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A TWO-STAGE ALGORITHM FOR PRODUCTION DISTRIBUTION OPTIMIZATION OF FRESH PRODUCTS

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The rise of e-commerce and the just-in-time system has imposed more stringent demands on fresh product supply chains. This paper addresses the challenges of production and distribution decision-making under uncertainty, considering the vehicle routing problem with time windows (VRPTW). Fresh products are distributed immediately after production, with any remaining perishable products deteriorating before they can be transported. To address these issues, a mathematical model is proposed for optimizing the production and distribution of fresh products. The objective optimization model for production scheduling and VRPTW is classified as an NP-hard problem. To tackle and optimize this complex problem, a two-stage algorithm combining ant colony optimization (ACO) and a fuzzy adaptive genetic algorithm (FAGA) is proposed. The approach begins by determining the critical combination parameters of the algorithm. Subsequently, analysis of the model's results reveals that production and distribution costs decrease significantly when integrated decision-making is employed. Additionally, the vehicle setup cost introduces a turning point in the overall target cost. Finally, a numerical experiment on VRPTW is conducted, with the results demonstrating the effectiveness of the proposed two-stage algorithm.

Keywords: Vehicle Routing Problem; Production Scheduling; Fresh Products; Ant Colony Optimization; Genetic Algorithm.

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1. INTRODUCTION

In the field of supply chain management (SCM), the complexity and critical importance of production distribution processes have garnered increasing attention, particularly in relation to ensuring product quality and timely delivery. A comprehensive approach to production-distribution planning (PDP) is crucial, especially within a multi-echelon network involving suppliers, producers, distributors, and customers, to maintain the integrity of perishable products. A significant challenge faced by food distributors lies in preserving the nutritional properties of fresh food during transportation. Due to the perishable nature of these products, they require specialized handling that differs from the management of non-perishable items, making the optimization of PDP essential for the sustainable development of the perishable products supply chain. Urbanization has exacerbated these challenges, leading to road congestion resulting in delays in delivery. Such delays, coupled with the stringent time window constraints imposed by customers, have increased operational costs for logistics companies. In response, logistics enterprises are increasingly focusing on enhancing the efficiency of their distribution operations. One potential strategy is the establishment of multiple warehouses to better meet customer demands, which can reduce operational costs, decrease overall transportation time, and improve the flexibility of the PDP process (Wen *et al.*, 2015).

For perishable products, maintaining freshness is paramount, making the issue of time windows central to research on fresh product logistics. The vehicle routing problem with time windows (VRPTW) specifically addresses the need for delivery vehicles to adhere to customer-specified time windows, with penalties or rejections resulting from any failure to meet these windows. Given the rapid degradation in value and quality of fresh products after production, timely production and distribution are critical, directly influencing suppliers' costs. While previous research has extensively explored various aspects of supply chain management, a significant gap remains in addressing the specific challenges of managing perishable products under conditions of urban congestion and strict delivery time windows. Addressing these challenges is vital for reducing food waste, optimizing logistics costs, and enhancing customer satisfaction.

This paper presents a two-stage optimization model that integrates ant colony optimization (ACO) with a fuzzy adaptive genetic algorithm (FAGA) designed specifically to tackle the challenges of production distribution planning for perishable products. Unlike the existing model, this research not only considers decay rates and time window constraints but also optimizes the supplier's total expected cost by determining optimal starting times, production quantities, and vehicle distribution routes. Comparative analysis with traditional methods demonstrates the superior efficiency and effectiveness of

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our approach. This paper makes the following key contributions: (1) Based on the characteristics of fresh products, which are distributed immediately after production and deteriorate before transportation, this study proposes a model aimed at minimizing the supplier's total expected cost. The model simultaneously determines the optimal starting time, production quantities, and vehicle distribution routes. (2) For the cost-minimization optimization model, a two-stage algorithm comprising ACO and FAGA is proposed for production distribution planning, considering decay rates and time window constraints. These meta-heuristic algorithms are designed to address routing problems in PDP. Experimental results demonstrate that the proposed methods are both feasible and effective.

The proposed optimization model integrates ACO and FAGA to address the identified gaps. Unlike previous research, which often treats production and distribution as distinct processes, this model unifies them within a single optimization framework. This integration enables more accurate and effective decision-making within the supply chain of fresh products. The model incorporates decay rates and time window constraints, both of which are critical in the logistics of fresh products. By addressing these factors, the model offers a more realistic and practical solution to the challenges posed by perishability and uncertainty. The hybrid application of ACO and FAGA represents a significant methodological advancement. ACO is utilized for the production scheduling stage, while FAGA is applied to vehicle routing. This combination enhances the robustness and efficiency of the solution, yielding superior results compared to the use of either algorithm in isolation.

The paper is structured as follows: Section 2 reviews the relevant literature. Section 3 introduces the objective function and associated constraints. Section 4 outlines the steps of the two-stage approach to the objective function, followed by experimental evaluations in Section 5. The conclusions are presented in Section 6.

2. LITERATURE REVIEW

The literature on VRP research concerning fresh products with time windows is extensive. Hsu *et al.* investigated the time-window VRP for fresh agricultural product distribution. They constructed a VRPTW mathematical model that optimizes distribution costs, considering the randomness of fresh product distribution. An improved time-oriented nearest neighbor domain algorithm was developed to address the model's characteristics. Osvald and Stirn (2007) included the perishability of fresh products as part of the total distribution cost, establishing a model to minimize these costs, which they solved using a tabu search-based heuristic algorithm. Shukla and Jharkharia (2013) designed an artificial immune algorithm to solve cold chain logistics problems in fresh agricultural product distribution. Zhang and Chen (2014) considered the specific characteristics of different frozen foods and developed a mathematical model incorporating constraints related to loading capacity and unit volume. Shao *et al.* (2015) used a fuzzy membership function to represent the time window, focusing on minimizing total delivery cost and maximizing customer satisfaction. They established a multi-objective route optimization model for fresh delivery, solved with a genetic algorithm. Peng (2019) addressed the inefficiencies in cold chain logistics route design by minimizing an objective function and solving it using a basic genetic algorithm.

Li Feng and Wei Ying (2010) studied time-dependent VRP (TDVRP) in the distribution of perishable products, using historical traffic data to construct a time-varying vehicle speed function with the goal of minimizing total distribution costs. A genetic algorithm was employed for problem-solving. Hu *et al.* (2017) developed a time-varying mixed VRPTW mathematical model that considered the time variability of energy consumption in refrigeration equipment, environmental temperature, and vehicle travel time. They implemented a two-stage hybrid algorithm that embedded variable neighborhood search and particle swarm optimization under an adaptive search mechanism. Liu and Fan (2017) sought to weaken the influence of dynamic traffic flow by establishing a customer satisfaction maximization model based on real-time traffic information and using an improved genetic algorithm for initial route planning and dynamic adjustment.

Subsequent studies focused on production scheduling and VRPTW in fresh products. Ferrucci *et al.* (2016) modeled dynamic demand generation based on historical customer demand data and designed proactive real-time control methods to handle disruptions during distribution. Wang *et al.* (2018) established a distributed production scheduling model aimed at minimizing processing time and total energy consumption, proposing a knowledge-based collaborative algorithm (KCA). Zhou *et al.* (2019) developed an improved ant colony algorithm to solve the time-dependent green vehicle routing problem. Building on previous research, Kumar and Aouam (2019) presented models explaining capacity, lead times, and batch sizes using queuing theory. Ghadimi, Aouam, and Vanhoucke (2020) extended this model to consider the limited budget for allocating capacity in a non-cyclic supply chain. Bogue *et al.* (2020) proposed a column generation algorithm and post-optimization heuristic based on variable neighborhood search. Shao *et al.* (2020) developed a distributed mixed-flow shop scheduling model that combined the characteristics of broadcast production with parallel machine scheduling. Zhou (2021) introduced an improved ant colony algorithm that considered multi-depot factors, optimizing vehicle travel time, reducing driving costs, saving energy, and reducing emissions. However, calculating vehicle travel time using the stage velocity-time function deviates from actual road traffic conditions, where vehicle speed changes are more continuous and smoother. Recent research has increasingly focused on hybrid algorithms for supply chain studies in broader areas (Rincon Garcia N. *et al.*, 2018; Tirkolaee, 2022). The comparison of this research and recent studies is shown in Table 1.

Table 1. Comparison on this research and recent studies

Author(s)	Research Methods	Research Objectives	Research Content	Differentiation
Wu D. & Wu C. (2022)	VNS-NSGA-II algorithm	Minimize economic cost and maximize customer satisfaction	Studied time-dependent split delivery for fresh agricultural products	Focuses on time-dependent split delivery but not on uncertain demand.
Pratap S., Jauhar S. K., *et al.* (2022)	Stochastic optimization with FPA and CSA	Optimize production inventory and routing with carbon footprint considerations	Developed a model for perishable food logistics, including carbon emissions	Considers carbon emissions but does not include uncertain demand.
Mousavi R., Bashiri M., *et al.* (2022)	Stochastic model with five-phase metaheuristic algorithm	Minimize production inventory routing and waste costs	Proposed a routing model for perishable products with uncertain demand	Focuses on routing and waste but not on production scheduling optimization.
Wangsa I. D., Vanany I., *et al.* (2023)	Mixed-integer linear programming	Optimize supply chain costs focusing on carbon emissions and food waste	Optimized inventories and deliveries in fresh-food supply chains	Primarily concerned with carbon emissions, not demand uncertainty.
Hashemi-Amiri O., Ghorbani F. (2023)	Bi-objective optimization using distributionally robust modeling	Mitigate demand and supply uncertainties in the food supply chain	Modeling for supplier selection, production scheduling, and routing	Accounts for demand uncertainties, but study background was limited to COVID-19
Zahran S. (2024)	Optimization with enhanced ant colony algorithm	Minimize delivery costs without sacrificing freshness	Optimized vehicle travel times in fresh agri-products e-commerce distribution	Focuses on delivery times, not production scheduling or supplier optimization.
Fernando W. M., Thibbotuwawa A., *et al.* (2024)	Integrated bi-objective VRP model	Optimize resource allocation, order scheduling, and route planning	Proposed a VRP model for agricultural product distribution in retail chains	Does not include optimization under uncertain demand conditions.
The Present Paper	Two-stage optimization model with ACO and FAGA	Minimize the total cost of the supplier under uncertain demand	Optimized production scheduling and VRP of fresh products	Combines production scheduling and supplier selection under uncertain demand

Previous studies have addressed the VRPTW for fresh products but often focused on isolated aspects such as distribution costs, perishability, or time window constraints rather than integrating these factors into a comprehensive model. Most literature does not account for the service time of retailers when generating the initial population, often relying solely on vehicle load and service time constraints at the distribution center. This omission can lead to computational complexity and inaccuracies. This paper addresses the stochastic nature of retailer demand and the significant impact of timely production and distribution on suppliers' costs. The model aligns more closely with current practices in fresh product production and distribution. The research introduces a fuzzy adaptive function that incorporates customer time requirements, improving the raw loss coefficient to reflect the time-sensitive value of fresh products. This approach leverages the exploratory strengths of ACO with the adaptive fine-tuning capabilities of FAGA, making it well-suited for tackling complex, real-world problems in production scheduling and VRPTW where demand is unpredictable. The proposed hybrid approach of ACO and FAGA quantifies the proximity of service times among retailers while simultaneously considering the effects of time and decay rate on distribution costs.

3. MATHEMATICAL MODELLING

In this study, retailer demand is bounded within a certain period and follows a normal distribution, indicating the inherent unpredictability of customer demand in both production scheduling and vehicle routing. This variability can substantially affect the efficiency of production schedules and delivery routes. In production scheduling, unforeseen fluctuations in demand may result in overproduction, stockouts, or the need for rescheduling. In the context of Vehicle Routing Problems with Time

Windows (VRPTW), fluctuating demand can alter the number of deliveries required or change the priority of specific deliveries, thereby complicating the routing process. Fresh products, which are assumed to decrease in value over time, present additional challenges. The production and distribution issues associated with time windows for fresh products are detailed as follows: fresh products must be distributed promptly after production within a complex distribution network. The supplier must determine the optimal production start time and the most efficient shipping route to ensure timely delivery to retailers.

The objective for suppliers is to minimize their costs. Suppliers are limited to producing one product at a time. Stockouts result in an out-of-stock penalty, while overproduction incurs a spoilage penalty due to the inability to ship the products immediately. The distribution center operates with a limited number of vehicles, each with a maximum load capacity. A fuzzy time window represents the distribution time required by customers. Deviations from this time window, either earlier or later, result in corresponding penalty costs. The overall goal is to minimize production and distribution costs. A summary of the notations used in Section 3 is provided in Table 2.

Table 2. Summary of notations in Section 3

Symbol	Description
i	index to retailers, $i = \{1,2,\cdots R\}$
k	index to vehicle, $k = \{1,2,\cdots K\}$
a_i	time of arrival at retailer i
c_m	production cost per unit of product m
c_{ij}	distribution time in retailer node i and j
e_i	starting service time of retailer i
l_i	ending service time of retailer i
K	number of total vehicles
U	setup cost of a vehicle
Q_{veh}	total capacity of vehicles
R	number of total retailers
s_i	service time of retailer i
p	time value of travel time
g_1	loss for ahead time windows
g_2	loss due to time delay
t_m	production time of unit products m
D_{im}	average demand of retailer$i$ to products$m$
$\hat{t}_{k,m}$	producing end time of products m for vehicle$k$
$t_{k,m}$	producing starting time of products m for vehicle$k$
δ_{m1}	decay in value of products m per unit of time
δ_{m2}	goodwill loss for shortage of per unit products m
$t_{k,s}$	Decision variables. time when the first product is produced for vehicle k in a route S
Q_{im}	Decision variables. quantity of production m for retailer i
x_{ijk}	Decision variables. vehicle k serves retailer (i,j), take 1; Otherwise, take 0

The objective of this model is to minimize the expected total cost of the supplier. The model can simultaneously determine the time of starting production, production quantities, and vehicle distribution routes. The objective of mathematics optimization form and constraints are set out as follows:

$$\begin{aligned} minZ = \sum_{k} U + \sum_{im} c_m Q_{im} + p \sum_{ijk} c_{ij} x_{ijk} + \sum_{im} \{\delta_{m1} max\{Q_{im} - D_{im}, 0\} + \delta_{m2} max\{D_{im} - Q_{im}, 0\}\} \\ + g_1 \sum_{i} max\{e_i - a_i, 0\} + g_2 \sum_{i} max\{a_i - l_i, 0\} \end{aligned} \tag{1}$$

$$\sum_{j} \sum_{k} x_{ijk} = 1 \quad i = 1, \dots, R \tag{2}$$

$$\sum_{j\in R} x_{ijk} - \sum_{j\in R} x_{jik} = 0, \forall i \in R, \forall k \in K \tag{3}$$
$$\sum_{i\in S}\sum_{j\in S} x_{ijk} \le |S| - 1, \forall S \in J, \forall k \in K \tag{4}$$
$$\hat{t}_{k,m} \le t_{k+1,1} \quad k = 1,\ldots,K-1 \tag{5}$$
$$\sum_{ijm} Q_{jm} x_{ijk} \le Q_{veh} \quad k = 1,\ldots,K \tag{6}$$
$$a_j = max\{a_i, e_i\} + s_i + c_{ij} \tag{7}$$
$$a_j = \hat{t}_{k,m} + c_{0j} \tag{8}$$
$$\hat{t}_{k,m} = t_{k,m} + t_m \sum_{ij} Q_{im} x_{ijk} \tag{9}$$
$$t_{k,m+1} = \hat{t}_{k,m} \tag{10}$$

Objective function formula (1) minimizes the supplier's total cost, which includes the setup cost of the vehicle, production cost, VRP cost, decayed or shortage cost, and time window penalty cost. Constraint (2) indicates that a retailer can only be served once at a time. Constraint (3) indicates vehicles serving retailer *i* must leave this node after service. Constraint (4) designates route constraint to eliminate the inner loop. Constraint (5) states that the end time of one vehicle shall not be later than the next vehicle's start production time. Constraint (6) is vehicle capacity limitation. Constraints (7) and (8) define the time to reach retailer j. Constraint (9) defines the end time for vehicle k to production m. Constraint (10) indicates that for the same vehicle k, the end time of producing products m is the start time of producing products *m+1*.

4. THE HYBRID APPROACH OF ACO AND FAGA

The proposed algorithm addresses the complex challenge of optimizing both production scheduling and vehicle routing with time windows, a problem known to be NP-hard, meaning it is computationally intensive and difficult to solve efficiently. Given the low probability of randomly generating feasible solutions, the algorithm begins by using a heuristic approach to create a set of viable solutions, which form the initial population for further optimization. The algorithm operates in four stages:

- Stage 1: Initialization. Define the problem parameters, including production constraints, vehicle capacities, time windows, etc.
- Stage 2: Initialize a population of ants (solutions) with random schedules or routes. Simulate the behavior of ants exploring the solution space, iteratively improving the solution based on pheromone trails. Use ACO to identify promising schedules or routes that balance production efficiency and vehicle routing with demand uncertainty.
- Stage 3: Take the promising solutions from ACO as the initial population for the genetic algorithm. Apply genetic operations like selection, crossover, and mutation, with fuzzy logic adapting these parameters based on the solution quality and problem specifics. Iterate until convergence, producing a finely-tuned solution that meets the optimization objectives.
- Stage 4: Final Output. The algorithm outputs an optimized production schedule and vehicle routing plan that is robust against demand randomness and satisfies the constraints of the problem.

Together, these four stages work to provide an optimized solution for both production scheduling and vehicle routing, balancing efficiency and feasibility in the distribution of fresh products. The hybrid two-stage algorithm of ACO and FAGA is shown in Figure 1.

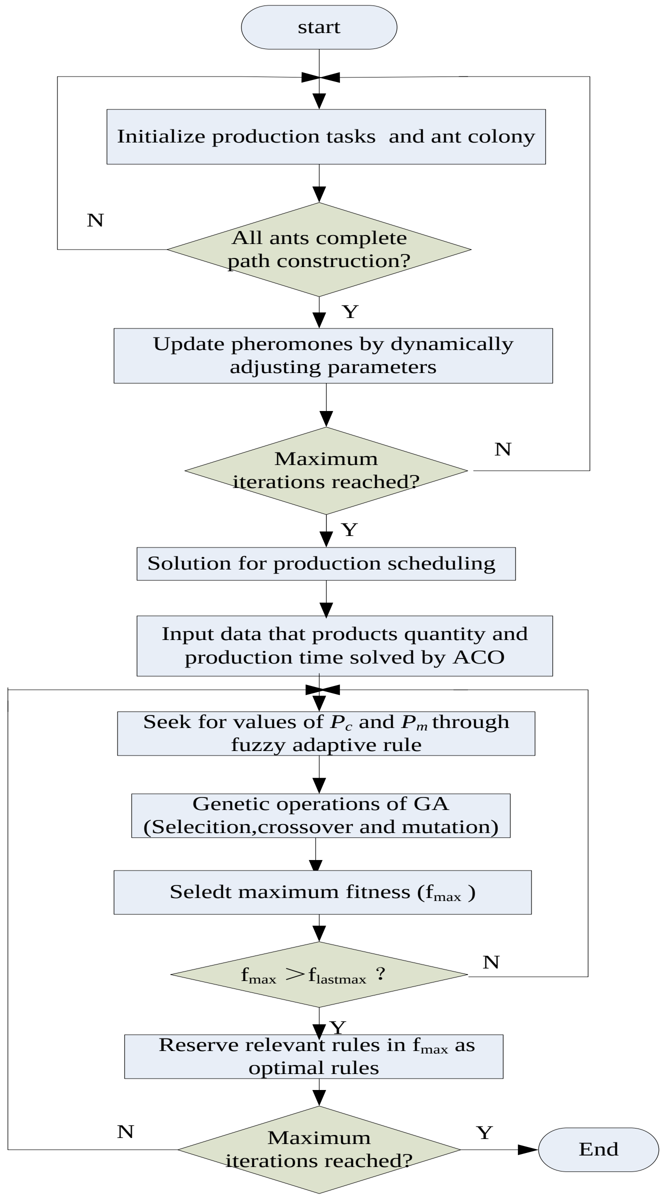

Figure 1. Algorithm process

4.1 ACO Algorithm

Production scheduling problems are typically optimized with a single objective, such as minimizing the Makespan of tasks. The Makespan represents the total time required for tasks to reside within the system, offering a comprehensive measure of production time. However, as product life cycles shorten and customer demands increase, enterprises face growing pressure to meet on-time delivery requirements. Consequently, minimizing penalties for early or delayed product delivery has become a crucial metric for evaluating scheduling system performance. ACO algorithm, initially proposed by Dorigo (1996) for solving the Traveling Salesman Problem (TSP), has been successfully applied to a range of combinatorial optimization problems, including those in traveling salesman, vehicle routing, and scheduling.

(1) Production task assignment
Each task process is treated as a node that an ant traverses, with ants following task priority constraints. The ant selects paths through each task process, which correspond to the choice of processing equipment. During this process, ants aim to minimize

the total load and distribute it evenly across devices, thereby selecting the route that yields the shortest processing time. The probability that ant k transfer from equipment i to equipment j in time$t$ was shown in Equation (11):

$$p_{ij}^{k}=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum s\in allowed_{k}\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} & ,j\in allowed_{k}\\ 0 & ,otherwise\end{cases} \tag{11}$$

where, allowed={$0，1，\ldots,n-1$}.τ_{ij} is the level of pheromone between equipment i and *j*. The η_{ij} is the intensity of the pheromone trail between equipment *i* and *j*. η_{ij} make the equipment with less load and short processing time has a high probability of being selected as the processing equipment. The α and β are the weight of importance for the pheromone level and heuristic information.

(2) Production task sequencing
The task assignment results obtained in the first stage are organized into distinct vector groups based on equipment, utilizing an equipment-specific e-based coding method. Each vector component contains detailed information, including task number, process number, equipment number, priority value, processing time, and available processing time. The objective is to optimize the processing sequence for each piece of equipment, thereby minimizing the maximum task completion time. As the ant traverses the tasks assigned to a particular piece of equipment, it determines the optimal task processing sequence. During the task sequencing stage, ants construct the solution sequence by selecting subsequent tasks using a pseudo-random proportional state transition rule.

Ant colony algorithm effectively combines the principle of information positive feedback and heuristic algorithm. The design of $\eta_{ij}$is the key to the ant colony algorithm. When the group size is large, it isn't easy to obtain the optimal solution in a short time. If the information amount of a path generated changes randomly too fast, search stagnation could easily occur. To control the change rate of information amount, the following method is adopted to select the next customer to be visited: ant k randomly generates a pseudo-random parameterq_0. The ant selects the next task *j* to be processed by equipment km using the state transition rule of pseudo-random proportion. The rule is given by Equation (12), and J is determined by Equation (13).

$$p_{ij}^{*,k}=\begin{cases}\dfrac{(\tau_{ij}^{*,k})^{\alpha}(t)(\eta_{ij}^{*,k})^{\beta}\,(t)}{\sum s\in allowed_{k}(\tau_{ij}^{*,k})^{\alpha}(t)(\eta_{ij}^{*,k})^{\beta}\,(t)} & ,j\in allowed_{k}\\ 0 & ,otherwise\end{cases} \tag{12}$$

$$j_{ij(k)}=\begin{cases}arg\ \max\{\tau_{ij(k)}\eta_{ij(k)}^{\gamma}\} & ,\ q\le q_{0}\\ J & ,q>q_{0}\end{cases} \tag{13}$$

$p_{ij}^{*,k}$is the probability that the ant *k* travels to order *i* and selects task *j*, $\tau_{ij}^{*,k}$is the pheromone level between task sequences on the device; $\eta_{ij}^{*,k}$ is task j elicits information at the order *i* arranged in device *k* Currently, *r* is the full load rate of the vehicle, $\gamma=\left(\sum_{i\in L_k} sum\_load_k(i)\right)/QV$, where QV is the maximum load constraint of the vehicle, L_k is the route K_{th} ant and $sum\_load_k(i)$ is the sum of customer demand of the route taken by the K_{th} ant, it can be seen that *r* can improve the diversity of task selection.

The pheromone is updated using the following rule:

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\sum_{l=1}^{L}\Delta\tau_{ij}^{l} \tag{14}$$

where ρ is a persistence or trail and lies between [0,1] and $(1-\rho)$ is the evaporation rate. The higher value of ρ suggests that the information gathered in the past iterations is forgotten faster. $\Delta\tau_{ij}^{l}$ is the pheromone deposited by kth ant when walking through the node *i* to *j*, when edge (i, j) is on the route constructed by ant k, then $\Delta\tau_{ij}^{l}=\frac{Q}{L_k}$. Q is the pheromone constant, and L_k is the length of tour of the kth ant. When edge *(i, j)* is not on the route constructed by ant *k*, then$\Delta\tau_{ij}^{l}=0$.

To make the algorithm find a better solution in the initial algorithm, the value of parameter ρ is set in [0, 1]. When there is a large-scale problem due to pheromone evaporation, the pheromones of the routes that have never been searched reduce to zero. It is necessary to reduce the algorithm's searchability in this route. Conversely, when the pheromone is more significant, it also affects the global search ability of the algorithm. At this time, changing the pheromone evaporation rate through setting the maximum and minimum value τcan be adaptively changed by Equation (15):

$$\begin{cases}\tau_{ij}(t+1)=(1-\rho)^{1+\lambda(n)}\tau_{ij}(t)+\Delta\tau_{ij}, if\tau \geq \tau_{max} \\ \tau_{ij}(t+1)=(1-\rho)^{1-\lambda(n)}\tau_{ij}(t)+\Delta\tau_{ij}, if\tau \leq \tau_{min}\{\end{cases} \tag{15}$$

$\lambda(n)$ is a function which is proportional to the number of convergence times; the more convergence times, the greater$\lambda(n)$. The route-solving process proceeds as follows:

Step 1: Problem and ant colony initialization. Begin by representing the production tasks as a graph, where nodes correspond to tasks and edges denote the relationships or transitions between tasks. An adjacency list is employed to capture these task relationships. The initial population is primarily generated using a random method, with a small subset of the initial species group created through heuristic rules. These rules prioritize the selection of key equipment by arranging processes with the shortest priority processing time and the longest remaining processing time.

Step 2: Path selection by ants. Each ant selects paths within the graph according to the heuristic rules of the ant colony optimization algorithm. Path selection is guided by a probability-based strategy that integrates pheromone concentration and heuristic information.

Step 3: Pheromone update. Following the path selection, pheromone concentrations are updated based on the quality of the paths chosen by the ants. This involves both pheromone evaporation and deposition to appropriately adjust the pheromone levels.

Step 4: Iteration. Steps 2 and 3 are repeated iteratively until a predefined stopping condition is met, typically determined by reaching a maximum number of iterations.

Step 5: Result decoding. The final step involves decoding the results based on the pheromone concentrations or the paths selected by the ants. The chosen paths are then converted into an optimal production scheduling plan.

4.2 Fuzzy adaptive genetic algorithms (FAGA)

Genetic algorithms (GA) have been prevalent in recent decades to solve optimization problems because of their robustness in finding the optimal solution (Orero SO, et al,1998). In traditional GA, the probability of crossover (P_c) and mutation (P_m) is constant through generations and often empirically determined, which vary according to aforethought criteria and are updated in response to some feedback on the actual status of the search. The most challenging problem of traditional genetic algorithms is how to achieve optimal accuracy in good time. The key to improvements is suitable mutation and crossover rates. Aimed at improving GA efficiency and avoiding suboptimal solutions by suitably controlling some key GA parameters, the fuzzy adaptive genetic algorithms (FAGA) proposed by Vannucci and Colla (2015) . FAGA modifies the GA parameters through a fuzzy inference system that interprets the search status. Pc and Pm are two genetic parameters that change dynamically during the generation of the genetic algorithm. Using fuzzy rules to make the algorithm more efficient. The rule base recreates adaptive strategies that make optimizations predictable to follow (Herrera *et al*., 2003). Best fitness, Pc and Pm consisted of fuzzy set low, medium, and high. Best fitness was used as input in the fuzzy rules, while the outputs were the *Pc* and the *Pm*. The fuzzy adaptation helps the algorithm dynamically adjust to the problem's specifics, such as varying demand or time window constraints, ensuring the final solution is robust and optimized.

4.2.1 Fuzzy adaptive parameter setting

The difference of samples can express the progress status of the genetic algorithm by Equation (16):

$$D_1=\frac{f_m-f_a}{f_m}\in[0,1] \tag{16}$$

f_a is the average fitness of the sample;f_m is the maximum fitness of individual samples.

The fitness function in a genetic algorithm is tailored to specific problems and requirements, resulting in its value varying depending on the issue being addressed. This variation makes it difficult to assess the current progress of the genetic algorithm solely based on the difference betweenf_m and f_a. To enhance the generality of the algorithm, a transformation is applied. During the initial stages of the genetic process, sample diversity tends to be high, leading to a relatively large value in Equation

(16). However, as the genetic process progresses, especially during the later stages or when the algorithm converges toward a local optimum, the value of Equation (16) diminishes. The difference among sample individuals can be quantified using Equation (17):

$$D_2 = \frac{f - f_a}{f_m} \in [-1,1] \tag{17}$$

Equation (17) also converts the value into the interval [-1, 1] by dividing byf_m, which increases the generality of the algorithm and facilitates fuzzy reasoning.

The fuzzy variable $D_1$is simply divided into three sets {low, medium and high}; similarly, the fuzzy variable $D_2$is divided into three sets {positive, zero, negative}; the output crossover rate P_c and variation rate $P_m$can also be divided into three sets {low, medium and high }.If $D_1$is "high", it indicates that the sample diversity is good, and the P_c and P_m should be "low". On the contrary, if D_1 is "low", then P_c and Pm should be "high". If $D_2$is "positive", it indicates that the individual is "excellent", while P_c and P_m should be "small". On the contrary, if D_2 is "negative", it indicates that the individual is "poor", while P_c and P_m should be "large". Therefore, based on the above rules, the following fuzzy reasoning process can be obtained:

If $D_1$is low and $D_2$is negative, then P_c and P_m are high;

If $D_1$is high and $D_2$is positive, then P_c and P_m is low.

Other rules can be obtained by similar reasoning. The summarized fuzzy rules are shown in Table 3.

Table 3. Fuzzy adaptive genetic operator rule table

D_1	D_2		
	positive	zero	negative
low	high	medium	high
medium	low	medium	high
high	low	medium	low

4.2.2 FAGA based on a fuzzy operator rule

In this level, FAGA based on a fuzzy operator rule is implemented as an optimization technique that can be used to achieve optimization objectives.

(1) Chromosome Coding and initial population generation

The encoding of the solution. Using the natural number coding method, the number of customer points is J, and number of vehicles is K, and each individual corresponds to a row vector of (J+K+1) dimension. The real numbers 1 to J represent the customer point, and 0 represents the distribution center to distinguish different vehicle routes. The starting and ending loci of each vehicle route must be 0. Figure 2 is a simple example of two available vehicles (K=2) and seven customers (J=7), the customer set J= {1,2..., 7}, 0 represents the distribution center, which is used to separate the driving route of two vehicles. Vehicle 1 starts from distribution center 0, visits customers 1, 4, and 5, and returns to the distribution center (0-1-4-5-0). Vehicle 2 starts from distribution center 0, visits customer points 2, 3, 6, 7, and returns to the distribution center (0-2-3-6-7-0).

0	1	4	5	0	2	3	6	7	0

Figure 2. A simple example of coding

The quality of the initial solution has a significant impact on the algorithm's performance. The hybrid insertion method is adopted to construct the initial solution to expand the search space and improve the quality of solutions. Specifically, when an individual is generated, the customer randomly arranges the earliest service start time in ascending order, the latest end time of service in ascending order, and random order to wait for insertion and inserts it to the feasible position with the lowest cost.

(2) Genetic operators
Due to multiple 0 in chromosomes, the traditional cross operation may result in various distribution centers being connected. The selection of the individuals is made according to Equation (18), (19).

$$p_c = \begin{cases} 0.9 - 0.2(f_1 - f_a)/(f_m - f_a), f \geq f_a \\ 0.9, others \end{cases} \tag{18}$$

$$p_m = \begin{cases} 0.1 - 0.09(f_m - f)/(f_m - f_a), f \geq f_a \\ 0.1, others \end{cases} \tag{19}$$

(3) In this paper, the fitness function is given by the objective function of the distribution problem:

$$f_N(a_k) = \frac{1}{1 + TC(a_k)} \tag{20}$$

a_k: a kind of distribution plan; $TC(a_k)$ the cost of distributing a_k.
The steps of the FAGA are as follows:
Step 1: Generate the initial population, set the algebra to 0, and the number of individuals is *M*. Input data that products quantity and production time solved by ACO in first stage.
Step 2: Perform selection operator, crossover operator, and mutation operator successively, and calculate the individual's fitness.
Step 3: Carry out a one-time series optimization of a complex system with fuzzy variable weights for the individual with the highest fitness.
Step 4: Get a new population *P(t+1)* generation and increase the algebra by 1.
Step 5: Judge whether it meets the optimization criteria. If not, return step 2; if so, end.

5. EXPERIMENTAL RESULTS

Matlab R2020b is used to compile algorithm in i7-6700 CPU 4GHz,16G RAM computer running, take PoP=30 to 60 and MaxN=30 to 300. Retailers' information is created, and a few are modified from Solomon's problem (Solomon MM, 1987). According to the trial design characteristics concerning relevant literature practice, the following example: a food processing factory produces five kinds of fresh products. The complimentary food has different production times, costs, and damage costs.

5.1 Determine the key combination parameters

In the context of ACO parameters, a higher pheromone heuristic factor increases the importance of pheromone trails, making ants more likely to select previously traversed paths. Conversely, a larger expected heuristic factor enhances the likelihood of ants exploring new routes. A lower global pheromone evaporation rate slows down the dissipation of pheromones, thereby aiding in the identification of superior solutions. Additionally, a higher global influence factor amplifies the impact of the current optimal solution on the overall optimization process. The pseudo-random probability q_0 is introduced for the ant colony system framework, and the parameter q_0 plays a crucial role in algorithm performance. Before verifying the algorithm's performance, the influence of different parameter combinations on the algorithm's performance is analyzed through simulation experiments to determine the better parameters combined configuration.

According to the experimental analysis of ACS by DORGO, the experimental values of α, β, q_0, ρ are set as {0.6,1,2,3}，{2, 3, 4, 5}，{0.5, 0.6, 0.7, 0.8}，{0.1,0.2,0.3,0.4}. The uniform table design is shown in Table 3. The numbers in Table 4 represent the value levels of parameters.

Set task number *T*=10, initial ant colony number A_n=100, iterations number *Iter*=150, initial pheromone value τ_0=10. Generate examples randomly, and the calculation examples of each parameter combination were independently run 20 times. When the parameter combination is 12, $\alpha = 2, \beta = 3, q_0 = 0.8, \rho = 0.1$The results are concentrated, and the degree of discretization is low.

In FAGA parameters, a Triple membership function is adopted for output parameters *Pc* and *Pm* (Tian D P,2008). The value range of restricted crossover probability *Pc* is [0.4, 1], and the value range of variation probability *Pm* is [0, 0.2], as shown in Table 5.

Table 4. Uniform test plan uniform table design

parameter	plan number															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
α	2	2	2	3	2	2	2	3	2	2	2	3	4	1	2	4
β	1	4	1	4	4	1	3	1	3	4	3	3	2	2	3	4
q_0	1	4	3	2	4	3	1	4	1	3	4	2	1	4	3	2
ρ	1	1	4	3	3	4	3	2	4	3	1	1	2	2	2	2

Table 5. Crossover and mutation probability

	Pc	*Pm*
higher	[0.85,1]	[0.15,0.19]
high	[0.75,0.85]	[0.08,0.14]]
medium	[0.65,0.8]	[0.04,0.07]
low	[0.5,0.75]	[0.02,0.05]
lower	[0.45,0.65]	[0.001,0.02]

5.2 Analysis of model calculation results

The experiment shown in Figure 3 can deduce the relationship between the vehicle's number, average loading ratio and optimization objective. With the increase of the number of vehicles, the average loading rate of vehicles decreases. The more vehicles used, the less time it takes to produce and deliver each vehicle. The objective cost includes the vehicle start-up cost, so as the vehicle number increases, it can't always decrease the total cost. After arrival in a particular value, it will lead to cost increases.

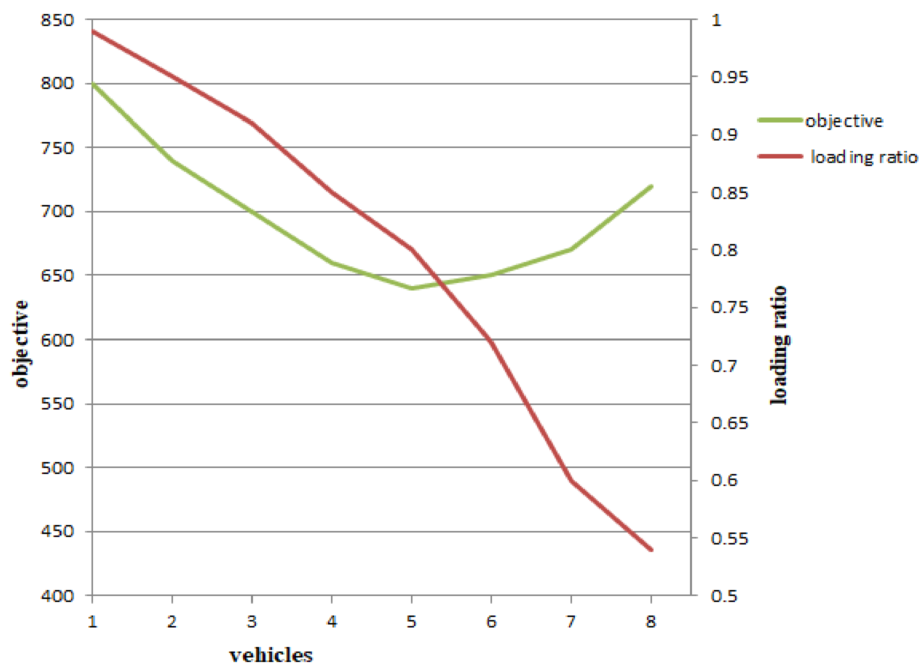

Figure 3. Relations between average loading ratio and the number of vehicles

There is a trade-off in vehicle number, decay rate, and objective cost. Considering fresh food, the generally preferred decay rate, which is greater than the time window punishment on the influence of the objective function, especially retailers have requirements in both products and time. At first, the supplier is preferred the product's decay rate and increased vehicles.

Still, when the decay rate and the time window are in the controllable cost, the supplier should consider the vehicle loading ratio, and vehicle start-up cost to avoid increasing total cost.

A series of tests with different proportions of retailers for the same vehicle size is run when the time varies from 0%, 10%, 20%, 30%, 40%, 50%. Such as TW(20%) means that 20% of retailers have a request for a time window. Figure 4 indicates that the objective function increases as the decay rate increases for all tests with different percentages of time windows required.

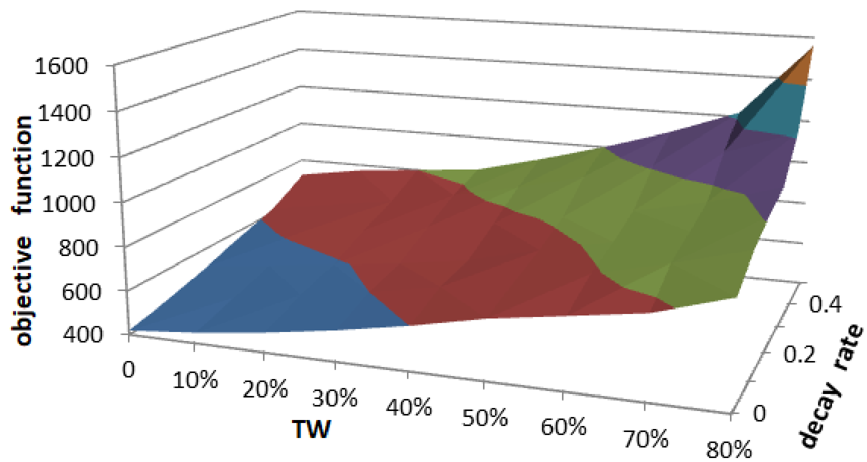

Figure 4. Objective values under different TW and decay rate

Figure 4 shows the effect on the objective function with the different combinations of the decay rate and time window penalty coefficients. The product decay rate is (0.1, 0.5), and the time window penalty coefficient is (0,0.8). When both the decay rate and the time window penalty coincide, the objective function increases accordingly. The effect of the decay rate on the objective function is greater than the time window penalty, especially when the retailer has requirements for both the product and the time; the supplier should prioritize the product's decay rate.

5.3 VRPTW numerical experiment

Classic VRPTW considers the following two factors: (1) the vehicle travels at a constant speed, and (2) all vehicles start from the same distribution center and return to the distribution center. The route model in this paper is a special case of VRPTW when partially constrained are relaxation, and the model collapsed into the classical VRPTW model. Therefore, the Solomon VRPTW's benchmark data is selected as numerical experiments on 18 examples of class C data to verify the effectiveness of the proposed algorithm. The vehicle capacity in this calculation example is both 200. All routes use a constant speed distribution, whose value is set to 1. Table 6 records the known optimal solution of classical VRPTW in the S_{best} column and the calculation time obtained by Kohl *et al.* (1999) in the T_{best} column as a reference for the experimental results. The optimal solution of the benchmark instance solved by the FAGA algorithm is recorded in the F_{best} column, and its calculation time percentage difference between S_{best} and F_{best} t is recorded in the Gap column (in seconds) in the CPU time column. Gap=(F_{best}-S_{best})/S_{best}×100. S_{best} data comes from http://web.cba.neu.edu/~msolomon/c1c2solu.htm.

Table 6. Experimental results of class C VRPTW benchmark dataset

example	n	Best known solution			FAGA best solution			
		vehicles	S_{best}	T_{time}	vehicles	F_{best}	Gap (%)	CPU time
c101	50	5	362.4	2.48	5	363.28	0.24	1.88
c102	50	5	361.4	13.99	5	361.41	0.00	3.02
c103	50	5	361.4	33.78	5	361.42	0.01	3.05
c104	50	5	358	884.5	5	363.21	1.46	5.83
c105	50	5	362.4	5.83	5	363.28	0.24	9.92
c106	50	5	362.4	1.25	5	363.27	0.24	68.56
c107	50	5	362.4	3.85	5	363.27	0.24	14.12

example	n	Best known solution			FAGA best solution			
		vehicles	S_{best}	T_{time}	vehicles	F_{best}	Gap (%)	CPU time
c108	50	5	362.4	8.21	5	363.26	0.24	4.05
c109	50	5	362.4	5.34	5	363.26	0.24	1.39
c101	100	10	827.3	5.86	10	829.02	0.21	9.69
c102	100	10	827.3	111.4	10	838.98	1.41	10.76
c103	100	10	826.3	679.7	10	840.57	1.73	8.53
c104	100	10	822.9	1216	10	828.48	0.68	13.17
c105	100	10	827.3	33.21	10	829.13	0.22	11.62
c106	100	10	827.3	23.7	10	830.52	0.39	11.96
c107	100	10	827.3	36.92	10	831.48	0.51	13.52
c108	100	10	827.3	42.2	10	828.15	0.10	10.67
c109	100	10	827.3	72.9	10	829.73	0.29	14.78

5.4 Algorithm comparison and analysis

To evaluate the performance of the proposed FAGA, the research compares it with a traditional GA that utilizes basic constant parameters. The termination criterion for both algorithms is based on the fitness value, which assesses the convergence rate at which each algorithm approaches the current optimal solution. Convergence is determined when the optimal fitness value is attained; otherwise, the algorithm is considered non-convergent. In the basic GA, the mutation and crossover probabilities are set at 0.05 and 0.85, respectively. To validate the effectiveness of the proposed algorithm, this experiment selected five groups of relevant test examples for analysis, as presented in Table 6. The optimal solutions obtained by the ACO-FAGA are compared with those derived from the Variable Neighborhood Search (VNS) algorithm (Hansen *et al.*, 2008) and the GA. In this comparison, M represents the optimal solution identified by the three algorithms, while t denotes their respective computational times in seconds.

As can be seen from Table 7, the average solving time of the VNS algorithm is 3.874s, the average solving time of GA is 3.862s, and the average solving time of ACO-FAGA in this paper is 3.744s. The average solving time of ACO-FAGA is 3.33%, improved on average compared with the optimal values of the previous two. Optimal solution gap percentage difference between FAGA and VNS, GA are recorded in the $M_{Gap(\%)}$. The results and solving time of the proposed algorithm are superior to the last two algorithms. Based on the above analysis, the algorithm in this paper has high quality and fast solution speed, which further verifies the algorithm's effectiveness.

Table 7. Simulation results of the three algorithms

	VNS		GA		ACO-FAGA		$M_{Gap(\%)}$(with ACO-FAGA)	
	M	t	M	t	M	t	VNS	GA
1	630.24	3.23	639.52	3.22	624.19	3.19	0.97	2.46
2	774.39	3.36	781.45	3.37	763.57	3.28	1.42	2.34
3	823.17	3.85	829.56	3.83	815.72	3.72	0.91	1.70
4	890.58	4.26	901.73	4.24	881.29	4.07	1.05	2.32
5	987.73	4.67	992.56	4.65	975.44	4.46	1.26	1.76

In comparison to previous studies, the contributions of this paper are distinct in several key ways. Chen *et al.* (2008) focused on the problem of production scheduling and vehicle routing for perishable food products, primarily utilizing time-oriented nearest neighbor domain algorithms, which were effective in generating feasible solutions quickly. However, their approach had limitations in handling complex scenarios involving stochastic demand or dynamic decay rates. Li and Wei (2010) applied a genetic algorithm that considered time-dependent vehicle routing. While the algorithm was adept at adjusting to traffic patterns, it did not integrate production scheduling with routing, limiting its application to scenarios where production schedules are flexible or predetermined. The ACO-FAGA approach in this research bridges this gap by simultaneously optimizing production and distribution, thus offering a more comprehensive solution to the VRPTW problem. Shao *et al.* (2015) and Peng (2019) explored genetic algorithms for optimizing fresh agricultural product distribution routes, incorporating time windows and customer satisfaction metrics.

Nevertheless, these studies did not integrate production scheduling with routing decisions, nor did they employ a two-stage approach that could more effectively balance the trade-offs between decay rates and time window penalties, as demonstrated in this paper. Hu *et al.* (2017) introduced a two-stage decomposition method for fresh product distribution, which shares similarities with this paper. However, the hybrid algorithm presented here offers enhancements in solving VRPTW by incorporating fuzzy adaptive mechanisms to dynamically adjust genetic algorithm parameters, leading to potentially better optimization outcomes. Mousavi *et al.* (2022) proposed a stochastic model with a five-phase metaheuristic algorithm that was highly effective in dealing with uncertainty, offering robust solutions for production routing problems in volatile environments. While their algorithm was computationally intensive, it provided comprehensive solutions that accounted for multiple variables. In this paper, the stages of the algorithm are appropriately simplified to enhance efficiency. In summary, this research advances the existing body of knowledge by offering a robust, integrated approach that optimizes both production and distribution processes in fresh product supply chains. It addresses the critical challenge of balancing decay rates, time window penalties, and cost minimization more effectively than previous models, thereby making significant contributions to the theory and practice of logistics management for perishable products.

5.5 Algorithm limitations and assumptions

Two-stage algorithms like Ant Colony Optimization (ACO) and Fuzzy Adaptive Genetic Algorithm (FAGA) are commonly used for solving complex optimization problems. However, they come with certain limitations and assumptions:

ACO can struggle with large-scale problems due to its high computational complexity. The convergence time can be very long as the problem size increases. With the increase of the number of products in the study, the complexity of ant colony production scheduling and the pathfinding time increase exponentially. In some cases, ACO algorithms can fall into a stagnation state where all ants follow the same path, leading to little or no improvement in finding better solutions. ACO assumes that all ants are homogeneous and follow the same set of rules, which may not be suitable for all problem types, especially those requiring diverse exploration strategies.

In FAGA, the integration of fuzzy logic with genetic algorithms increases the complexity of the algorithm. Designing appropriate fuzzy rules and membership functions requires expertise and can be difficult to generalize across different problems. Similar to ACO, FAGA can suffer from slow convergence, especially if the fuzzy rules are not well-tuned. FAGA assumes that fuzzy logic is the right approach to handle uncertainties and imprecision in the problem space. However, this assumption may not hold true for all types of optimization problems. The algorithm assumes that the fuzzy rules and membership functions are well-defined and accurately reflect the problem domain. Poorly designed rules can lead to ineffective adaptation and suboptimal solutions.

Both ACO and FAGA have been widely used and have shown success in various domains, but their effectiveness can be limited by issues such as parameter sensitivity, computational complexity, and assumptions regarding the problem environment. Addressing these limitations often involves a trade-off between algorithm simplicity and the robustness needed to handle complex, dynamic, or large-scale optimization problems.

6. CONCLUSION AND FUTURE RESEARCH

A hybrid algorithm combining ant colony optimization and a fuzzy adaptive genetic algorithm is proposed and applied to Solomon's standard test examples to enhance the accuracy and efficiency of solving integrated production and vehicle routing problems with time windows. The results demonstrate that: (1) The hybrid algorithm exhibits robust route-searching capabilities and high solution accuracy, making it particularly suitable for specific cases involving cluster and random distribution problems with relaxed time window constraints. (2) The sensitivity of the algorithm to the number of iterations underscores the importance of selecting an appropriate iteration count. (3) To increase the likelihood of achieving optimal solutions, a two-stage parallel search algorithm with an inheritance mechanism is developed by effectively integrating production scheduling and vehicle routing optimization. (4) Key algorithm parameters are identified through uniform testing and statistical analysis, ensuring the algorithm's optimal performance. (5) The proposed algorithm is validated through several examples, with experimental results confirming its efficiency and the high quality of the solutions.

The paper addresses a critical issue in supply chain management for perishable products, particularly in the context of fresh products. The significance of this problem is underscored by several key factors:(1) Perishability of products: Fresh products, such as food items, are highly perishable and require timely production and distribution to maintain quality and minimize waste. The deterioration of these products directly impacts both supplier costs and consumer satisfaction. Hence, optimizing the supply chain for these products is essential for reducing losses and ensuring product quality. (2) Complexity of supply chains: The problem involves complex decision-making processes that include production scheduling and VRPTW. This complexity is further amplified by the need to consider perishability, stochastic demand, and urban traffic conditions. Addressing these intertwined challenges is crucial for improving the efficiency and sustainability of supply chains for fresh products. (3) Economic impact: Efficiently managing the production and distribution of perishable products can lead to significant cost savings and increased profitability for businesses. It also has broader implications for food security, waste reduction, and resource optimization, making it a problem of considerable economic and societal importance.

The timeliness of the problem is highlighted by contemporary trends. The rise of e-commerce and just-in-time (JIT) delivery systems has placed new demands on supply chains, particularly for perishable products. Consumers now expect fast and reliable delivery, which adds pressure to optimize logistics operations in real time. This research focus on addressing these modern challenges makes the research highly relevant. Increasing urbanization has led to more congested cities, making it more difficult to adhere to delivery schedules, especially when dealing with perishable products. The manuscript's attention to these challenges is timely, as it reflects current and pressing issues in urban logistics.

The practical implications of the research are substantial: (1) Improved supply chain efficiency: By integrating production scheduling with VRPTW in a novel two-stage optimization model, the research provides a practical tool for companies to enhance the efficiency of their supply chains. This can lead to more reliable delivery schedules, reduced waste due to spoilage, and lower operational costs. (2) Scalability to real-world applications: The proposed model is designed to handle the complexities of real-world supply chains, making it scalable and adaptable to various industries dealing with perishable products. Its application can be extended beyond fresh products to other sectors where timing and perishability are critical. (3) Potential for adoption in smart logistics systems: As companies increasingly adopt smart logistics systems that rely on real-time data and advanced algorithms, the research offers a robust framework that can be integrated into these systems. This can lead to better decision-making and more responsive supply chain operations. (4) Contribution to sustainable development: By optimizing the production and distribution of perishable products, the research contributes to sustainability by reducing food waste, minimizing carbon emissions from unnecessary transportation, and ensuring that resources are used more efficiently.

The problem addressed by the research is both significant and timely, with practical potentials that extend to various aspects of supply chain management and logistics. The research offers a valuable contribution to the field by addressing a critical and contemporary issue, applying advanced optimization techniques, and providing solutions with real-world applicability. Its relevance to current trends in e-commerce, urbanization, and technological advancement further underscores its importance and potential impact on industry practices**.** The analysis reveals that the product deterioration rate significantly impacts production costs and distribution strategies, highlighting the need for further exploration of manufacturer-retailer coordination under these conditions. Future research should focus on developing an advanced ACO-based algorithm to address multi-objective production-distribution optimization, particularly for perishable products. Additionally, incorporating environmental factors such as vehicle carbon emissions and fuel consumption could facilitate the simultaneous optimization of economic and ecological outcomes. To enhance the flexibility of urban delivery, future studies should also examine strategies for minimizing the number of vehicles required, considering the diversity of vehicle types.

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