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Research on the Optimization of Material Distribution Routes for Power Grid Technology Upgrading Projects Considering Fuzzy Time Windows

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Abstract:

As China refines its strategy for green and ecologically sustainable development, the construction of innovative power systems that can integrate new energy generation has emerged as a central focus in contemporary power system development. This paper studies how to build an efficient distribution mechanism of power materials, focusing on optimizing the distribution route of materials in the power system. Based on this, a distribution route optimization model combining fuzzy time window for power grid technical transformation projects is proposed. The model uses multi-objective planning to minimize distribution costs and maximize the timeliness of material delivery for technical renovation projects. A fuzzy membership function processes the expected and maximum tolerance time windows, transforming them into a comprehensive satisfaction level for delivery timing. The model is solved with the elitist non-dominated sorting genetic algorithm (NSGA-II). The optimization results are analyzed, leading to recommendations for improving distribution. Arithmetic examples validate the proposed algorithm's feasibility, offering an effective solution for optimizing material distribution paths in grid technical reform projects. The findings provide valuable insights to support the safe operation of the power grid.

Keywords: Fuzzy time window, vehicle routing problem, non-dominated sorting genetic algorithms, power grid technology upgrading project

INTRODUCTION

A stable electricity supply is crucial for the operation and development of the modern economic society. It is a fundamental infrastructure that ensures and drives the progress of economic production and serves as an essential energy support for modern industrial production. As the primary entity responsible for maintaining the power grid, the power grid company plays a crucial role in optimizing the allocation of energy resources and supporting national economic development. However, as the grid continues to upgrade, its structure becomes increasingly complex, regional interconnections expand, and the need for a higher proportion of renewable energy access grows, the risk of power outages increases. Therefore, Power grid technology upgrading projects (hereinafter referred to as "grid upgrade projects") aimed at ensuring grid reliability have become particularly important. The effective implementation of these grid upgrade projects not only helps prevent potential faults but also plays a crucial role in ensuring the stable operation of the power grid.

Currently, although some studies have addressed the optimization of power material distribution, most remain confined to the traditional logistics optimization framework, which fails to fully reflect the actual conditions of power material allocation and distribution[1]. Therefore, in view of the complexity of power grid upgrading project, it is urgent to conduct quantitative research on the unique properties of power materials combined with actual needs. The establishment of efficient power distribution mechanisms is crucial to ensure the project progresses, which is closely related to the Vehicle Routing problem (VRP), an area of research dating back to the 1950s and 1960s. It was first introduced by Dantzig and Ramser in 1959[2] to address the optimal routing problem for gasoline tanker fleets traveling between bulk cargo docks and numerous fueling stations. Early studies primarily focused on the basic problem formulation and solution methods. As demand grew and application areas expanded, various variants of the VRP emerged, including the capacitated VRP and time window VRP, among others. Cheng[3], considering carbon emission factors, found that increasing customer satisfaction leads to higher distribution costs. However, when satisfaction is maintained at 0.9, the research subject achieves maximum profit. Ding[4], building upon carbon emission costs, introduced partial charging strategies, carbon tax policies, and time-of-use electricity pricing mechanisms to optimize delivery routes, thereby further reducing costs. Zhou[5] proposed solutions based on Internet of Things technology to solve the problems existing in the distribution management of power materials. Zhang[6] and other scholars focused on electricity logistics distribution, analyzed various issues in logistics management, and put forward optimization strategies. Zhang[7] proposed a distribution model aimed at minimizing the maximum inventory at a single point of demand in response to the shortage of emergency relief materials, and discussed three solutions. Zhang[8] constructed an optimization objective function that considered cost and carbon emissions. On the basis of traditional genetic algorithm, factors such as fitness sharing and climbing algorithm are included. Simulation shows that the improved algorithm can significantly reduce carbon emissions and total cost. Li[9] analyzed the existing issues in the distribution system of the research subject, applying the fuzzy analytic hierarchy process (AHP) to study site selection problems, optimizing delivery routes using a route-saving method, and proposing optimization solutions such as selecting reasonable models and strengthening information and warehouse management. Huang[10], guided by ERP and lean logistics theories, analyzed warehousing and distribution issues and proposed solutions such as building reserve warehouses and simplifying approval processes. To address the lack of informatization, she recommended developing a logistics system and intelligent warehouses. Wang et al.[11] applied a two-stage heuristic algorithm-genetic algorithm considering spatiotemporal distance based on Pareto variable neighborhood search (STVNS-GA) to solve the multi-objective vehicle routing problem considering perishability. Salazar-González et al.[12], considering the ability to split customer demands and the potential use of customers as temporary collection and delivery hubs, proposed a new branch-and-bound algorithm to find optimal solutions. This approach addresses a relaxed mixed-integer programming model, allowing all feasible solutions and some infeasible ones. Figliozzi et al.[13] used travel time data obtained from highway sensor archives, time-dependent vehicle routing algorithms, and problem instances with different types of binding constraints to analyze the impact of congestion on commercial vehicle emissions. Errico et al.[14] developed an efficient labeling algorithm by appropriately selecting label components, determining extension functions, and using partial routing in the column generation step to reduce the lower and upper bounds on cost. Fernando et al.[15] introduced an integrated bi-objective VRP model. The proposed model includes two objective functions: minimizing the total distribution cost while ensuring timely product delivery to retail stores. Tadaros et al.[16] studied a hierarchical multi-exchange switch multi-echelon VRP problem involving large-capacity vehicles and proposed two general variable neighborhood search procedures utilizing intelligent reordering mechanisms. Cai et al.[17] addressed the complexity of the multi-task VRP by integrating three strategic pillars: knowledge, resources, and search-sharing strategies, and introduced a three-party shared evolutionary multi-task algorithm. Sze et al.[18] focused on dynamic traffic information and proposed an adaptive variable neighborhood search algorithm to generate routes in a static environment, which are then adjusted according to dynamic conditions, achieving path optimization for dynamic VRP.

In the VRP problems mentioned above, customer time is typically quantified using fixed time values. However, in real-life scenarios, the optimization of delivery routes is constrained by these fixed time values, which can lead to delivery personnel operating at theoretically optimal speeds for rapid delivery. This, in turn, causes the entire distribution system to maintain an artificially high operational efficiency. As a result, the use of time windows for optimization has become a key focus of academic attention. Meng[19] utilized fuzzy membership functions to fuzzify the various time windows of customers, transforming them into levels of customer satisfaction with the service. He then developed a bi-objective model and employed a two-stage solution approach to achieve a balance between maximizing customer satisfaction and minimizing delivery costs. On the other hand, Yang[20] proposed using triangular fuzzy numbers to represent fuzzy demands and adopted a "route-first, cluster-second" approach to address multi-center constraints. This method effectively tackled the challenges posed by fuzzy demands, focusing specifically on the vehicle routing problem for simultaneous goods delivery from multiple open distribution centers. Sun [21] took into account constraints such as vehicle loading capacity and time window, and established a dual-objective model of minimizing total transportation cost and number of vehicles. The study compared the performance of the simulated annealing algorithm with the classical ant colony algorithm, with results demonstrating the proposed algorithm's strong adaptability. Qie[22] constructed a multi-objective optimization model, incorporating practical considerations such as road networks, green requirements, and customer satisfaction metrics—including the accuracy of logistics timing and the freshness of delivered goods. Wang[23] addressed the simultaneous pickup and delivery problem for electric vehicles by analyzing the characteristics of physical, spatiotemporal, and state networks. An improved dynamic programming algorithm was proposed to effectively solve the problem. Cao[24] tackled large-scale depot routing problems by developing a mathematical model with soft time windows and a three-stage solution algorithm. The approach involved fuzzy cluster analysis and the use of MATLAB software to segment materials into regions, prioritize key customers, and optimize route scheduling with an improved immune algorithm. Furthermore, a disturbance management strategy was introduced to handle demand fluctuations. Xu et al.[25] focused on two objectives: minimizing total travel costs and maximizing the average customer satisfaction. To achieve these goals, they employed a global-local-neighborhood particle swarm optimization algorithm to solve the model. Zheng[26], considering time-varying traffic flows, improved the Ito algorithm and developed a vehicle routing problem model with multiple fuzzy time windows. Simulation experiments validated the correctness of both the model and the algorithm, demonstrating their effectiveness in minimizing total delivery costs and average consumer dissatisfaction. Osvald et al.[27] integrated perishability into the overall delivery cost and proposed a heuristic algorithm for fresh vegetable distribution, leveraging tabu search with perishability as a central consideration. Mitra et al.[28] formulated a mathematical model for a multi-depot vehicle routing problem with time windows and split deliveries. The model aimed to minimize total vehicle rental costs, route costs, and penalties for unmet demands. They introduced an elite genetic algorithm and a hybrid local search genetic algorithm to solve the problem. Govindan et al.[29] addressed a two-stage location-routing problem with time windows by designing a multi-objective optimization model tailored to supply chain network distribution issues. They proposed a novel multi-objective algorithm combining particle swarm optimization with adaptive variable neighborhood search. Cetin et al.[30] emphasized cost minimization by considering vehicle arrival times at each customer and estimating the probability of arrivals. The optimization problem was addressed using an intelligent algorithm based on iterative local search.

In summary, an optimization model is established under practical constraints, and through the innovation of the model and algorithm, great progress has been made in the vehicle routing problem. Focusing on decarbonization and future development, the researchers analyzed the key problems and proposed the optimization plan, which provided a solid theoretical basis for the material distribution in the power grid renovation project. Current research on vehicle routing problems has the following shortcomings: (1) Limited attention is paid to delivery time requirements. Most clustering methods give priority to cost reduction and profit maximization, ignoring factors such as distribution point location, time window and material order diversity, which affect integration efficiency. (2) There are few researches on material distribution of power grid reconstruction projects, mainly focusing on material management or emergency supply. (3) The optimization goal is single, the existing model is mainly to minimize the transportation and fixed costs, and rarely consider the efficiency of customer service. Based on these observations, this paper conducts further research and proposes a fuzzy clustering method based on material similarity. By considering factors such as fixed costs, carbon emission costs, transportation costs, and penalty costs, a multi-objective optimization mathematical model is developed. The model aims to maximize customer satisfaction while minimizing costs. The goal is to achieve a high-precision simulation of logistics operations in power grid retrofit projects and provide more targeted, practical recommendations for the material distribution tasks of power grid companies.

The rest of this paper is structured as follows: Section 2 develops a bi-objective model designed to minimize total costs and maximize average customer satisfaction, with a focus on fuzzy treatment of time windows. Section 3 applies the model to a company case, determining the optimal delivery route and comparing it with the results of the single-objective model to validate the effectiveness of the proposed approach. Finally, Section 4 draws some conclusions and discusses the implications of the research.

MODEL BUILDING

Based on the fuzzy treatment of the time window, a bi-objective model for optimizing the material distribution route for power grid technological transformation projects is constructed, aiming to minimize the average satisfaction with the delivery arrival and the total cost. The objective is to find the optimal distribution route and strategy.

Fuzzy time windows represent a form of temporal constraint that lies between hard and soft time windows. Compared to hard time windows, fuzzy time windows offer more flexibility in the timing requirements for delivery tasks, allowing for completion within a certain range of time. However, compared to soft time windows, fuzzy time windows still impose certain restrictions, and exceeding the time range may lead to some degree of inconvenience or additional costs. By considering the temporal flexibility and cost-effectiveness of delivery tasks, fuzzy time windows can meet customer demands while maintaining a balance between delivery efficiency and cost control.

Model Assumption

In general material distribution research, the objective function of route optimization model is usually to minimize the total cost, and less attention is paid to the time requirement of delivery service or the customer experience related to delivery time. In the power grid technical transformation project, in addition to reducing distribution costs, it is also necessary to pay attention to the timeliness of project completion. Therefore, on the basis of previous studies, this paper introduces the time window factor and adopts the fuzzy processing method to transform the timeliness of delivery into satisfaction for evaluation, so as to reflect the project demand more comprehensively. Given the numerous unpredictable influencing factors or emergencies encountered during the route optimization of material distribution for power grid technical renovation projects, it is necessary to reasonably simplify the actual distribution problem and make assumptions to ensure accurate route planning while effectively addressing the optimization problem:

(1) The route optimization model assumes a single distribution center supplying materials to multiple construction sites requiring materials for technical renovation projects.

(2) Vehicles travel at a constant speed during distribution services and return to the distribution center upon completing the service.

(3) All distribution vehicles are of the same model, with identical rated cargo capacities, fuel consumption coefficients, and no need for refueling during operation, maintaining a non-empty load state throughout.

(4) Distribution services are provided to all material demand points, with each demand point served by only one vehicle.

(5) Carbon emission costs are solely related to the distance traveled during distribution and the vehicle's load weight.

Distribution Cost Analysis

This study considers not only transportation costs (vehicle maintenance, fuel, wages), but also fixed costs (warehouse rental, equipment depreciation) and carbon emissions costs to address the complexity of material allocation in grid upgrade projects. These factors highlight the dual responsibility of companies to meet their environmental obligations while achieving economic benefits. In addition, financial penalties for late delivery or operational errors are included to improve delivery efficiency and service quality. The research results provide a comprehensive optimization framework for the material allocation of power grid reconstruction projects.

Transportation Costs

In the material distribution process for technical renovation projects, transportation costs mainly include vehicle operation expenses, fuel costs, toll fees, and vehicle maintenance costs. The transportation cost incurred during the logistics distribution process C_1 is expressed as:

$$C_1 = \sum_{k=1}^{m} \sum_{i,j=0}^{n} d_{ij} c_{ij} x_{ijk} \tag{1}$$

Where:

n: Total number of customer demand points;

i, j: Customer demand points, where $i, j \in [1, \ n]$;

m: Number of distribution vehicles;

k: Specific vehicle, where $k \in [1, m]$;

d_{ij}: Distance between demand points i and j;

C_{ij}: Unit transportation cost per distance between i and j;

$x_{ijk} = 1$ if vehicle k travels from demand point i to demand point j, and $x_{ijk} = 0$ otherwise.

Fixed Costs

Fixed costs are constant expenses incurred during transportation, including vehicle acquisition, labor, depreciation, amortization, and equipment wear and tear. These costs are independent of the vehicle's load or travel distance and are incurred at the outset of the distribution process. Fixed costs C_2 in logistics distribution can be expressed as:

$$C_2 = \sum_{k=1}^{m} f_k \tag{2}$$

Where f_k denotes the fixed cost associated with the k-th vehicle.

Carbon Emission Costs

Carbon emission costs in material distribution are influenced by the vehicle's load weight and travel distance. As materials are loaded or unloaded, the carrying capacity changes, affecting fuel consumption over a given distance:

$$\theta_q = \beta(q + q_0) + \alpha \tag{3}$$

The variables are defined as follows: θ_q represents the fuel consumption per unit distance for a vehicle carrying a load of q, where q is the cargo load weight and q_0 denotes the vehicle's own weight. α and β are fixed constants.

$$\theta_{\max} = \beta(q_{\max} + q_0) + \alpha \tag{4}$$

$$\theta_{\max} = \beta(q_{\max} + q_0) + \alpha \tag{5}$$

$$\theta_0 = \beta q + \alpha \tag{6}$$

Where:

$q_{\max}$ represents the vehicle's rated load capacity.

$\theta_{\max}$ denotes the fuel consumption per unit distance when the vehicle is fully loaded.

θ_0 denotes the fuel consumption per unit distance when the vehicle is completely empty.

By solving equations (4), (5), and (6) together, the relationship between the vehicle's load weight and its fuel consumption per unit distance within a specified time period can be derived:

$$\theta_q = \theta_0 + \frac{\theta_{\max} - \theta_0}{q_{\max}} q \tag{7}$$

The total carbon emission costs C_3 for material distribution in grid upgrade projects are given by:

$$C_3 = c_0 \sum_{k=1i,}^{m} \sum_{j=0}^{n} \eta \theta_{q_{ij}} d_{ij} x_{ijk} \tag{8}$$

Where:

q_{ij} represents the load weight of the vehicle when transporting materials from demand point i to demand point j;

c_0 denotes the carbon emission cost per unit of fuel consumption;

η is the CO_2 emission coefficient;

$\theta_{q_{ij}}$ represents the fuel consumption per unit distance when the vehicle carries a load of q_{ij}.

Penalty Costs

In vehicle routing problems, factors such as travel distance, time window constraints[31], and traffic conditions are typically considered to determine the optimal delivery route. However, real-world operations often encounter challenges like traffic congestion and road closures, forcing delivery vehicles to take detours or arrive late. These disruptions lead to additional time costs and resource wastage.

To quantify these losses, penalty costs are introduced, encompassing waiting costs and delay charges incurred when transportation fails to arrive on time. Customers generally define an optimal service window and an acceptable service window. Deliveries made within the optimal time window avoid additional fees, while those within the acceptable service window incur moderate additional costs. Deliveries exceeding the acceptable time window are rejected, resulting in significantly higher penalty costs.

The fuzzy time window membership function is shown in Figure 1.

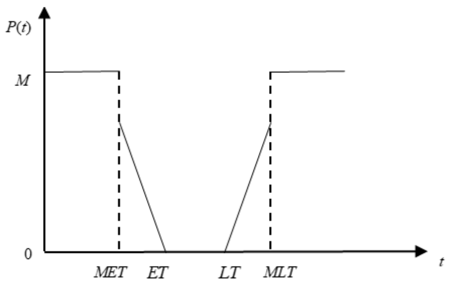

Figure 1. Fuzzy time window membership function

Based on Figure 1, we can derive the following:

$$C_4(j) = \begin{cases} M, t_{jk} < EET_j \\ \delta_1(ET_j - t_{jk}), EET_j \le t_{jk} < ET_j \\ 0, ET_j \le t_{jk} \le LT_j \\ \delta_2(t_{jk} - LT_j), LT_j < t_{jk} \le LLT_j \\ M, t_{jk} > LLT_j \end{cases} \tag{9}$$

The penalty cost C_4 in this paper is given by:

$$C_4 = \delta_1 \sum_{j=1}^{N}\sum_{k=1}^{K} \max\{ET_j - t_{ik}, 0\} + \delta_2 \sum_{j=1}^{N}\sum_{k=1}^{K} \max\{t_{jk} - LT_J, 0\} \tag{10}$$

Where:

t_{ik} represents the time at which vehicle k arrives at delivery point i;

δ_1 denotes the unit waiting cost per unit time for the vehicle;

δ_2 represents the unit late cost per unit time for the vehicle;

$[ET_j, LT_j]$ is the expected time window for delivery point j;

$[EET_j, LLT_j]$ is the acceptable time window for delivery point j.

Customer Satisfaction Analysis

In vehicle routing optimization, customer satisfaction is the key index to evaluate the distribution scheme[32]. In practice, delivery time requirements are often flexible, with a preference for specific time frames rather than fixed moments. Fuzzy logic makes the time window flexible and provides an effective way to understand the material demand and improve the satisfaction. Fuzzy membership function is used to model the expected delivery start time, reflect time preference, and effectively optimize the delivery plan[33].

This paper measures time satisfaction through the average satisfaction level of the material distribution points. Specifically, it takes into account the expected satisfaction of all customer points and calculates their average to balance the demands and preferences of different distribution points. When the actual delivery time falls within the expected time window $[ET_i, LT_i]$, the satisfaction level is 1. The early service time window is $[EET_i, ET_i]$, and the delayed service time window is $[LT_i, LLT_i]$. When the delivery time is less than EET_i or greater than LLT_i, the satisfaction level is 0. The specific membership function is shown in Figure 2 and equation (11).

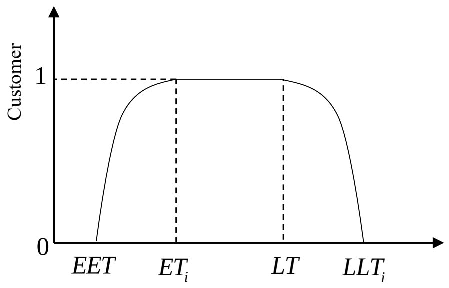

Figure 2. Time satisfaction function

$$S(t_i)=\begin{cases} 0, & t_i < EET_i \\ \dfrac{t_i - EET_i}{ET_i - EET_i}, & EET_i \leq t_i < ET_i \\ 1, & ET_i \leq t_i \leq LT_i \\ \dfrac{LT_i - t_i}{LL_i - LT_i}, & LT_i < t_i \leq LLT_i \\ 0, & t_i > LLT_i \end{cases} \tag{11}$$

In summary, the average satisfaction level function for n distribution points is as follows:

$$Z_2 = \frac{\sum_{i=1}^{n} S(t_i)}{n} \tag{12}$$

Model Construction

According to the above analysis of the cost of each part, grid upgrade projects material distribution path optimization objective function is:

$$\mathrm{MinZ}_1 = C_1 + C_2 + C_3 + C_4 \tag{13}$$

$$MaxZ_2 = \frac{\sum_{i=1}^{n} S(t_i)}{n} \tag{14}$$

S.T.

$$\sum_{j=1}^{n}\sum_{k=1}^{m} x_{ijk} \leq m, i = 0 \tag{15}$$

$$\sum_{k=1}^{m} x_{ik} = 1 \tag{16}$$

$$\sum_{k=1}^{m} x_{ik} = 1 \tag{17}$$

$$\sum_{i=0}^{n}\sum_{k=1}^{m} x_{ij}{}^{k} = 1, j = 1, 2....n, i \neq j \tag{18}$$

$$\sum_{j=0}^{n}\sum_{k=1}^{m} x_{ij}{}^{k} = 1, i = 1, 2....n, i \neq j \tag{19}$$

$$\sum_{k=1}^{m}\sum_{j=0}^{n} x_{0jk} = \sum_{k=1}^{m}\sum_{i=0}^{n} x_{i0k} \tag{20}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m} x_{ij}{}^{k} \leq m, i = 0 \tag{21}$$

$$w_j = \max\left\{ET_j - t_{ik} - t_i - t_{ij}\right\} \quad (22)$$

$$EET_{i},, t_{ik} + w_{i},, LLT_i, i = 1, 2 \ldots n \quad (23)$$

Where Eq. (13) denotes that the total cost of path-optimized distribution is minimized; Eq. (14) denotes that the average satisfaction is maximized; Constraint (15) denotes that the number of transport vehicles cannot exceed the total number of available vehicles; Constraints (18) and (19) denote that each demand point is served only once; Constraint (20) denotes that the starting and ending points of the distribution vehicles must both be the distribution center; Constraint (21) denotes that the total amount of goods on each selected distribution route cannot exceed the maximum load capacity of the vehicles; Constraint (22) indicates the time limit for the arrival of distribution vehicles at the demand point; and Constraint (23) indicates the service time constraint for customer points under the fuzzy time window.

MODEL SOLVING

Distribution Path Optimization Solution Output

According to the actual situation such as the list of technical reform project requirements of the power grid company, the basic parameters set for the path optimization model are shown in Table 1:

Table 1. Basic parameters

Parameter symbol	Parameter definition	Parameter value
f_k	denotes the fixed cost associated with the k-th vehicle	400yuan
v	Average speed of vehicle movement	60km/h
C_{ij}	Unit transportation cost per distance between i and j	8yuan/km
c_0	denotes the carbon emission cost per unit of fuel consumption	3yuan/km
θ_0	denotes the fuel consumption per unit distance when the vehicle is completely empty	15L/km
θ_{max}	denotes the fuel consumption per unit distance when the vehicle is fully loaded	31L/100km
η	CO_2 emission coefficient	2.66kg/L
α , β	fixed constants	
$\theta_{q_{ij}}$	represents the fuel consumption per unit distance when the vehicle carries a load of q_{ij}	(5+0.18q)yuan/km
δ_1	denotes the unit waiting cost per unit time for the vehicle	60yuan/h
δ_2	represents the unit late cost per unit time for the vehicle	90yuan/h

The path model is optimized through simulation using a non-dominated sorting genetic algorithm with an elite strategy. The algorithm parameters are as follows: population size *NP*=80, maximum number of iterations *Maxgen*=350, number of objectives *M*=2, crossover rate *Pc*=0.9, and mutation rate *Pm*=0.1.

Figures 3 and 4 illustrate the iterative process of average satisfaction and cost. In Figure 3, satisfaction increases steadily and stabilizes after the 190th generation, reaching an optimal value. Similarly, Figure 4 shows that costs gradually decline and stabilize after the 220th generation, indicating that optimal delivery costs have been reached.

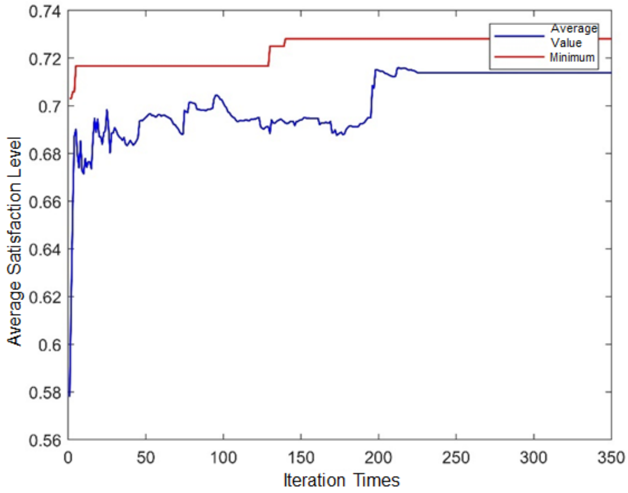

Figure. 3 Iterative graph of average customer satisfaction

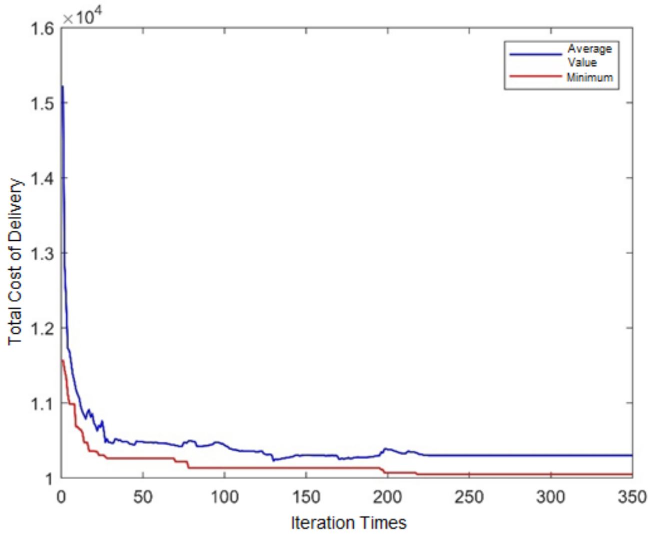

Figure. 4 Iterative diagram of total cost of distribution

The final Pareto solution set for the power grid retrofit project material distribution route model is shown in Figure 5. Each point in the figure represents a distribution scheme. As the total delivery cost increases, customer average satisfaction and total delivery cost are positively correlated, which aligns with real-world scenarios.

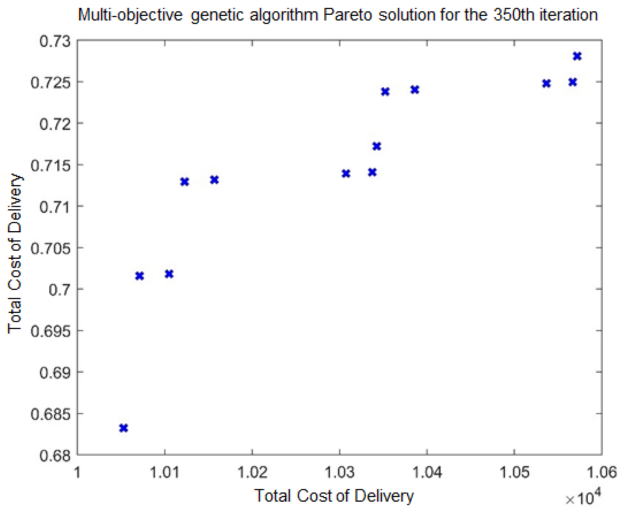

Figure 5. Pareto front surface solution set

After optimization using MATLAB, the delivery scheme that balances maximum average satisfaction with minimum total cost was selected, resulting in the optimal delivery route, as shown in Figure 6.

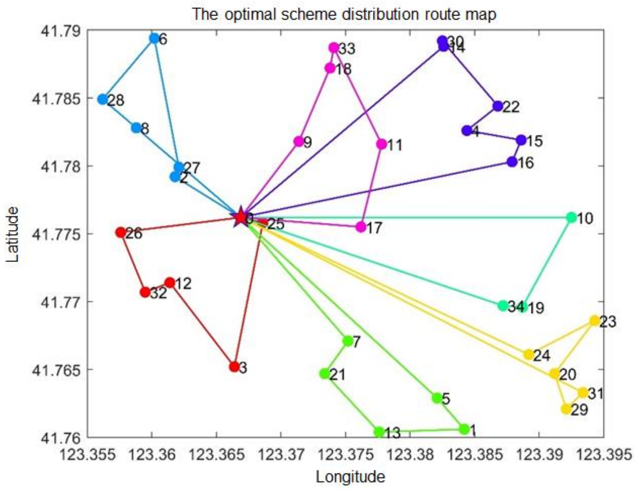

Figure 6. Optimal solution distribution route

The total delivery cost for the optimal solution is 10,052.8 yuan, with an average satisfaction of 68.3%. The specific delivery routes for each vehicle are detailed in Table 2 below:

The route for vehicle 1 is 0→25→3→12→32→26→0, with a vehicle operating cost of 18.08, fixed cost of 400.00, carbon emission cost of 594.08, penalty cost of 349.14, and a total route cost of 1, 361.297.

The route for vehicle 2 is 0→31→29→20→23→24→0, with a vehicle operating cost of 31.34, fixed cost of 400.00, carbon emission cost of 1,084.67, penalty cost of 106.52, and a total route cost of 1, 622.527.

The route for vehicle 3 is 0→7→21→13→1→5→0, with a vehicle operating cost of 24.61, fixed cost of 400.00, carbon emission cost of 776.58, penalty cost of 493.73, and a total route cost of 1, 694.921.

The route for vehicle 4 is 0→10→19→34→0, with a vehicle operating cost of 24.39, fixed cost of 400.00, carbon emission cost of 767.09, penalty cost of 0.00, and a total route cost of 1, 191.480.

The route for vehicle 5 is 0→8→28→6→27→2→0, with a vehicle operating cost of 18.01, fixed cost of 400.00, carbon emission cost of 642.87, penalty cost of 351.59, and a total route cost of 1, 412.469.

The route for vehicle 6 is 0→14→30→22→4→15→16→0, with a vehicle operating cost of 26.13, fixed cost of 400.00, carbon emission cost of 1,014.52, penalty cost of 109.99, and a total route cost of 1, 550.636.

The route for vehicle 7 is 0→9→18→33→11→17→0, with a vehicle operating cost of 19.20, fixed cost of 400.00, carbon emission cost of 615.93, penalty cost of 184.35, and a total route cost of 1, 219.482.

Table 2. Optimized distribution solution routes

Vehicle route number	Distribution Route	distribution volume (*t*)
1	0→25→3→12→32→26→0	6.1
2	0→31→29→20→23→24→0	6.5
3	0→7→21→13→1→5→0	5.4
4	0→10→19→34→0	4.4
5	0→8→28→6→27→2→0	6.6
6	0→14→30→22→4→15→16→0	9.2
7	0→9→18→33→11→17→0	5.9

Comparison Analysis

The comparison between the results of the single-objective models for total delivery cost and average customer satisfaction is shown in Figure 7.

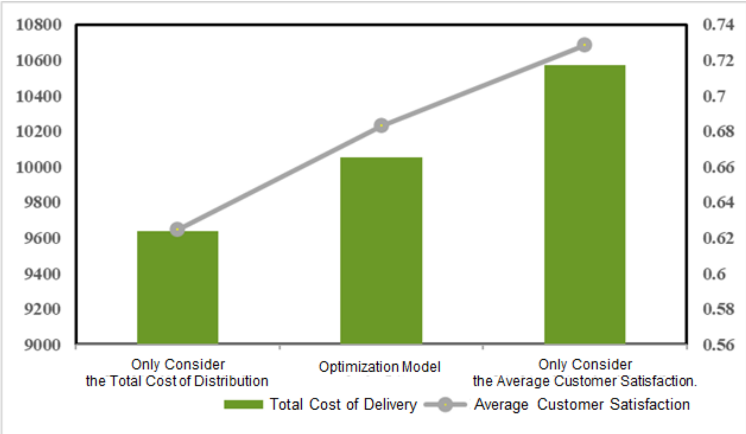

Figure 7. Comparison of optimized model and single-objective scheme

Figure 6 shows that when only distribution cost is considered, material distribution cost is optimal, but customer satisfaction is reduced and service quality is affected. By contrast, focusing solely on satisfaction increases costs significantly. Compared with the single objective scheme, the proposed route optimization model achieves a balance between reducing cost and improving customer satisfaction.

Validity Analysis

The effectiveness analysis evaluates whether the algorithm consistently produces high-quality solutions across scenarios. NSGA-II, by classifying individuals into non-dominated levels, balances diversity and convergence while efficiently approaching the Pareto front, making it widely used in practice. Despite its advantages in handling large-scale problems and improving solution speed, uncertainties in its solutions necessitate thorough effectiveness analysis to ensure result credibility.

In order to verify the effectiveness of the algorithm, we run it 15 times in MATLAB and analyze the mean and variance of the objective functions Z1 and Z2. The mean values were 10052.8 and 0.689, and the variances were 23.8 and 1.21, respectively. The results of 9 runs are consistent, which proves the stability of NSGA-II algorithm in optimization.

Time Window Sensitivity Analysis

The time window not only influences penalty costs during the distribution process but also affects customer satisfaction. This section evaluates the specific effects of adjusting the time windows for each customer demand point. The results are summarized in Table 3.

Table 3. Results of time window sensitivity analysis

	Fixed costs	Transportation cost	Cost of carbon emissions	Penalty cost	Average satisfaction
Original program	2800	162	5644	1611	68.3%
20% reduction in time window	2800	160	5465	1586	47.4%
10% reduction in time window	2800	161	5459	1593	51.1%
10% enlargement of time window	2800	163	5521	1716	79.2%

As indicated in Table 3, while penalty costs exhibit significant fluctuations, other cost components show relatively minor changes. However, the variation in average satisfaction is notably pronounced. For the material distribution network of power grid retrofit projects, changes in time window ranges may necessitate re-optimization of delivery routes to balance low delivery costs with the fulfillment of customer time window constraints, thereby enhancing customer satisfaction.

When the time window narrows, delivery costs remain almost unchanged, but the average customer satisfaction decreases sharply. Conversely, as the time window expands, average satisfaction levels improve. Overall, while variations in the time window have a relatively small impact on delivery costs, they significantly influence average customer satisfaction.

CONCLUSIONS AND IMPLICATIONS

Aiming at the problems of high cost and low efficiency of material distribution in power grid upgrading project, a path optimization model based on fuzzy time window is proposed. This model minimizes costs while ensuring customer satisfaction. A non-dominated sorting genetic algorithm using elite strategy is implemented in MATLAB to solve the model. The results of this paper are as follows:

(1) In addition to focusing on cost minimization, this study also considers distribution timeliness, which is translated into a measurable satisfaction level. This approach ensures that the research outcomes aim to minimize total cost while maximizing average satisfaction. Furthermore, constraints are imposed on various factors, including the number of transport vehicles, the number of services, the start and end points, vehicle load, delivery time, and service time. These constraints are integrated into the construction of the distribution path optimization model.

(2) The example analysis shows that the distribution cost of the optimal scheme is 10052.8 yuan, the average satisfaction rate is 68.3%, and there are 7 optimal routes. Considering only cost minimization reduced costs, but satisfaction decreased by 6.3%, while focusing only on satisfaction increased costs by 550 yuan. Compared with the single objective scheme, the proposed model takes into account both higher satisfaction and cost savings.

(3) The sensitivity analysis of the time window reveals that, except for significant changes in penalty costs, other cost variations are minimal, while the average satisfaction level fluctuates significantly. When the time window is narrowed, the distribution cost remains largely unchanged, but customer satisfaction decreases sharply to some extent. Conversely, when the time window is expanded, the average customer satisfaction level increases. Overall, changes in time window costs have a minimal impact on distribution costs but a significant effect on average customer satisfaction levels.

Based on the above research findings, this paper proposes the following recommendations for material distribution in grid upgrade projects:

(1) Implement specialized inventory management for power materials

Enterprises should leverage historical data, market trends, and demand forecasting models to predict the future demand for power materials accurately. This enables the formulation of reasonable procurement plans and inventory management strategies. Batch management should be applied to incoming power materials, with the establishment of batch files and a traceability system. By monitoring and analyzing inventory data in real-time, inventory levels and strategies can be dynamically adjusted based on changes in demand and supply chain conditions. Close collaboration with suppliers, carriers, and customers is essential, along with the creation of a supply chain information platform to facilitate real-time data sharing and transparency. This improves supply chain visibility and responsiveness, reduces information asymmetry, and prevents inventory backlogs.

(2) Enhance the distribution process for electric power materials

Collect and analyze historical distribution data, including distribution times, traffic conditions, and distribution point demand, to identify patterns and bottlenecks. Utilize predictive analytics to forecast future demand and develop corresponding distribution plans to avoid delays or surpluses. Employ dynamic route planning with real-time traffic information and GIS to account for current road conditions and congestion during the distribution process. Implement intelligent vehicle scheduling systems, centralize distribution points, and prioritize bulk distribution to high-demand areas or customers. These measures can optimize scheduling, reduce costs, and improve efficiency. Additionally, conduct regular reviews of the distribution process, including performance evaluations and cost-benefit analyses, to assess the effectiveness of optimization measures. Continuously adjust and refine the distribution strategy based on these assessments.

(3) Promote decarbonization in material distribution

Replace traditional fuel vehicles with electric vehicles, hybrid vehicles, or vehicles powered by clean fuels during the distribution of power materials. When using electric vehicles, further reduce carbon emissions by leveraging renewable energy sources for charging. In urban or congested areas, consider low-carbon distribution methods such as bicycles, electric bicycles, or walking. Additionally, adopt innovative distribution technologies like drones and implement batch and centralized distribution models. Collaboration with other supply chain participants and the use of monitoring and reporting tools can further enhance efficiency and effectively reduce carbon emissions in the distribution process.

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