l_i: the upper limit of time that satisfies workstation i
e_i: the lower limit of time that satisfies workstation i
c_k: unit driving cost of the distribution cart
c_e: unit penalty cost incurred by the early arrival of the distribution cart
c_l: unit delay cost incurred by the late arrival of the distribution cart
c_a: fixed start-up cost of the distribution cart
S: driving speed of the distribution cart
ρ_o: fuel consumption amount of the distribution cart with no loading of goods
ρ^*: fuel consumption amount of the distribution cart with full loading of goods
Q: rated loading capacity of the distribution cart
e_o: CO_2 emission coefficient of fuel
d: driving distance of a distribution cart
p_e: carbon tax price in the carbon emissions trading market
x_{ijk}: whether distribution cart k is driving between workstation i and workstation j, with 1 indicating Yes and 0 indicating Not

x_{ij}^{k}: The load of the Kth material distribution vehicle between stations i, j is denoted by x
y_{ik}: whether workstation i is being served by distribution cart k, with 1 indicating Yes, and 0 indicating Not

3.2. Mathematical Model

A multi-objective optimization model with the shortest total path of logistics distribution, a maximum workstation service satisfaction, and the least number of distribution carts is constructed as follows:

$$\min f_1 = \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} d_{ij}x_{ijk} \tag{1}$$

$$\min f_2 = \sum_{i=0}^{N}\sum_{k=1}^{K}\{\max[(e_i - T_i), 0] + \max[(T_i - l_i), 0]\} \tag{2}$$

$$\min f_3 = \sum_{k=1}^{K}\sum_{j=1}^{N} x_{0jk} \tag{3}$$

$$\min\, f_4 = \sum_{k=1}^{k}\sum_{i,j=0}^{n} p_e e_o \rho(x) x_{ij}^{k} d_{ij} \tag{4}$$

$$S.T. \sum_{i=1}^{N} q_i y_{ik} \leq Q \tag{5}$$

$$\sum_{k=1}^{K} y_{ik} = 1 \tag{6}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} x_{ijk} = \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} x_{jik} = 1 \tag{7}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ijk} \leq |N| - 1 \tag{8}$$

$$\sum_{i=0}^{N} x_{ijk} = \sum_{j=0}^{N} x_{jik} = y_{ik} \tag{9}$$

$$x_{ijk} = \begin{cases} 1, k\ \ from\ position\ \ i\ to\ \ j \\ 0, others \end{cases} \tag{10}$$

$$y_{ik} = \begin{cases} 1, positon\ \ l\ \ served\ \ by\ \ k \\ 0, others \end{cases} \tag{11}$$

In the multi-objective optimization model listed above, "i = 0" and "j = 0" represent the starting point and the ending point of a distribution cart, respectively, and d_{ij} represents the distance between workstation i and workstation j. Equation (1) is a function calculating the shortest total driving distance of all distribution carts. Equation (2) is a function calculating the maximum workstation service satisfaction, also meaning the smallest penalty cost. Equation (3) is a function calculating the smallest number of distribution carts used. Formula (4) is a function calculating the cost of carbon emissions. Formula (5) indicates that the loading quantity of each distribution cart should not exceed its maximum loading capacity. Formula (6) indicates that each workstation can be served by only one distribution cart. Formula (7) indicates that all distribution carts start from the distribution warehouse, and finally return to the distribution warehouse. Formula (8) is to eliminate bypasses. Formula (9) indicates that the distribution cart arriving at and departing from a workstation should be the same cart. Moreover, decision variables are provided with Formulas (10) and (11). The model constructed above is a multi-objective optimization model. For the convenience of model solving, with the application of the unit distribution cost c_k, unit wait penalty cost c_e, unit delay penalty cost c_l, and fixed start-up cost of distribution cart c_a, in this study the model mentioned above has been transformed into an optimization model of a single objective, that is to calculate the total cost of all the distribution carts fulfilling their distribution tasks. The adjusted objective function is shown as follows:

$$\begin{aligned} \min f = & \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} c_k d_{ij} x_{ijk} + \sum_{k=1}^{K}\sum_{i=0}^{N}\{c_e \max[(e_i - T_i), 0] + c_l \max[(T_i - l_i), 0]\} \\ & + \sum_{k=1}^{K}\sum_{j=1}^{N} c_a x_{0jk} + \sum_{k=1}^{k}\sum_{i,j=0}^{n} p_e e_o \rho(x) x_{ij}^{k} d_{ij} \end{aligned} \tag{12}$$

4. Algorithm Design

The optimization of the material distribution paths for shop stations in discrete assembly manufacturing enterprises belongs to the NP-hard problem, which has a high problem complexity. Researchers both at home and abroad have proposed various algorithms to solve such problems, which have been mainly categorized into the two main categories of exact algorithms and heuristic algorithms. The known exact algorithms are suitable for solving problems of a small scale and low complexity, but for large-scale vehicle routing problems (VRPs), due to the complexity of the solution process, exact algorithms may not be able to obtain the optimal solution, leading scholars to propose the utilization of heuristic algorithms. The ant colony algorithm and the forbidden search algorithm are the more widely used types of heuristic algorithm applications. The ant colony algorithm has more global search capability and a higher computational efficiency compared to the forbidden search algorithm. The genetic algorithm has a strong applicability in solving vehicle path problems, and can also solve complex VRP problems as well, and it is widely used by both domestic and foreign scholars due to its good solution performance. Table 1 shows a summary of the advantages, disadvantages, and applicability of five common modern heuristic algorithms. The ant colony optimization algorithm is a positive feedback swarm intelligent optimization algorithm, which encompasses the advantages of parallelism, a strong robustness, adaptability, and the ability to be easily combined with the other algorithms. However, the convergence speed of this algorithm is relatively slow, making its solution tend to be a solution of local optimization. In order to solve the above problems, this paper improves on the basis of the standard genetic algorithm. These improvements focus on two aspects: first, in order to increase the search space, the crossover operator was designed to shuffle the paths of chromosomes randomly according to the probability after crossover; and second, three variants were taken for the mutation operator for mutation. With reference to the study by Tan et al. [37], this study has improved the basic ant colony optimization algorithm to solve the model constructed above.

Table 1. Comparison of the characteristics of modern heuristics.

No.	Algorithm Type	Advantage	Disadvantage	Scope of Application
1	Ant colony algorithm	Good positive feedback mechanism and easy association with other algorithms.	Long search time, need to constantly adjust variables, and slow solution speed.	It is applicable to multi-objective optimization problems.
2	Simulated annealing algorithm	High robustness, and permits parallel processing at multiple constraints	The accuracy of the results is not high, and the running time is long and inefficient.	Applicable to the modification of existing path problems.
3	Particle swarm algorithm	The algorithm is simple and fast to compute, with a strong global search capability.	It is not applicable to discrete problems and tends to converge prematurely.	Solved in combination with other algorithms.

Table 1. *Cont.*

No.	Algorithm Type	Advantage	Disadvantage	Scope of Application
4	Taboo search algorithm	Strong local search ability and is prone to premature convergence.	The solution is complex, computationally inefficient, and dependent on the initial solution obtained.	Solving large-scale problems.
5	Genetic algorithm	High computational efficiency and strong bureau search capability.	Poor local search capability.	VRP and other complex realities that fit the problem.

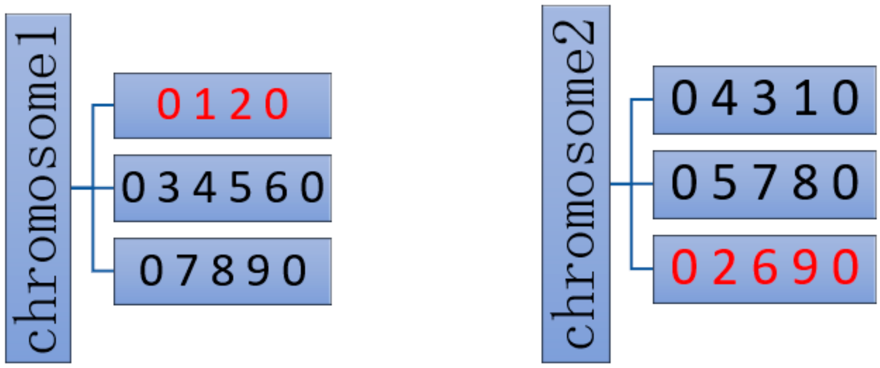
The algorithm-solving process is shown below:

Step 1: Initialize the algorithm, and assign values to all variables, with an initial population randomly generated.
Step 2: Perform the fitness evaluation and Pareto sorting to select the better individuals to form a new population.
Step 3: Perform a binary tournament selection to update the population.
Step 4: Pair up the chromosomes for path crossing.
Step 5: Perform chromosome mutation (including division, integration, and partial exchange) by probability.
Step 6: Judge whether the chromosomes are a feasible solution. If not, then remove the chromosomes not satisfying the condition and select again from the parent better individuals who are placed in the population.
Step 7: Judge whether the ending condition of the algorithm has been satisfied. If yes, then output the current optimal solution. If not, then return to Step 2.

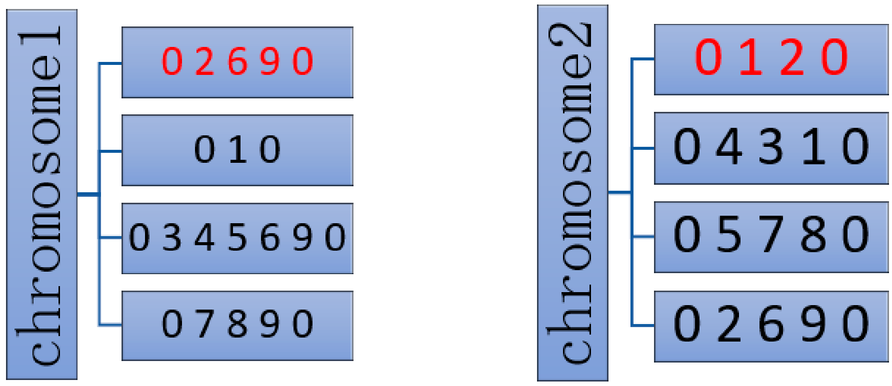
The algorithm is described as follows:

(1) Encoding: Use the real number coding method to perform the genotype encoding, and each gene position should correspond to its real client number. For example, if the number of gene positions in a path is 6 (i.e., there are six clients with a client number of 1, 3, 4, 6, 7, and 9, respectively), and the routing order is as follows: $0 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 7 \rightarrow 9 \rightarrow 6 \rightarrow 0$, then this path has a genotype of 01437960.
(2) Fitness measurement: Use an objective function as the indicator for fitness measurement.
(3) Pareto optimal sequencing: Perform the Pareto optimal sequencing based on the fitness of each individual, with the best individual assigned a sequencing level of 0, and the next best individual assigned a sequencing level of 1, and so on.
(4) Operator selection: Use the method of the binary tournament to select the operator.
(5) Operator cross-over: As shown in Figure 1, set a cross-over probability and generate a random number between 0 and 1. If the random number is lower than the cross-over probability, then use two better paths in two chromosomes randomly selected from the population to perform a two-point cross-over. After the cross-over, remove the redundant workstations on each chromosome. In order to increase the search space, randomly shuffle the paths of chromosomes by probability after the cross-over.
(6) Operator mutation: Three mutation methods are used to perform the mutation [38].
    (a) Partial exchange: Randomly select two paths in a same chromosome and exchange some gene positions between these two paths to generate new paths.
    (b) Combine short paths: Combine two relatively short paths in a chromosome to form a long path.
    (c) Split long path: Split any too-long path in a chromosome with gene positions randomly selected.

Each mutation type occurs by probability, and after mutation, each path is randomly shuffled by probability.



Step 1: Select better paths in the two chromosomes to perform a two-point cross-over.



Step 2: Insert the swapped paths into the two chromosomes and remove the redundant individuals.

Figure 1. Diagram of the operator cross-over.

5. Analysis of Algorithm Example

We used Solomon's VRPTW standard problem set with 100 workstations as a test example in this study. In this set, problems can be divided into six groups, termed the C1, C2, R1, R2, RC1, and RC2 groups. Among these groups, the C group includes the problems with clustered data, meaning that the workstations in these problems are distributed into clusters according to their space locations or time windows. Meanwhile, the workstations in the problems of the R group are evenly distributed in terms of spatial location. In terms of problem complexity, the problems of the RC group lie between the problems of group C and group R, with mixed characteristics of the problems from these two groups. In addition, for problems of the C1, R1, and RC1 groups, the time window of the distribution warehouse is narrow, and the loading capacity of each distribution cart is relatively low. Therefore, in these problems, each distribution cart can only serve a small number of workstations. For the problems of the three other groups, the time window of the distribution center is wide, and the loading capacity of each distribution cart is also high. Therefore, in these problems, a distribution cart can serve multiple workstations. In the experiment, we used a PC with a P4-1.7G CPU and 256 M memory. The operating system and development software used were WinXP and VC++6.0, respectively. The parameters were set as follows: the population size N was set as 100, the maximum number of evolutional generations Maxgen was set as a number ranging from 100 to 10,000 according to different examples, the cross-over rate Pc was set as 0.8, and the mutation rate Pm was set as 0.08, respectively. The model-related parameters are shown in Table 2. This paper adopts a carbon tax system to link the carbon emissions with their carbon emission costs, and thus measure the carbon emission costs and assumes that the tax rate of carbon tax is relatively stable, but basically determined over a period of time. These specific values were obtained from the special report "Designing the Structure of China's Carbon Tax System", jointly published by the National Development and Reform Commission and the Ministry of Finance. The values of the CO_2 emission factors for the fuels were obtained from the Chinese Academy of Engineering.

Table 2. Model parameters.

Parameter Symbols	Parameter Name	Parameter Values
Q	Maximum load capacity of material distribution vehicles	100 kg
V_o	Average travel rate of material distribution vehicles	50 m/min
F_k	Fixed cost per material distribution vehicle	RMB 100/Vehicle
$\mathrm{C_p}$	Transport costs per unit distance traveled by vehicle	RMB 2/km
μ_1	Waiting costs for early arrival	RMB 20/h
μ_2	Delay costs for late arrivals	RMB 60/h
e_o	Carbon emissions per unit of fuel consumption	2.8 kg/L
λ	Carbon emissions per unit of cargo transported per unit of distance	0.0075 g/kg·km
ρ_o	Fuel consumption per unit distance when the vehicle is unladen	0.122 L/km
ρ^*	Fuel consumption per unit distance when the vehicle is fully loaded	0.388 L/km
p_e	Carbon tax	RMB 2/kg

Figure 2 shows the diagram of the cart paths of the test example C201 solved with the algorithm proposed in this study. In this example, the workstations were distributed into clusters, the distribution center had wide time window, and each distribution cart was able to serve multiple workstations. It was solved with a maximum evolutional generation number of 1000 and a computational running time of 28.5 s. The solution obtained in this study was found to be consistent with the known optimal solution obtained in foreign studies [39]. Meanwhile, this solution satisfied the conditions for the smallest number and shortest driving distance of distribution carts. Figure 3 shows the diagram of the cart paths of test example R103. In this example, the workstations were evenly distributed, the distribution center had a narrow time window, and each distribution cart was only able to serve a few workstations. It should be noted that it was much more difficult to solve the problems of group R1 than the problems of group C. Thus, the test example R103 was solved with a maximum evolutional generation number of 10,000 and a computational running time of 268.6 s. Compared with the existing optimal solution, the solution obtained in this study achieved a shorter total driving distance. A comparison between the path of test example R103 solved with the algorithm proposed in this study, and the path of the known optimal solution is shown in Table 3.

Figure 2. Diagram of the cart paths of test example C201 (comprising 3 carts and a total driving distance of 591.56).

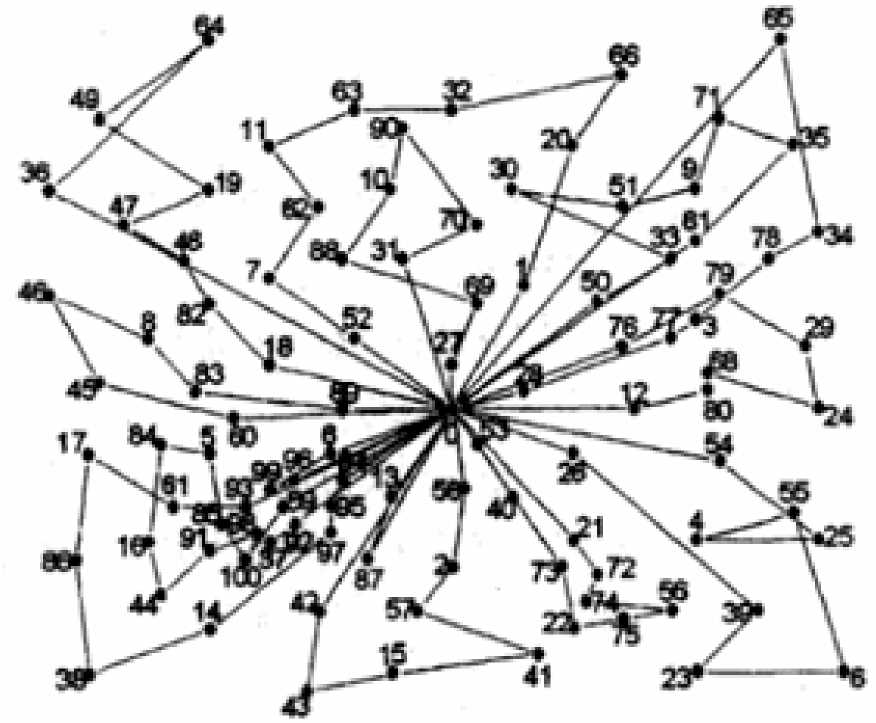


Figure 3. Diagram of the cart paths of test example R103 (comprising 15 carts and a total driving distance of 1268.34).

Table 3. Comparison between the paths of the specific solution of the R103 problem and the known optimal solution.

Item	Known Optimal Solution in the Existing Literature	Optimal Solution Obtained with the Algorithm Proposed in This Study
Total driving distance	1292.68	1268.34
Number of carts	13	13
Cart fixed cost	1300	1300
Transportation cost	2585.36	2536.68
Penalty cost	0	0
Carbon emission cost	7070.96	5524.89
Total cost	10,956.32	9361.57
Loading rate	81%	86%
Solution path	0 60 45 83 5 99 6 0	0 50 33 30 51 9 71 35 81 0
	0 71 65 78 34 35 81 77 28 0	0 65 34 78 3 77 28 0
	0 2 22 75 56 4 25 54 0	0 96 99 6 0
	0 7 19 11 8 46 47 48 82 18 89 0	0 87 13 60 45 46 8 83 890
	0 94 96 95 97 87 13 0	0 27 69 88 10 90 70 31 0
	0 27 69 30 9 66 20 51 1 0	0 76 79 29 24 68 80 12 0
	0 42 43 15 57 41 74 72 73 21 58	0 36 64 49 19 47 48 82 18 0
	0 40 53 12 68 80 0	0 94 95 97 14 38 86 17 61 93 0
	0 50 33 76 79 10 31 0	0 40 53 26 39 23 55 4 25 540
	0 36 64 49 63 90 32 70 0	0 42 43 15 41 57 2 58 67 0
	0 92 98 14 44 38 86 16 61 85 91 100 37 0	0 92 37 98 91 44 16 84 5 85 100 59 0
	0 26 39 23 67 55 24 29 3 0	0 52 7 62 11 63 32 66 20 1 0
	0 52 62 88 84 17 93 59 0	0 73 22 75 56 74 72 21 0

With the algorithm proposed in this paper, we have solved the typical problems among all the six types of Solomon's problems. A comparison between the solutions obtained in this study on these typical problems and the existing optimal solutions proposed in foreign studies, as well as the solutions provided by other scholars in China [40], is shown in Table 4. Among these solutions, the smallest cart quantity solution and the shortest driving distance solution are non-dominant solutions that were obtained with the algorithm proposed in this study. It should be noted that we have obtained other non-dominant solutions when solving several of the other test examples, with the cart quantities of these non-dominant solutions falling between the cart quantities of the smallest cart quantity solution and the shortest driving distance solution. Due to typographical reasons, these results have not been listed in the table at this time. In addition, the deviation items listed in the table refer to the deviations between the shortest driving distance solution obtained in this study and the existing optimal solution in terms of the driving distance. The "-" symbol in the table indicates that no result is available on the corresponding test in any of the literature cited. The underlined data are the data of results that were consistent with or are better than the known optimal solution.

Table 4. Comparison of solution results on typical problems among all six types of problems.

Name of Typical Problem	Results of the Literature [39] (Number of Carts/Distance)	Results of the Literature [40] (Number of Carts/Distance)	Smallest Cart Quantity Solution (Number of Carts/Distance)	Shortest Driving Distance Solution (Number of Carts/Distance)	Deviation
C101	10/828.94	-	10/828.94	10/828.94	0
C201	3/591.56	-	3/591.56	3/591.56	0
R101	19/1645.79	21/1814.60	18/1699.52	21/1695.32	3.01%
R103	13/1292.68	16/1389.71	13/1268.34	15/1268.34	−1.88%
R201	4/1252.37	15/1371.91	6/1359.47	7/1244.47	−0.63%
R202	13/1191.70	13/1430.62	13/1168.52	7/1121.09	−5.93%
RC101	14/1696.94	20/1826.68	17/1765.71	17/1765.71	4.05%
RC201	4/1406.91	-	3/1336.23	5/1322.17	−6.02%
RC205	4/1297.19	13/1582.64	3/1430.26	4/1351.28	4.17%

These experimental results show that there are minor deviations existing between the solution obtained with the algorithm proposed in this study and the known optimal solution, and the solution obtained in this study was found to be significantly better than the results presented in the literature [18]. Therefore, with the algorithm proposed in this study, the path problem of distribution carts with time windows can effectively be resolved. Notably, this algorithm was found to be effective in solving some cluster (group C) problems (with obtained solutions being found to be consistent with the known optimal solutions) and problems with the wide time windows of the distribution centers (groups R2 and RC2) (with the total driving distances of the obtained solutions being shorter than those distances of the known optimal solutions). The unique advantage of this study is that the multi-objective optimization problem of workshop logistics distribution with time tolerance has been described as a MOP problem. Therefore, each calculation can generate two (or more than two) non-dominant solutions, which can be used by decision-makers with a requirement of the smallest cart quantity or the shortest driving distance. For instance, in the test example RC201, in between the smallest cart quantity solution and the shortest driving distance solution listed in the table, there is one more non-dominant solution with a cart quantity of seven and a total driving distance of 1331.02. Compared with the known optimal solution, these solutions have used more distribution carts but decreased the total driving distance to a large extent. For those cases with the total driving distance (corresponding to which are travel times, fuel consumption, and transfer rates) as a priority objective, these non-dominant solutions are valuable. In contrast, under the traditional single-objective method, each calculation can only yield one solution, which is not flexible for a decision-maker to make a choice.

6. Conclusions

In order to address the problems of low efficiency, poor workstation service satisfaction, high distribution costs, and non-greening during the logistics distribution processes in discrete smart manufacturing workshops, a mathematical model of multi-objective optimized workshop green logistics distribution paths has been constructed in this study, with low costs, a high efficiency, and workstation service satisfaction taken into consideration. Then, this mathematical model was solved with an improved ant colony optimization algorithm. A "time window span" was introduced in the basic ant colony optimization algorithm to prioritize the services to workstations with a relatively high level of urgency in material demand, with the aim of improving workstation service satisfaction. The results of the algorithm examples show that the multi-objective optimization model of smart manufacturing workshop logistics distribution constructed in this study based on time tolerance and the introduction of a "time window span" in the basic ant colony algorithm are both flexible and extensible for solving the logistics distribution problem. Thus, the method proposed in this study is effective, and can provide a good reference for decision-makers.

In many industries and fields, intelligent manufacturing technology and related industries are already very mature, can completely replace the traditional equipment manufacturing industry, and also completely realize zero labor and fully automatic production modes. At the same time, the development of intelligent manufacturing will have a significant impact on the readjustment of the manufacturing structure model, and even develop a whole new manufacturing model, which will also bring about favorable conditions such as lower production costs, increased production efficiencies, shorter production cycles, and higher production capacities, and can also enable production to achieve further personalization, customization, and innovation. In addition, this flexible and fast production mode can also bring more convenience to the downstream operation and sales and can make more rapid responses to the changes occurring in the market. The rapid development of smart manufacturing technologies and models is both significant and challenging for the transformation and upgrading of China's traditional manufacturing industry.

Nowadays, green and low carbon have become the basic guiding principles and important criteria for China's economic, social, and ecological development and transformation, among which, for the manufacturing industry is to vigorously develop green manufacturing and intelligent manufacturing. China's manufacturing industry is one of the major carbon emitting regions and countries of the world, and therefore, the global manufacturing industry, especially China's manufacturing industry, needs to contribute to the "double carbon" goal through technological innovation and creativity. Green manufacturing mainly aims to reduce energy consumption, while smart manufacturing aims to improve quality and efficiency. The two promote each other and are inseparable, and both are inevitable choices for the high-end development of Chinese manufacturing. Through the concept of "green development", to guide China's traditional equipment manufacturing industry to green manufacturing and intelligent manufacturing, coordinated innovation and development, focusing on reducing emissions, reducing energy consumption, achieving the goal of carbon peak, and carbon neutral environmental protection are all required. Most of China's traditional manufacturing enterprises in the production process cause a large loss of resources, and at the same time produce a large amount of sewage, and with the traditionally high energy consumption, the high pollution equipment manufacturing production model has not met the general interests of China's long-term sustainable development, which encompasses the urgent need for more scientific assessment methods so that more individuals can follow the environmental regulations used to build a new manufacturing industry environmental protection development concept and sustainable development system.

The problem model constructed in this paper is based on the traditional vehicle path problem model, taking into account the impact of vehicle type, time constraints, carbon emissions, and the timeliness of distribution on the traditional vehicle path problem modeling, in terms of both the depth and difficulty of the study. At the theoretical level, this paper broadens the research theories and methods in the field of vehicle path problems. At the practical level, it provides some reference for the logistics enterprises to optimize distribution routes, reduce carbon emissions, etc., so as to achieve the goal of effectively reducing the logistical costs. This paper compares the case algorithm in the existing literature of intelligent manufacturing enterprises with the algorithm established in this paper for distribution path optimization, which can solve the practical problems of the related companies to some extent, but there are still many shortcomings, and the following problems need to be improved in future research. The model established in this paper only considers the case of one distribution center, while in practice, enterprises often establish multiple distribution centers in order to speed up both their efficiency and save costs, and the problem model of multiple distribution centers should be established in the future. Furthermore, this paper considers the static vehicle path problem, and further considerations need be given to the influence of dynamic factors, such as the traffic road conditions during vehicle travel, in the future. The discussion of the model in this paper is only for the vehicle path problem with fuzzy time windows, while in real life, the customer demand time is usually mixed time windows. In the distribution process, the customers' demand for their goods as well as the types of goods are different, and enterprises attach different levels of importance to them. In this paper, only the weight of goods was considered, while the influence of the volume of goods was not considered, and these issues need to be paid further attention to in future models.

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