IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 14 September 2023, accepted 27 September 2023, date of publication 2 October 2023, date of current version 9 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3321073

RESEARCH ARTICLE

Robust Optimization of Electric Vehicle Paths in Uncertain Environments

AOBEI ZHANG, YING ZHANG, AND YANQIU LIU
School of Management, Shenyang University of Technology, Shenyang 100870, China
Corresponding author: Aobei Zhang (zab@smail.sut.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 70431003, and in part by the Science and Technology Plan Project of Liaoning Province under Grant 10100028.

ABSTRACT In the face of uncertainty in customer demand and dynamic traffic conditions, determining the optimal logistics distribution route under deterministic conditions becomes challenging. To address this issue, we propose a novel approach by adopting Robust Optimization Models for Electric Vehicle Path Optimization. Our robust optimization model incorporates two uncertainty sets, namely the convex set and the box set, to tackle variations in demand and speed. By introducing deviation coefficients, we compare the objective function values of the robust optimization model with those of the deterministic model. This enables us to understand the trade-offs between robustness and optimality. To find solutions for various instance sizes, we apply an improved genetic algorithm to solve the constructed model efficiently. Our case study results demonstrate that while the optimal objective function value of the robust optimization model may be higher than that of the deterministic model, it ensures the feasibility of the path even amidst demand fluctuations and dynamic traffic conditions. Moreover, we analyze the economic returns of velocity and demand under both uncertainty sets with different data sizes, using the deviation coefficients. These discoveries provide valuable perspectives for pertinent departments, assisting them in rendering well-informed choices and attaining practical significance in real-world scenarios. To recapitulate, our study introduces an innovative methodology for addressing the challenges of optimizing electric vehicle routes in the face of unpredictable demand fluctuations and time-dependent speed variations. By demonstrating the effectiveness of our proposed robust optimization model, we contribute to the advancement of logistics and transportation systems in a volatile and uncertain environment.

INDEX TERMS Uncertain demand, robust optimization, time varying speed, electric vehicle, genetic algorithm, deviation factor.

I. INTRODUCTION

The transportation industry's rapid development has resulted in significant environmental and energy challenges. To address these issues, countries worldwide are embracing the concept of a "low-carbon economy" to achieve sustainable economic and social progress. Guided by the principles of the "low-carbon economy," the transformation of new energy vehicles has become a crucial undertaking in urban development. Electric vehicles (EVs), in comparison to traditional fuel vehicles, offer numerous advantages such as energy efficiency, environmental friendliness, and policy support. With the continuous advancement of battery and charging infrastructure, EVs have emerged as indispensable tools for sustainable logistics and transportation. Despite their advantages, EVs have certain limitations, including extended charging times, limited battery capacities, and restricted battery life and range. Consequently, researchers are actively engaged in discussing how to efficiently manage electric vehicle scheduling and optimize distribution path planning within the constraints of existing technical conditions. By addressing these challenges, we can pave the way for sustainable urban development and effectively promote the adoption of EVs in our transportation systems.

The associate editor coordinating the review of this manuscript and approving it for publication was Chi-Tsun Cheng.

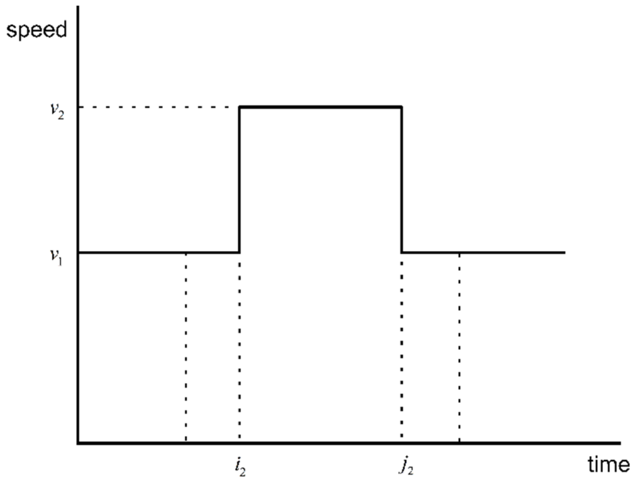


FIGURE 1. Time-varying travel speed of the road section.

The Electric Vehicle Routing Problem (EVRP) is an extension and expansion of the traditional Vehicle Routing Problem (VRP). Due to the limited range of electric vehicles, they require multiple stops during transport to recharge energy. Currently, research on electric vehicle path optimization problems mainly focuses on charging strategies. This includes the optimization of the number of charging station visits, charging waiting time, charging time, and whether to fully charge or not. Keskin et al. presented the EVRP problem with soft time windows and charging station waiting times, dividing the day into five time periods with varying queue lengths. They utilized the M/G/1 queuing system to calculate the queuing time for each time slot [1]. Erdelic conducted a comparative analysis of the application of single-charge and multiple-charge strategies in the electric vehicle path problem. Subsequently, Erdelic investigated partial charging strategies as well as full charging strategies. The comparative analysis revealed that the partial charging approach resulted in shorter waiting times and reduced total travel time. However, it also led to an increase in the psychological burden of drivers, an upsurge in the number of vehicles, and an extension in the driving distance [2], [3].

Meanwhile, Desaulniers examines the EVRP by incorporating time window constraints across four distinct charging strategies, varying the number of charging instances [4]. Froger develops an EVRP model that incorporates charging stations with capacity constraints. The study focuses on optimizing the path, taking into account the non-linear charging function, multiple charging techniques, en route charging, and variable power [5]. In the investigation of nonlinear charging functions, Liang et al. introduced a precise heuristic algorithm for electric vehicles utilizing such functions. The inherent nonlinearity in the battery charging process necessitates the incorporation of a sophisticated set of recursive functions within the pricing algorithm. This enables the evaluation of path and cost decisions [6]. The above literature indicates a strong correlation between the choice of charging strategy for electric vehicles and their energy consumption. Therefore, an important aspect of EVRP research is to investigate various influencing factors and models that affect the energy consumption of electric vehicles. Basso et al. proposed a two-stage electric vehicle path problem with an improved energy consumption estimation model based on terrain and speed. This model takes into account not only the distance traveled but also other crucial factors such as effective load, speed profile (acceleration and braking), road topography, instantaneous powertrain efficiency, and auxiliary equipment (air conditioners, refrigerators, etc.) that can affect the energy consumption of electric vehicles [7]. Xiao et al. introduced a novel fixed arc bypass technique. For each arc, an optimal fixed charging station access detour is designated, and a comprehensive multi-factor power usage model is formulated [8]. Kancharla investigated the impact of vehicle load on the energy consumption of electric vehicles [9]. Liu et al. investigated the impact of road traffic flow and driver behavior on the energy consumption of electric vehicles [10] Xu et al. conducted an analysis of a nonlinear minimization model for the energy consumption rate of electric vehicles, taking into account the influence of road slope [11].

The objective environment and transportation situation of VRP problems in real life are characterized by uncertainty. With the continuous development of optimization theory and the improvement of computer capabilities, uncertainty optimization has garnered unprecedented attention from the academic community. In the VRP model, uncertainty in the parameters arises from four main aspects. First, there can be excessive data deviation due to lost statistics and the data collection process. Second, incomplete cognition can lead to deviations between existing models and real life. Third, force majeure factors such as weather can introduce uncertainty. Fourth, some non-convex linear models that are difficult to solve may require simplified descriptions. Uncertainty optimization theory is divided into two categories of methods: ex ante and ex post analysis, depending on the stage of analysis. Among the ex ante analysis methods are stochastic planning, fuzzy planning, and robust optimization, while sensitivity analysis is the most typical ex post analysis method. Fuzzy planning, proposed by Zhang et al., is applied to address the EVRP in uncertain environments. To construct a fuzzy electric vehicle path optimization model based on reliability theory, fuzzy numbers are utilized to represent the uncertainties associated with service time, energy consumption, and transportation time [12]. Song et al. introduced a novel dynamic path planning strategy, which relies on fuzzy logic and an enhanced ant colony algorithm [13]. In the realm of fuzzy programming, acquiring fuzzy membership functions for uncertain parameters relies on the subjective insights of the decision maker. As a result, fuzzy planning inherently leans towards subjectivity. Conversely, stochastic programming addresses the task of devising plans that contend with stochastic data. This field can be categorized into three distinct classes based on differing decision rules: expectation models, opportunity-constrained planning models, and their interconnected counterparts. Francesc et al. developed an energy consumption prediction model for electric gas vehicles, taking uncertainties into account. The model incorporates stochastic speed to mitigate the impact of human interventions on consumption [14]. Although the sensitivity analysis method is relatively simpler compared to other uncertainty optimization methods, it serves solely as an evaluation and analysis tool.

Robust optimization has emerged as a methodology derived from robust control theory, aiming to rectify the limitations inherent in conventional optimization techniques. Diverging from stochastic and fuzzy planning approaches, robust optimization operates independently of a probability distribution model encompassing uncertain parameters or a fuzzy affiliation function entailing uncertain parameters. Its efficacy resides in ensuring constraint satisfaction for derived solutions as long as these uncertain parameters fall within the designated uncertainty set, thereby imbuing the solutions with notable robustness. Ji et al. proposed an anti risk two-level stochastic lowest cost consensus model with asymmetric adjustment costs. Afterwards, proposed several new maximum expert consensus models to address uncertainty and risks in the consensus formation process [15], [16]. These models can all be solved using robust optimization methods. The application of robust optimization offers a viable approach to tackle the manifold uncertainties inherent in the VRP. Guo et al. proposed a two-stage, robust, and dynamic multi-objective path planning method that takes into account the impact of both load and travel distance on energy consumption [17]. Hu et al. investigate the VRP under conditions of uncertain demand and travel time [18]. Sungur et al. proposed a robust optimization method to address demand uncertainty in the VRP. The results demonstrate that this robust optimization method effectively prevents unmet demand occurrences [19].Hooge et al. addressed uncertainties in both travel time and service time by developing a robust VRP model. The primary objective of their model was to minimize the expected travel time while reducing the risk of time window violations [20]. Based on the robust optimization theory, Sun et al. have proposed a novel weakly robust optimization model. This model is designed to address the open VRP while taking into account predetermined time windows under travel time uncertainty [21]. Yuliza addresses the challenge of robust path optimization for waste transportation, considering uncertainties in waste volume and travel time. To tackle potential delays caused by congestion and engine failure during garbage transportation, Yuliza proposes a robust pairwise open capacity VRP [22], [23]. Zhang proposed a model for distributionally robust optimization [24]. In the context of electric vehicle path optimization, Pelletier et al. address the EVRP considering various uncertainties, including driver behavior, weather conditions, and road situations. The primary objective is to ascertain the most cost-effective optimal path, aiming to minimize overall expenses [25]. Jeong et al. established an adaptive and robust EVRP model to address the challenges posed by partial charging and energy consumption uncertainty [26].

In summary, numerous prior studies on electric vehicles for logistics distribution have focused on aspects such as charging methods and charging queues, while fewer have explored uncertainties. Therefore, this research introduces the robust optimization method to address the EVRP problem, considering the characteristics of speed, stochasticity, and uncertain demand. We construct an electric vehicle path optimization model and a robust optimization model to handle speed and demand uncertainty sets separately. Additionally, we design an improved genetic algorithm to find solutions. The experimental results are compared to analyze the effectiveness of these models concerning each distribution cost variation and the uncertainty set.

II. PROBLEM DESCRIPTION AND METHOD DESIGN

A. RESEARCH HYPOTHESES

There is only one distribution center with an ample number of electric vehicles for distribution. The geographical location of each customer point in relation to the charging station is known, along with their service hours, time windows, demand, and fluctuations. It is a requirement that a vehicle's starting point must be a distribution center. The remaining assumptions are as follows: (1) all electric vehicles have identical specifications, and both the load and driving distance must not exceed the vehicle's maximum capacity. (2) The distribution process should comply with both the time window constraint and the power constraint. (3) If an electric vehicle does not have sufficient power to complete the distribution requirements, it must go to the nearest charging station for charging and exchange, considering only the full charging situation. (4) The average driving speed of the vehicle at different times of the day is known, along with the range of speed fluctuations under the influence of weather and other conditions.

What are the distinctions between deterministic conditions for electric vehicles and the logistics distribution model under robust optimization? How do their comparison results for distribution costs differ? What sets the deviation coefficients apart under an uncertainty set? Is there a guideline for selecting uncertain sets at various scales?.

B. SYMBOL DESCRIPTION

$M = \{1, 2, \cdots, m\}$ denotes the total number of electric vehicles in use. $N = \{0, 1, 2, \cdots, n\}$ indicates the distribution center and customer point of aggregation. $W = \{0, 1, \cdots, w\}$ indicates charging station collection. q_i indicates the demand of customer i. P_1 denotes the fixed cost per unit of electric vehicle. P_2 denotes the transportation cost per unit time of electric vehicle. P_3 denotes the price per unit of electricity consumption. P_4 denotes the charging price per unit time. Q, D denotes the maximum load and maximum distance of electric vehicle respectively. a_{ik}, $[B_i, E_i]$ denotes the time of arrival of vehicle k at node i, and the time window of node i, respectively. x_{ij}^k denotes the $0-1$ variable, $x_{ij}^k = 1$ when electric vehicle k is transported in section i, j, otherwise $x_{ij}^k = 0$. y_j^k denotes the $0-1$ variable, if the electric vehicle k delivers for customer point j, $y_j^k = 1$, otherwise $y_j^k = 0$. z_i^k denotes the $0-1$ variable, $z_i^k = 1$ when EV k is charging at i charging station, otherwise $z_i^k = 0$.

C. THE METHOD OF REPRESENTATION OF UNCERTAINTY SETS

1) METHOD OF REPRESENTING DEMAND UNCERTAINTY

Customer demand is significantly influenced by the external environment, as indicated by the uncertainty set formation method described in the literature [44]. First assume that the demand q_i has l scenario sets and belongs to a bounded closed set $U_q = \left\{ q_i \middle| q_{i0} + \sum_{l=1}^{s} z_{il} q_{il}, z_i \in Z \right\}$. where q_{i0} is the average demand of customer i. q_{il} is the deviation of the demand of the lth scenario from the mean. z_i is the weight of the corresponding deviation. Z is a bounded closed set. Different weight vectors correspond to completely different types of bounded closed sets. The two sets of Z are: the convex set $Z_1 = \left\{ z_i \middle| z_{il} \geq 0, \sum_{l=1}^{s} z_{il} \leq 1 \right\}$ and the box set $Z_2 = \{z_i \,|-1 \leq z_{il} \leq 1\}$. [19].

2) METHOD OF REPRESENTATION OF SPEED UNCERTAINTY

The time of day is divided into $T = \{[i_1, j_1], [i_2, j_2], [i_3, j_3], [i_4, j_4]\}$, which are morning peak, smooth driving time, and evening peak. The velocity changes in adjacent time periods, and Figure 1 shows the velocity change in different periods. To illustrate the calculation, let the distance of the vehicle on the travel arc in each time period be d and the departure time be h. The following is an example of the first three periods used to calculate the travel time t_h.

When $h \leq (i_2 - \frac{d}{v_1})$ or $h \geq j_2$

$$t_h = \frac{d}{v_1} \tag{1}$$

When $(i_2 - \frac{d}{v_f}) < h < i_2$

$$t_h = \frac{d}{v_2} + \frac{v_1 - v_2}{v_2}(i_2 - h) \tag{2}$$

When $i_2 \leq h < (j_2 - \frac{d}{v_2})$

$$t_h = \frac{d}{v_2} \tag{3}$$

When $(j_2 - \frac{d}{v_c}) < h < j_2$

$$t_h = \frac{d}{v_1} - \frac{v_1 - v_2}{v_1}(j_2 - h) \tag{4}$$

In the above equations, equation (1) indicates the vehicle departure time during the morning and evening peak periods of the roadway, excluding the transition period. It provides a formula for calculating the time when a vehicle normally travels at the regular congestion speed. Similarly, equation (2) represents the calculation of the departure time during the transition period between general congestion and smooth driving. Equation (3) pertains to the time calculation during the period of smooth traffic, while equation (4) deals with the calculation of time during the transition period from smooth to general congestion.

TABLE 1. Speed impact rate in different weather.

Weather	Sunny	Rainy	Snowy	Foggy
Impact rate	0	0.4	0.7	0.6

Weather conditions significantly influence the urban road traffic system, affecting people, roads, and vehicles. Severe weather conditions, in particular, can lead to considerable changes in the state of the traffic network. To analyze this impact, we refer to actual monitoring data from the China Automotive Technology Research Center-China Automotive Condition Information System Platform. The data reveals that weather conditions and traffic congestion both play a role in the fluctuation of driving speed. Table 1 presents the average influence of various weather conditions on driving speed.

Vehicle travel speed in different weather $v = \overline{v}(1 - \rho_b)$, $\overline{v}$ is the travel speed and ρ_b is the impact rate in different weather. Similar to the representation of the demand uncertainty set, the uncertainty set of the velocity between any two customer points is defined as $U_v = \left\{ v_{ij} \middle| \overline{v_{ij}} + \sum_{t=1}^{u} y_t v_t, y_t \in Y \right\}$, where $\overline{v_{ij}}$ is the average travel speed on road segment i, j and v_t is the deviation of the speed value from the average value in the tth weather. The two sets of Y are: the convex set $Y_1 = \left\{ y_t \middle| y_t \geq 0, \sum_{t=1}^{u} y_t \leq 1 \right\}$ and the box set $Y_2 = \{y_t \,|-1 \leq y_t \leq 1\}$.

III. MODEL BUILD

A. DETERMINISTIC EV PATH OPTIMIZATION MODEL

The objective of this study is to develop a vehicle path optimization model aimed at minimizing the total distribution cost. The total distribution cost comprises fixed costs, transportation costs, energy costs, and charging costs.

1) FIXED COSTS AND TRANSPORTATION COSTS

$$C_1 = K \times P_1 + P_2 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijk} x_{ij}^k \tag{5}$$

where: K is the number of vehicles used, m is the number of available vehicles ($k = 1, 2, \cdots, m$), and t_{ijk} is the travel time of electric vehicle k in section i, j.

2) ENERGY COSTS

Electric vehicles' energy consumption is influenced by various factors, including load, speed, and transport time. In the context of a time-varying road network, the power consumption of a vehicle on a specific road section is represented as

$$E_{ijk} = \sum_{t}^{n} P\left(Q_{ik}, v_{ijk}^{t}\right) * t_{ijk} \tag{6}$$

$$P(Q_k, v) = \frac{(Q_0 + Q_k) \cdot g \cdot f \cdot v + \frac{C_d \cdot A \cdot v^3}{21.15}}{3600\eta} \tag{7}$$

Thus, the energy cost of electric vehicles is represented as

$$C_2 = P_3 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=1}^{n} x_{ij}^{k} t_{ijk} E_{ijk} \tag{8}$$

where: $P(Q_k, v)$ is the operating power, g is the acceleration of gravity, A, C_d, f is the wind-blown area of the electric vehicle, the air resistance coefficient and the friction resistance coefficient of the car, η is the mechanical transmission efficiency of the system, and Q_0, Q_k is the no-load and current load of the electric vehicle, respectively.

3) CHARGING COSTS

When the electric vehicle's remaining power is insufficient to meet the distribution requirements for reaching the next service point, it must head to the nearest charging station for a quick recharge. The cost of charging is directly associated with the charging time.

Charging time is $t_{ik}^{c} = \frac{E_{\max} - E_{ik}}{r_c} z_i^k$, charging costs is

$$C_4 = P_4 \sum_{k=1}^{m} \sum_{i=0}^{w} t_{ik}^{c} \cdot z_i^k \tag{9}$$

where: $E_{\max}$ is the maximum battery capacity of the EV, E_{ik} is the power left in the EV at the charging station i, and r_c is the charging efficiency of the charging station.

In summary, the deterministic electric vehicle path optimization model incurs a total distribution cost of

$$\min C_1 = K \times P_1 + P_2 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} t_{ijk} x_{ij}^{k} + P_3 \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=1}^{n} x_{ij}^{k} t_{ijk} E_{ijk} + P_4 \sum_{k=1}^{m} \sum_{i=0}^{w} t_{ik}^{c} \cdot z_i^k \tag{10}$$

The constraints are as follows

$$\sum_{k=1}^{m} \sum_{i=1}^{n} x_{ij}^{k} \le m, \quad i = 0 \tag{11}$$

$$\sum_{k=1}^{m} \sum_{j=1}^{n} x_{ij}^{k} = \sum_{k=1}^{m} \sum_{j=1}^{n} x_{ji}^{k}, \quad i = 0, k = 1, 2, \cdots, m \tag{12}$$

$$\sum_{k=1}^{m} y_i^k = 1, \quad i = 1, 2, \cdots, n \tag{13}$$

$$\sum_{i=1}^{n} q_i y_i^k \le Q, \quad \mathrm{i} \ne j, \quad k = 1, 2, \cdots, m \tag{14}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ij}^{k} \le D, \quad \mathrm{i} \ne j, \quad k = 1, 2, \cdots, m \tag{15}$$

$$a_{ik} + t_{ik} \ge B_i \tag{16}$$

$$a_{ik} + t_{ik} \le E_i \tag{17}$$

$$\sum_{k=1}^{m} \sum_{i=0}^{w} E_{ik}^{a} \left(1 - z_i^k\right) + E_{\max} = \sum_{k=1}^{m} \sum_{i=0}^{w} E_{ik}^{l} \tag{18}$$

$$E_0 \le E_{ik}^{a} \le E_{\max} \tag{19}$$

According to Eq. (12), the number of electric vehicles in the distribution system must be greater than or equal to the number of distribution routes. Equip. (13) specifies that the starting point for each distribution task should be a distribution center. Furthermore, Eq. (14) states that each demand point can only be served by one electric vehicle, and just once. Additionally, Eq. (15) sets a constraint that the total demand quantity of customer points within each distribution route should not exceed the maximum carrying capacity of electric vehicles. Eq. (16) enforces a limitation on the total distribution distance of each distribution path, which must not exceed the farthest distribution distance of electric vehicles. Eqs. (17) and (18) represent the time window constraints. Eq. (19) addresses the requirement for electric vehicles to arrive fully charged at the charging station and leave after charging. Lastly, Eq. (20) defines the power constraint for electric vehicles serving each customer point.

B. ROBUST OPTIMIZATION MODEL FOR ELECTRIC VEHICLE PATHS

The analysis of the deterministic model reveals that uncertainty in demand arises solely in constraint (15). Therefore, it is essential to focus our study on the uncertain set of constraints (15) and the variation in vehicle speed. Accordingly, we establish the corresponding robust optimization model.

Taking the demand uncertainty set as an example, the robust corresponding equation in place of the constraint (15), conditional on the convex set Z_1, is

$$\sum_{i}^{n} y_i^k q_{i0} + \max \sum_{i}^{n} y_i^k \{\max q_{il}, 0\} \le Q \tag{20}$$

The constraint holds for all q_i that match the set Z_1, i.e., the condition can be satisfied when the worst condition $\max\left(\sum_{i}^{n} y_i^k q_i\right) \le Q$ holds.

Similarly, the robust corresponding equation in place of the constraint (15), conditional on the set of boxes Z_2, is

$$\sum_{i}^{n} y_i^k q_{i0} + \max \sum_{i}^{n} y_i^k \sum_{l}^{u} |q_{il}| \le Q \tag{21}$$

In summary, the constraint (15) of the deterministic problem is replaced by equation (20) or (21). It is transformed into a robust optimization model under the demand uncertainty set Z_1, Z_2. Similarly, add the uncertain velocity constraint $U_v = \left\{ v_{ij} \middle| \overline{v_{ij}} + \sum_{t=1}^{u} y_t v_t, y_t \in Y \right\}$, i.e., construct a robust optimization model under two uncertain sets.

The objective function value increases under an uncertainty constraint. The deviation coefficient is used to represent the relative deviation of the optimal objective value of the robust optimization model from the value obtained under deterministic conditions.

$$F = \frac{C_r - C_d}{C_d} \times 100\% \tag{22}$$

where: C_r is the objective value of robust optimization under uncertainty, and C_d is the objective value under deterministic conditions.

IV. ALGORITHM RESEARCH

In tackling robust EVRP models, the utilization of exact algorithms leads to slow search speeds. Consequently, heuristic algorithms are commonly employed to address such NP-hard problems. Among these, the genetic algorithm stands out as an efficient parallel search algorithm well-suited for solving global optimization problems. Below are the specific steps of the genetic algorithm in handling EVRP problems:

Step 1: Encoding and Decoding. In the context of the Electric Vehicle Routing Problem (EVRP), the path selection should take into account not only the impact of the load but also the necessity to visit a charging station for recharging when the electric vehicle's power is low. To represent the order in which each customer is visited in the instance, we employ a coding scheme using natural numbers. Each customer is assigned a unique number, starting from 1 and incrementing up to n. The distribution center is assigned the number 0. If there are m charging stations, they are assigned numbers from n+1 to n+m. The first set of customer nodes is organized in integer order, and the distribution center (0) is strategically inserted among the customer points based on constraints like the maximum vehicle load and the demand at each node. The decision of whether the electric vehicle should proceed to the nearest charging station for recharging is determined by evaluating the remaining power in the vehicle. If recharging is necessary, the charging station number is inserted after the customer point number in the sequence.

For example, the customer point order is represented by the integer arrangement (6, 2, 5, 4, 3, 1, 7, 10, 9, 8). After considering the load and time window constraints, the distribution center is inserted, resulting in the modified arrangement (0, 6, 2, 5, 0, 4, 3, 1, 7, 0, 10, 9, 8, 0). Furthermore, to address low power issues in electric vehicles, a charging station is included in the arrangement, leading to the final arrangement (0, 6, 2, 11, 5, 0, 4, 12, 3, 1, 7, 0, 10, 9, 8, 0). Decoding is the reverse process of encoding, which means the path resulting from decoding this chromosome can be broken down into three separate paths:

Path 1: 0, 6, 2, 11, 5, 0
Path 2: 0, 4, 12, 3, 1, 7, 0
Path 3: 0, 10, 9, 8, 0

These paths indicate the use of three electric vehicles for delivery, with a total of two charges required along the route.

Step 2: Population Initialization. The population size is typically selected to fall within the range of 20 to 200 individuals. If the number of chromosomes is too small, the global optimal solution may not be obtained. Conversely, if the number of chromosomes is too large, it will result in increased computation and negatively impact the efficiency of the solution. Thus, for this study, the number of chromosomes is set to 100. The coding rules for each chromosome can be understood by referring to the coding example presented in Step 1. Specifically, customers are randomly generated, and a single chromosome is created by inserting the distribution center and charging station in accordance with the load and power constraints. This process is repeated until 100 chromosomes are generated, constituting the initial solution.

Step 3: Determination of the Fitness Function. In this step, we establish the fitness function for the EVRP model under both deterministic conditions and robust optimization, with the primary objective of minimizing the overall cost. A crucial factor in the evolutionary process is the fitness value associated with each chromosome. A higher fitness value indicates an increased likelihood of being selected for inheritance in the subsequent generation. To align with this principle, the fitness function is defined as the inverse of the objective function.

Step 4: Selection. To begin with, the elite retention strategy was employed for selection. This involves sorting the fitness values by magnitude. The top 5% of chromosomes are retained as the elite group for the subsequent generation, while the remaining 95% of chromosomes are selected using the roulette wheel selection method. A set of chromosomes with high fitness are chosen for crossover and mutation to form the population of the next generation.

Step 5: Crossover. During the chromosome coding process in the EVRP problem, the insertion of the charging station number occurs, followed by the crossover and mutation operations. However, the original insertion position of the charging station will be disrupted, leading to the generation of several inferior solutions in the offspring. To address this issue, it is necessary to remove the inserted genes before performing the crossover and mutation operations. The crossover operation involves selecting non-duplicated genes from the parent chromosomes and sequentially placing them into the offspring. For instance, let's consider the parents P1 (1, 2, 3, 4, 5, 6, 7) and P2 (6, 4, 2, 3, 7, 1, 5). After the crossover, we obtain the offspring O1 (1, 6, 2, 4, 3, 5, 7, 1) and O2 (6, 1, 4, 2, 3, 7, 5).

Step 6: Mutation. Genetic variation occurs during the process of genetic manipulation to prevent premature local convergence and ensure chromosome diversity. Chromosome mutation is a necessary step. During the mutation operation, a few gene positions on the parent chromosome are randomly

TABLE 2. Model parameter values.

parameter	parameter values	parameter	parameter values
P_1	100 yuan/veh	Q_0	$2t$
P_2	50yuan/h	g	$9.81\,m/s^2$
P_3	0.5 yuan/kwh	f	0.015
P_4	1yuan/min	C_d	0.6
∂	0.01	η	1.46
E_0	5kw/h	E_c	4kw/h
A	$6\,m^2$	r_c	2 kw/h

TABLE 3. Deterministic model path results.

Number	Path	Load (kg)	Charge times	Charge time (h)
1	0-18-0	15	0	0
2	0-14-9-6-29-8-**32**-24-11-13-16-**31**-7-0	100	2	2.05
3	0-19-15-2-26-30-20-**31**-21-3-10-17-**32**-28--0	95	2	1.75
4	0-12-4-25-1-5-**32**-23-27-22--0	95	1	1.20

selected and then rearranged, while the other positions remain unchanged.

Step 7: Evolutionary reversal operation is applied to enhance the quality of solutions and accelerate local convergence. This operation is carried out on chromosomes that have already undergone selection and crossover mutation operations. During the reversal process, two random integers are generated to define the positions within the chromosome. The sequence between these two positions is reversed, resulting in a new chromosome. For example, let's consider parent P1 (1,2,3,4,5,6,7). If two random integers, 3 and 6, are generated, the offspring O1 will be (1,2,6,5,4,3,7) after the reversal. It is important to note that only reversals resulting in improved fitness values are considered valid.

The number of iterations is set to 500 in the algorithm calculation. Once the iteration count reaches 500, the output result is automatically terminated.

V. EXAMPLE ANALYSIS

A. DATA AND PARAMETER SETTINGS

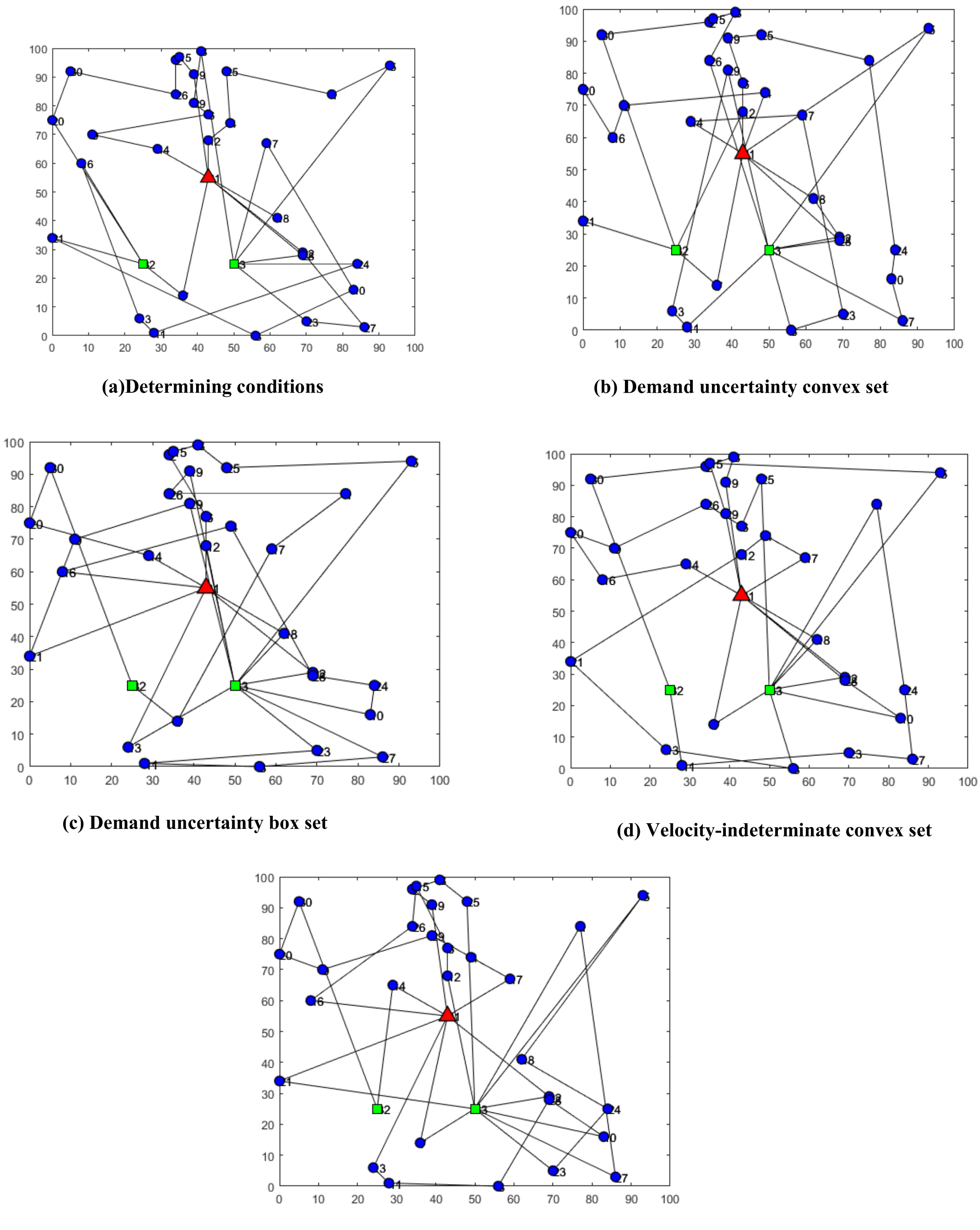
The experimental data utilized in this study were sourced from the figshare database, specifically the R-2-30 dataset (https://doi.org/10.6084/m9.figshare.10288326). This dataset comprises information gathered from 30 customers who utilized two distinct charging stations. Given the current status of the EV charging infrastructure, its widespread adoption is still evolving. As such, this study opted to simulate data using two charging stations of different capacities to enhance the accuracy of the analysis.

The speed of vehicles in urban road traffic is subject to time variations, with different speeds observed during congestion and normal driving. Congestion occurs during the morning and evening peak hours, specifically from 7:00 to 9:00 and 17:00 to 20:00. The average speed during congestion periods is 25 km/h, whereas the normal driving speed is 40 km/h.

To address this traffic speed optimization problem, we employed a genetic algorithm implemented on a computer processor with a clock speed of 2.20 GHz and 4 GB of memory. The optimization was performed using MATLAB (R2018b), and the relevant parameters were set as outlined in Table 2.

B. ANALYSIS OF THE RESULTS

The genetic algorithm is employed to solve two optimization models for the R-2-30 example: one under deterministic conditions, focusing on path optimization, and the other under two uncertainty sets, addressing demand and speed in a robust optimization framework. The resulting vehicle transportation



(a)Determining conditions

(b) Demand uncertainty convex set

(c) Demand uncertainty box set

(d) Velocity-indeterminate convex set

(e) Velocity-indeterminate box set

FIGURE 2. Determining the distribution roadmap under uncertainty.

paths are presented in Table 3, Table 4, and Table 5, while the path optimization diagram is visualized in Figure 2.

As shown in the figure and table above, the number of distribution paths for the model under traditional deterministic and robust uncertainty conditions remains the same. However, a comparison between the traditional distribution path results and the robust optimization results reveals that the latter exhibits a higher number of average and concentrated distribution paths for each vehicle. Under the traditional model's distribution paths, the demand is influenced by the external environment, making it impossible to maintain a stable value. For example, some customers along path 2 experience a 5% increase in demand, leading to an overload of vehicles and rendering path 2 infeasible. These instances highlight the vulnerability of the traditional model to small changes in demand, resulting in solutions that become infeasible. To address the possibility of demand fluctuations causing infeasibility of the optimal path under

TABLE 4. Robust model path results under demand uncertainty.

Uncertainty sets	Number	Path	Load (kg)	Charge times	Charge time (h)
Uncertain convex set	1	0-4-9-16-20-21-**31**-12-0	66.3	1	1.45
	2	0-6-19-25-1-24-10-27-**32**-22-18-0	96.6	1	0.75
	3	0-14-17-23-3-**32**-26-8-15-2-30-**31**-7-0	96.6	2	2.47
	4	0-5-**32**-11-13-29-**32**-28-0	51	2	2.74
Uncertainty Box Collection	1	0-16-4-28-24-10-**32**-18-0	75.6	1	0.94
	2	0-21-9-29-**32**-23-11-3-27-**32**-13-0	86.4	2	2.35
	3	0-14-20-30-**31**-7-17-1-26-19-**32**-22-0	86.4	2	2.22
	4	0-6-2-15-8-25-5-**32**-12-0	81	1	0.94

TABLE 5. Robust model path results under speed uncertainty.

Uncertainty sets	Number	Path	Load (kg)	Charge times	Charge time (h)
Uncertain convex set	1	0-29-15-5-**32**-22-0	45	1	1.02
	2	0-14-16-20-9-26-6-25-**32**-10-28-0	100	1	0.91
	3	0-19-8-2-30-**31**-11-23-27-24-1-**32**-7-0	85	2	1.80
	4	0-17-4-12-21-13-3-**32**-18-0	75	1	0.89
Uncertainty Box Collection	1	0-13-11-3-28-10-**32**-21-0	55	1	1.19
	2	0-17-4-29-9-20-30-**31**-14-0	60	1	1.14
	3	0-19-2-8-25-**32**-23-24-18-5-**32**-22-0	95	2	2.24
	4	0-16-26-15-6-12-**32**-27-1-**32**-7-0	95	2	2.30

deterministic conditions, it is crucial to seek a robust solution that can accommodate all potential demand scenarios. After demand fluctuation, if the path continues to be based solely on deterministic conditions, there is a risk of the total worst-case path capacity exceeding the maximum capacity of the car, necessitating a rescheduling of the vehicle. In contrast, the robust optimization model ensures that all four paths remain feasible regardless of demand variations, thereby offering a more reliable solution.

From Tables 3, 4, and 5, it can be seen that the number of charges and charging time under robust optimization exceeds that of the traditional optimization model. This difference primarily arises because both optimization models generate paths that ensure meeting the demand fluctuation and speed variation in adverse weather conditions. The paths are free from demand overload and untimely responses during extreme weather events. However, achieving this comes at the expense of the objective function and the amount of power consumption during charging. To address this, a deviation factor is introduced to represent the percentage of the objective function under uncertainty. The experimental results for each cost are presented in Table 6, where QD represents the model solution results under deterministic conditions. XT and XH represent the model solution results under the convex set of demand uncertainty and the box set, respectively. ST and SH denote the model solution results under the convex set of speed uncertainty and the box set, respectively. GC stands for fixed cost, YC for transportation cost, NC for energy cost, CC for charging cost, and TC for the total cost. All units are in Yuan.

From Table 6, it is evident that the distribution cost is higher under both uncertainty and robust optimization compared to the traditional model. This increase is primarily due to transportation costs. The impact of demand uncertainty on costs is relatively consistent across both sets. However, there is a significant disparity in costs caused by speed uncertainty under the two aggregations. The relative deviation coefficient F takes on values of 25.37% and 72.23% under the two scenarios of speed uncertainty, respectively. This represents a 46.86% increase in F under the box ensemble compared to the convex ensemble. Notably, the transportation time increases significantly to accommodate path optimization during low-speed conditions under extreme weather, and transportation cost is closely linked to the transportation time.

C. ROBUSTNESS ANALYSIS

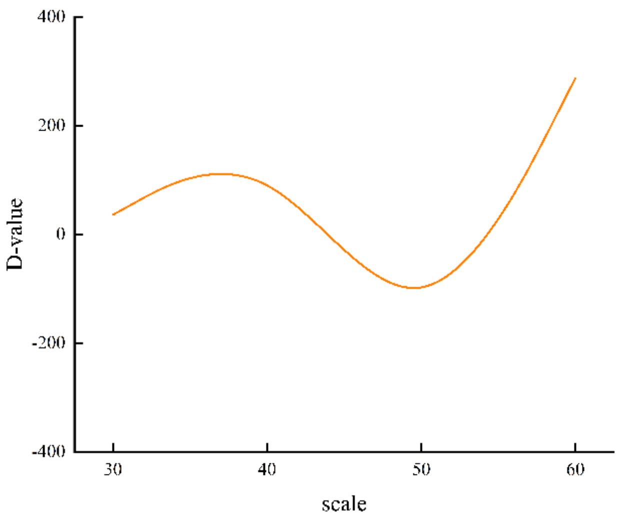
1) DEMAND UNCERTAINTY

Table 7 presents the distribution costs under two different scenarios of demand uncertainty. The results were obtained for four instances: R30, R40, R50, and R60, respectively. Furthermore, Figure 3(a) illustrates the total cost difference between the two different aggregate sizes.

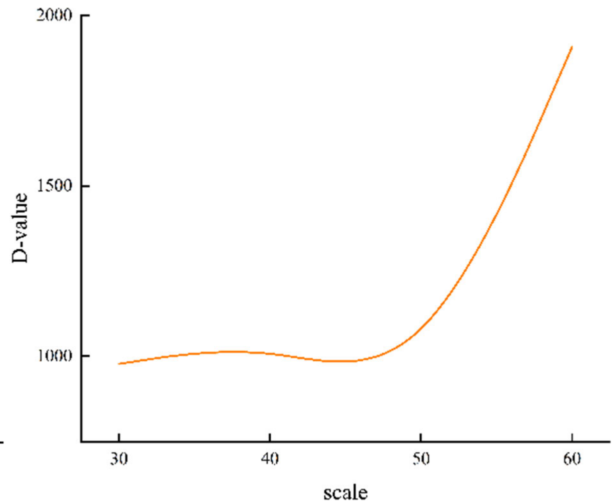
Table 7 shows the distribution cost difference between the two sets under different scales, exhibiting a slow-growing trend. Specifically, the convex set incurs higher total distribution costs than the R40 instance, while the box set distribution cost is higher for the remaining instances. These findings indicate a stable difference in total distribution costs across various scales. However, accurately concluding the optimal

TABLE 6. Distribution cost comparison.

COST	QD	Demand		Speed	
		XT	XH	ST	SH
GC	600	600	600	600	600
YC	896.32	933.14	959.52	1470.85	2380.86
NC	303.27	326.72	325.24	283.353	327.75
CC	286.98	243.91	253.17	261.78	285.22
TC	2086.57	2101.77	2137.93	2615.98	3593.84
F	0	0.73%	2.46%	25.37%	72.23%



(a) demand uncertainty set



(b) speed uncertainty set

FIGURE 3. Variation of total cost difference under uncertainty set.

TABLE 7. Comparison of results under different size demand uncertainty sets.

Scale	R30		R40		R50		R60	
	XT	XH	XT	XH	XT	XH	XT	XH
GC	600	600	750	750	900	900	1050	1200
YC	933.14	959.52	1429.93	1220.51	1315.32	1534.06	2053.40	2081.81
NC	326.72	325.24	429.40	397.78	423.74	464.09	576.63	586.48
CC	243.91	253.17	291.24	339.64	305.82	312.99	485.46	584.70
TC	2101.77	2137.93	2900.58	2707.93	2944.88	3211.15	4165.49	4452.99
Difference	36.16		192.65		266.27		287.5	

objective function values of the convex set and the box set under different locations, demands, and other information remains challenging. In practical applications, it is essential to consider the bounded set type to which the demand uncertainty belongs.

2) SPEED UNCERTAINTY

Table 8 presents the distribution costs of speed uncertainty under two aggregations, which are solved for R30, R40, R50, and R60 instances. Additionally, Figure 3(b) illustrates the total cost difference between the two aggregates of varying sizes.

As shown in Table 8, both the charging and power consumption costs escalate with the size increment. The transportation costs witness the most substantial rise, primarily attributed to decreased speed and prolonged transportation time. The variance in total distribution cost between the convex set and the box set remains relatively stable, except for the R60 instance size. The surge in difference from 50 to 60 poses a significant concern for customers. Consequently, in real-world applications, when faced with a considerable difference, exercise caution while selecting the uncertain set and employing robust optimization algorithms.

TABLE 8. Comparison of results under different size speed uncertainty sets.

Scale	R30		R40		R50		R60	
	ST	SH	ST	SH	ST	SH	ST	SH
GC	600	600	750	750	900	900	1050	1050
YC	1470.85	2380.86	1919.87	2900.71	2414.44	3334.84	2819.49	4551.67
NC	283.353	327.75	344.96	376.09	420.69	415.55	468.43	535.03
CC	261.78	285.22	275.84	309.45	365.24	333.53	549.70	658.70
TC	2615.98	3593.84	3290.69	4336.25	4100.37	4983.93	4887.62	6795.41
Difference	977.86		1045.56		883.56		1907.79	

VI. CONCLUSION

The volatility of the optimal path of electric vehicle logistics distribution cost under deterministic conditions is significant. Once the demand increases at a customer point, it may lead to overloading the current path vehicle, rendering the optimal solution infeasible. To address this issue, the robust optimization method was introduced into the electric vehicle distribution path optimization. The robust optimization models for electric vehicle paths with uncertain speed and uncertain demand are constructed, respectively. An improved genetic algorithm is employed to solve the problem. Experimental results demonstrate that the number of charges, charging time, and distribution cost of the model under robust optimization are higher than those of the traditional optimization model. However, both robust optimization models produce paths that can guarantee meeting demand fluctuations and speed variations in adverse weather conditions. There is no overload of demand on the paths, and they do not experience untimely responses to extreme weather. Regarding robust optimization models under different uncertainty sets of economic efficiency, deviation coefficients are introduced to represent the percentage of the objective function under uncertain sets. The relative deviation coefficient F has values of 25.37% and 72.23% under the two sets of speed uncertainty, respectively. It is 46.86% higher under the box set than under the convex set. Finally, the experimental comparison of the optimization models under two uncertainty conditions at different simulation data scales indicates that the difference in total distribution cost remains stable under different scales of analysis. However, accurately concluding the optimal objective function values of the convex set and the box set under different locations, demand, and other information proves challenging. The bounded set type to which the demand uncertainty belongs needs to be considered in practical applications.

Limitations of this study and future research directions. (1) Path planning and optimization in uncertain environments require a large amount of real-time data, including vehicle status, traffic conditions, weather conditions, etc. In some cases, this data may not be easily obtained or there may be delays. Future research can seek to reduce dependence on real-time data to adapt to a wider range of application scenarios. (2) In the robust optimization of electric vehicle paths in uncertain environments, our model often needs to estimate the uncertainty of the environment. However, accurately modeling uncertainty remains a complex issue that can be influenced by various factors such as sensor errors and environmental dynamics. Future research needs to better address these challenges in order to improve the accuracy and reliability of models. (3) Study how to achieve robust path optimization in large-scale transportation systems, considering the collaborative driving of hundreds or thousands of electric vehicles. In addition, improve the real-time performance of the algorithm to cope with rapidly changing traffic and environmental conditions. (4) Future research can focus more on the combination of robust optimization of electric vehicle paths and sustainability goals, including reducing carbon emissions, energy efficiency, and optimizing electric vehicle charging infrastructure.

ACKNOWLEDGMENT

The authors would like to thank the helpful comments and suggestions of the editor and anonymous referees.

REFERENCES

[1] M. Keskin, G. Laporte, and B. Çatay, "Electric vehicle routing problem with time-dependent waiting times at recharging stations," *Comput. Oper. Res.*, vol. 107, pp. 77–94, Jul. 2019.
[2] T. Erdelić, T. Carić, M. Erdelić, and L. Tišljarić, "Electric vehicle routing problem with single or multiple recharges," *Transp. Res. Proc.*, vol. 40, pp. 217–224, Jan. 2019.
[3] T. Erdelić and T. Carić, "Goods delivery with electric vehicles: Electric vehicle routing optimization with time windows and partial or full recharge," *Energies*, vol. 15, no. 1, p. 285, Jan. 2022.
[4] G. Desaulniers, F. Errico, S. Irnich, and M. Schneider, "Exact algorithms for electric vehicle-routing problems with time windows," *Oper. Res.*, vol. 64, no. 6, pp. 1388–1405, Dec. 2016.
[5] A. Froger, O. Jabali, J. E. Mendoza, and G. Laporte, "The electric vehicle routing problem with capacitated charging stations," *Transp. Sci.*, vol. 56, no. 2, pp. 460–482, Mar. 2022.
[6] Y. Liang, S. Dabia, and Z. Luo, "The electric vehicle routing problem with nonlinear charging functions," 2021, *arXiv:2108.01273*.
[7] R. Basso, B. Kulcsár, B. Egardt, P. Lindroth, and I. Sanchez-Diaz, "Energy consumption estimation integrated into the electric vehicle routing problem," *Transp. Res. D, Transp. Environ.*, vol. 69, pp. 141–167, Apr. 2019.
[8] Y. Xiao, Y. Zhang, I. Kaku, R. Kang, and X. Pan, "Electric vehicle routing problem: A systematic review and a new comprehensive model with nonlinear energy recharging and consumption," *Renew. Sustain. Energy Rev.*, vol. 151, Nov. 2021, Art. no. 111567.
[9] S. R. Kancharla and G. Ramadurai, "Electric vehicle routing problem with non-linear charging and load-dependent discharging," *Expert Syst. Appl.*, vol. 160, Dec. 2020, Art. no. 113714.

[10] Z. Liu and Z. Song, "Network user equilibrium of battery electric vehicles considering flow-dependent electricity consumption," *Transp. Res. C, Emerg. Technol.*, vol. 95, pp. 516–544, Oct. 2018.
[11] M. Xu, Q. Meng, and K. Liu, "Network user equilibrium problems for the mixed battery electric vehicles and gasoline vehicles subject to battery swapping stations and road grade constraints," *Transp. Res. B, Methodol.*, vol. 99, pp. 138–166, May 2017.
[12] S. Zhang, M. Chen, W. Zhang, and X. Zhuang, "Fuzzy optimization model for electric vehicle routing problem with time windows and recharging stations," *Expert Syst. Appl.*, vol. 145, May 2020, Art. no. 113123.
[13] Q. Song, Q. Zhao, S. Wang, Q. Liu, and X. Chen, "Dynamic path planning for unmanned vehicles based on fuzzy logic and improved ant colony optimization," *IEEE Access*, vol. 8, pp. 62107–62115, 2020.
[14] F. C. López and R. Á. Fernández, "Predictive model for energy consumption of battery electric vehicle with consideration of self-uncertainty route factors," *J. Cleaner Prod.*, vol. 276, Dec. 2020, Art. no. 124188.
[15] Y. Ji, H. H. Li, and H. J. Zhang, "Risk-averse two-stage stochastic minimum cost consensus models with asymmetric adjustment cost," *Group Decis. Negotiation*, vol. 31, pp. 261–291, Jul. 2022.
[16] Y. Ji and Y. Ma, "The robust maximum expert consensus model with risk aversion," *Inf. Fusion*, vol. 99, Nov. 2023, Art. no. 101866.
[17] Y.-N. Guo, J. Cheng, S. Luo, D. Gong, and Y. Xue, "Robust dynamic multi-objective vehicle routing optimization method," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 15, no. 6, pp. 1891–1903, Nov. 2018.
[18] C. Hu, J. Lu, X. Liu, and G. Zhang, "Robust vehicle routing problem with hard time windows under demand and travel time uncertainty," *Comput. Oper. Res.*, vol. 94, pp. 139–153, Jun. 2018.
[19] I. Sungur, F. Ordóñez, and M. Dessouky, "A robust optimization approach for the capacitated vehicle routing problem with demand uncertainty," *IIE Trans.*, vol. 40, no. 5, pp. 509–523, Mar. 2008.
[20] M. Hoogeboom, Y. Adulyasak, W. Dullaert, and P. Jaillet, "The robust vehicle routing problem with time window assignments," *Transp. Sci.*, vol. 55, no. 2, pp. 395–413, Mar. 2021.
[21] L. Sun, Q.-K. Pan, X.-L. Jing, and J.-P. Huang, "A light-robust-optimization model and an effective memetic algorithm for an open vehicle routing problem under uncertain travel times," *Memetic Comput.*, vol. 13, no. 2, pp. 149–167, Jan. 2021.
[22] E. Yuliza, F. Maya, and S. S. Supadi, "Heuristic approach for robust counterpart open capacitated vehicle routing problem with time windows," *Sci. Technol. Indonesia*, vol. 6, no. 2, pp. 53–57, Apr. 2021.
[23] E. Yuliza, F. M. Puspita, and S. S. Supadi, "Robust optimization for the counterpart open capacitated vehicle routing problem with time windows," in *Proc. 4th Sriwijaya Univ. Learn. Educ. Int. Conf. (SULE-IC)*, 2020, pp. 556–560.
[24] Y. Zhang, Z. Zhang, A. Lim, and M. Sim, "Robust data-driven vehicle routing with time windows," *Oper. Res.*, vol. 69, no. 2, pp. 469–485, Mar. 2021.
[25] S. Pelletier, O. Jabali, and G. Laporte, "The electric vehicle routing problem with energy consumption uncertainty," *Transp. Res. B, Methodol.*, vol. 126, pp. 225–255, Aug. 2019.
[26] J. Jeong, B. Ghaddar, N. Zufferey, and J. Nathwani, "Adaptive robust electric vehicle routing under energy consumption uncertainty," 2022, *arXiv:2204.10913*.

AOBEI ZHANG is currently pursuing the Ph.D. degree with the School of Management, Shenyang University of Technology. His major is logistics engineering and management. His research interests include complex system decision-making and optimization, logistics path optimization, and intelligent optimization algorithms.

YING ZHANG was born in 1964. She is currently a Ph.D. Supervisor with the School of Management, Shenyang University of Technology. She has presided over and completed eight projects, including the Natural Science Foundation of Liaoning Province, the Liaoning Doctoral Start-Up Fund Project, the Liaoning Science and Technology Research Project, and the Key Support Project of Shenyang Science and Technology Bureau. She has participated in six projects of the National Natural Science Foundation of China and 863 projects. She has published more than 30 academic papers. She edited *Soft Computing Methods* (Science Press). Her research interests include complex system modeling and optimization, logistics optimization management and control in an agile manufacturing environment, e-commerce-based pricing models and optimization decisions, bidding process optimization strategies and methods, and the research and use of soft computing methods.

YANQIU LIU was born in April 1963. He is a member of the CPC and a Professor. He is currently the Head of the Teacher Work Department of the Party Committee, Shenyang University of Technology, the Director of the Human Resource Management Division, and a Supervisor of Ph.D. students. As a Project Leader, he has completed more than 20 projects, including one major project of the National Natural Science Foundation of China, one special project of the Ministry of Education for Postgraduate Education, the Natural Science Foundation of Liaoning Province, the Science and Technology Plan of Liaoning Province, and the Science and Technology Plan of Shenyang City. He has published more than 100 academic papers in international and domestic important journals, including 20 SCI retrieved, 30 EI retrieved, seven CSSCI retrieved, one monograph in Science Press, and one textbook in People's Post and Telecommunications Press. His main research interests include complex system optimization designs and intelligent control.