Delft University of Technology

Additional Graduation Work, Research Project

CIE5050-09

Electric Vehicle Pickup-and-Delivery Problem with Soft Time Windows, Partial Charging, and Uncertain Travel Time

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Abstract

Electric vehicles (EVs) take advantage of reducing fossil-based environmental pollution and developing a more sustainable logistics network. Compared with internal combustion engine vehicles (ICEVs), EVs have new technical characteristics like limited battery capacity and long charging time at charging stations. With the diffusion of EVs, vehicle routing problems (VRPs) of EVs draw transportation service providers' attention, which extends VRPs with intra-route charging considerations. In real-life practice, the punctuality of pre-planned vehicle routing may be affected by uncertain travel time caused by traffic congestion, which derives undesirable penalty costs for violating time windows. Besides, long intra-route charging time at charging stations presents an even greater challenge to trade-off between completing tours with enough electricity and providing delivery service on time. This assignment aims to investigate the impact of travel time uncertainty and electric vehicle characteristics on planning fleet size, vehicle routing, and charging schedules. A pickup and delivery problem of electric vehicles is studied in this assignment, which considered flexible fleet size, partial charging policy, soft time windows and uncertain travel time. The problem is formulated as a two-stage stochastic linear programming model. The fleet size, vehicle routing, and charging decisions are determined in the first stage. After the realization of travel times, the second stage determines specific charging times at charging stations. The objective is to minimize the total operational cost, which consists of travel costs of vehicle usage and charging, and the expected penalty cost of earliness, delay and overtime. The sample average approximation method is applied to model the stochastic programming to the deterministic equivalent and the Gurobi Optimizer is used to solve this mixed-integer programming. A computational experiment is conducted based on a small data set with one depot, 9 pickup and delivery requests, 5 charging stations at service vertices and 3 available electric trucks. The travel times along the delivery tour are assumed to follow Gamma distribution. To investigate the trade-off between travel costs and penalty costs, 12 instances are conducted in the experiment by tuning parameters of time windows, the uncertainty of travel time, and the importance of punctuality. The experiment results showed an increasing vehicle fleet size could improve the level of service but also derive more vehicle usage costs. Besides, the intra-route charging operations impact vehicles' departure times at each charging station, which subsequently impacts service start time at customer vertices. Longer intra-route charging time has the potential to enhance punctuality in instances with tight time windows or congested traffic conditions. Moreover, different operator inclination leads to different fleet size and charging time preference. Instances attaching more importance to punctuality have a larger fleet size and longer intra-route charging time.

1 Introduction

Road vehicles release excessive energy-related carbon emissions annually, which is one of the non-negligible causes of global warming and climate change. Currently, a mode shift from internal combustion engine vehicles (ICEV) to electric vehicles (EV) is a worldwide practice in the transport sector, which helps to curb CO_2 emissions and achieve carbon neutrality. Governments in European countries have also implemented attractive incentive measures to reduce the cost of purchasing and using EVs and promote the construction of charging facilities. In addition, the EU plans to stop the sales of new ICVs in 2035 (Council of European Union, 2021), which also promotes more EV purchases and usages. Due to the diffusion of EVs, the implementation of subsidy incentives, the development of charging facilities and the limitation of greenhouse gas emission regulation, more and more logistics companies have started adopting EVs to provide more sustainable transport services.

With the increasing fleet proportion of EVs, more and more studies considered the EV application case in vehicle routing problems (VRPs). The electric vehicle routing problems (EVRPs) are extensions of traditional vehicle routing problems with ICEVs. Though EVs take advantage of reducing air pollution and fossil reliance, more issues should be considered when designing an efficient EV routing plan to process all customer orders. Compared with ICEVs, EVs have limited battery capacity and require intra-route charging operations to finish the delivery tour without running out of electricity, which occupies operating time and leads to additional operating costs (Felipe et al., 2014). Besides, the scarcity of public charging stations increases the difficulty of planning routing and charging schedules (Montoya et al., 2017). In addition to the above considerations in a deterministic environment, uncertain factors also affect the outcome of VRP, including uncertainty of customer demand, road environment and resources (Soeffker et al., 2022). Uncertain customer demand in EVRPs consists of unknown demand quantities and uncertain service time. The sources of uncertainties in the road environment include weather, traffic congestion and road closures, which affects the energy consumption and travel times of EVs. Resource uncertainties could be the availability of public charging stations (Montoya et al., 2017).

As discussed above, long charging times at charging stations are not neglectable. Charging locations and charging times should be carefully considered when planning vehicle routes to satisfy all customer demands. In practice, uncertainties of weather and traffic conditions impact travel times along delivery routes. Uncertain travel times could influence the reliability of pre-planned routines and result in unexpected earliness or delay of delivery service, which increases the operational cost of remedial measures. Besides, the uncertain travel time may occupy the reserved charging time, which causes conflict between ensuring punctuality and avoiding battery depletion. Departing more vehicles for delivery service could alleviate the problem and improve the level of service. Also, increasing the fleet size increases the possibility of finishing delivery routes without intra-route charging operations. The potential benefit may be obtained if EVs charge more in the depot with a lower energy price during the off-peak time. On the other hand, a larger fleet size also means more fixed costs of vehicle usage and longer delivery distances for providing service to all customers, which increases travel costs. Therefore, how to trade off between reducing travel costs and ensuring punctuality is an interesting topic to be studied.

The research focuses on the pickup and delivery problem (PDP) with travel time uncertainties, a variant of VRP with paired pickup and delivery demands. And following features of the problem could be considered: Firstly, each pickup and delivery request should be served by the same electric truck within a soft time window. Applying the soft time windows is a more practical case because vehicles cannot always arrive at the service point on time. Customers can receive service outside the expected time window, but a violation of time windows will cause customer dissatisfaction, which leads to unwanted penalty costs. Secondly, due to the restriction of maximum range, some delivery tours need to be completed with intra-route charging operations. The problem considers the popularity of charging facilities in parking lots and allows electric trucks to use fast-charging facilities at service vertices before providing service to customers. Thirdly, the travel time of electric trucks along the route might be uncertain and occupy pre-arranged charging time, which leads to more challenges in deciding fleet size, route plan and charging schedules. Simply overlooking these uncertainties and solving the problem in a deterministic environment may obtain a vehicle routing with low reliability, which leads to a high possibility of violating time windows in practice and causes additional penalty costs for the low level of service.

Therefore, the research objective is to get insight into the formulation of electric vehicle PDP with a soft time window, partial charging policy and uncertain travel time. By conducting a simple computational experiment, the research also explored how travel time uncertainties affect the optimum EV routing plan and what is the trade-off between travel costs and penalty costs of unpunctuality. In the following, two research questions about travel time uncertainties are formulated, which will be answered in this research:

- How should travel time uncertainties in electric vehicle pickup and delivery problems be formalized, and what kind of framework could be developed to model such problems?
- How do travel time uncertainties in electric vehicle pickup and delivery problems affect the optimal routing plan, charging schedule and electric vehicle fleet size?

The report is organized as follows: Section 2 presents a brief review of related literature about EVRP and VRP with uncertainties. Section 3 presents the description of electric vehicle pickup and delivery problems with soft time windows, partial charging and stochastic travel time. In sections 4 and 5, the mathematical model of the routing problem and the method to solve the model are discussed. Section 6 conducts computational experiments with a simple logistics network consisting of one depot and eight pickup and delivery requests. Section 7 presents the conclusion and future study direction of the assignment.

2 Literature Review

Literature related to the studied pickup and delivery problem is discussed in this section. Firstly, studies regarding electric vehicle routing problems are reviewed. Secondly, the literature on vehicle routing problems with stochastic travel times is reviewed.

2.1 Electric Vehicle Routing Problem

EVRPs extend VRP with considerations of the technical characteristics of EVs. In this context, constraints of EV energy consumption, battery depletion, charging policies, and charging process are considered by researchers. One of the earliest research about EVRP is made by Schneider et al. (2014), who incorporated concepts of detouring to charging stations into VRPs with time windows. Most reviewed literature assumes that charging stations are always available and the capacity of charging stations does not restrict the design of the charging schedule. But in practice, the scarcity of chargers in a public charging station will limit the number of simultaneous charging operations. Among reviewed studies, only Froger et al. (2021) and Lam et al. (2022) considered the availability of charging stations. The capacity of charging stations was represented as the number of chargers in their models.

The battery is an important element that should be considered in the charging schedule. Battery depreciation will happen due to the large current during fast charging and discharging (Abdulaal et al., 2017) and some research considered the cost of battery replacement in their objective functions. Abdulaal et al. (2017) defined the corresponding cost as the loss of battery life using a fixed loss rate. Guo et al. (Guo et al.) expressed the battery wearing cost as a piecewise linear function of the SOC. Most reviewed literature assumes energy consumption of the battery follows a linear function. In practice, the energy consumption of a battery may be nonlinear, which is associated with factors like vehicle speed, vehicle load, traffic conditions and so on. Masmoudi et al. (2018) studied the dial-a-ride problem with a more realistic energy consumption function.

Due to limited battery capacity, intra-route charging operations are necessary to help EVs complete long delivery tours. Charging policy is important for designing an intra-route charging schedule, which can be classified into complete charging (Shao et al., 2018; S. Zhang et al., 2019), partial charging (Keskin & Catay, 2016; Cortes-Murcia et al., 2019; Montoya et al., 2017; Uhrig et al., 2015; Guo et al., 2022; Lam et al., 2022), and combining charging and discharging (Lin et al., 2021; Abdulaal et al., 2017). Shao et al. (2018) proposed hybrid genetic algorithm combined with dynamic Dijkstra algorithm to obtain the optimal routes, charging schedule and paths with minimum operational costs. The complete charging strategy was adopted and the charging time was assumed as constant in their model. Swapping a fully charged battery in the battery swap station can be regarded as a special complete charging policy, which occupies little operating time compared with charging operations. S. Zhang et al. (2019) developed a location-routing problem that integrated the allocation of battery swap stations and the routing of electric vehicles. Partial charging allows the fleet operator to decide on charging time and charging type, which increases the complexity of EVRP. Besides, the partial charging policy needs to consider the pattern of the battery charging process. Keskin & Catay (2016) developed an Adaptive Large Neighborhood Search method to solve the EVRP with partial charging and time windows. The problem assumed charging the battery has a linear pattern with a constant charging rate and the experiment results showed that applying partial charging may have better performance than applying complete charging. Cortes-Murcia et al. (2019) also considered a linear partial charging process. The studied problem utilized long charging times at charging stations and allowed customers to visit the parking lot by walking when EVs are charging. The results showed that this strategy can reduce EV charging time and driving distance. These two research all assumed a linear charging process. But in practice, the charging process of a battery shows a nonlinear pattern. Montoya et al. (2017) applied a piecewise-linear charging function in the EVRP, which is an approximation of the charging pattern experimented by Uhrig et al. (2015). Different charging technologies and charging functions were considered in this research. The result showed that simply considering a linear charging function may lead to infeasible or costly solutions. Guo et al. (2022) and Lam et al. (2022) also considered nonlinear partial charging with the same piecewise linear approximation of EV charging process. With the development of Vehicle-to-Grid (V2G), EVs equipped with V2G equipment are allowed to sell excess electricity to the grid, which offers the possibility of making a profit from electricity price variations. Lin et al. (2021) considered this technique and proposed the EVRP considering the policy of charging/discharging under time-variant electricity prices. Abdulaal et al. (2017) also considered a stochastic demand of the grid and modelled it with a hidden Markov model.

2.2 Electric Vehicle Routing Problem with Uncertainties

EVRPs in stochastic environments are widely studied in this period. The sources of uncertainty in stochastic vehicle routing problems include uncertain demand, uncertain environment, and uncertain resources. The technical characteristics of EVs and the requirement of intra-route charging operations improve the complexity of the stochastic vehicle routing problem.

Customer demand is a factor that is often unknown during the route planning stage. S. Zhang et al. (2019) considered this uncertainty in a location-routing problem and proposed two policies to deal with customer demand uncertainties, respectively recourse policy and preventive restocking policy. The former allows a replenishment trip if the EV is unable to service customers' demands. The latter allows the EV to return to the depot with a part load, which is a preventive measure for satisfying remaining demands. Liu et al. (2023) developed a two-stage adaptive robust model to consider the demand uncertainty and plan robust optimal vehicle routings.

Charging EVs at the charging stations occupies longer time periods than fueling ICVs at gasoline stations. The limited capacity of charging stations could lead to unexpected long waiting times for charging at charging stations. Abdulaal et al. (2017) considered the uncertain charging demand at charging stations and potential delays that could occur due to uncertain waiting times at charging stations. The charging station stochastic was modelled as a Markov decision process and the VRP was solved by genetic algorithms.

Energy consumption of batteries are always uncertain due to factors of weather, road conditions and driver behaviours (Pelletier et al., 2019). This uncertainty is an important concern in EVRP to avoid running out of charge and alleviate drivers' range anxiety. Pelletier et al. (2019) considered an urban logistics case that delivery routes are shorter than range of EVs and intra-route charging operation is unnecessary. The objective was to find robust delivery routes and the problem was formulated as a robust programming. Soysal et al. (2020) considered the requirement of intra-route charging to extend vehicle range and proposed a chance-constrained model. The stochastic constraints were rewritten into linear approximations.

Punctuality is one of the most important customer concerns, which is affected by uncertainties of travel time and service time along the delivery route. L. Zhang et al. (2022) studied the VRP with the application of the shared autonomous electric vehicle, which considered stochastic travel time and customer service time. The robust programming technique was adopted to plan conservative and robust vehicle routes and charging schedules. Another widely applied framework for VRP with uncertain travel time is stochastic programming. Tas et al. (2013) assumed soft time windows and expected recourse cost of violating time windows were considered in the objective function. Wang et al. (2023) considered hard time windows and proposed a chance-constrained model to ensure an acceptable route success probability under the stochastic environment with uncertain travel time.

In reviewed literature, no research studied EVRP with uncertain travel time in the framework of stochastic programming. The research, therefore, studies a PDP with partial charging policies, soft time windows, and uncertain travel time. These uncertainties are modelled with the stochastic optimization and customer dissatisfaction derived from unpunctuality is considered a penalty cost in the objective function.

3 Problem Description

The investigated problem in this assignment can be described as an extension of the pickup-and-delivery problem, which considers applying an electric truck fleet, the partial charging policy at service points and stochastic travel times along delivery routes. In this case, the fleet responsible for pickup-and-delivery requests is combined exclusively with electric trucks, which have limited range and may need to charge at charging stations during the tour. Though rapid charging operation can extend the driving range, intra-route charging occupies operational time and affect the level of service provided by the fleet. The uncertain travel times may occupy pre-planned charging time and leads to the dilemma between avoiding unpunctuality and avoiding running out of battery, which impacts the reliability of vehicle routing and charging schedules. EVs breaking down halfway leads to a more severe consequence than violating time windows. More recourse cost is required for battery charging and continuing failure delivery tasks. Therefore, the vehicle routing and charging schedule must ensure EVs are able to complete delivery tours with enough electricity. The violation of time windows may happen in the actual operation to give priority to completing the intra-charging requirement, which results in additional penalty costs of customer dissatisfaction and working overtime. If the penalty costs of earliness, delay, and overtime are not affordable, increasing the fleet size of electric trucks could be a more economical scheme with a high level of service. The problem can be defined as follows:

Denote the transportation network as a connected digraph $G = (V, A)$, where $V = \{0, 1, ..., 2n + 1\}$ is the vertex set and $A = \{(i, j), i, j \in V, i \neq j\}$ is the arc set. There is a depot with a fleet of k electric vehicles available for providing service, where electric vehicles should depart from and return to. Vertices $\{0\}$ and $\{2n+1\}$ denote this depot as route origin and route destination respectively for the convenience of developing the mathematical model. All vehicles are assumed to be homogeneous with the same capacity Q and battery capacity B. There are n customer requests that should be responded to within the planning horizon $[e_0, l_{2n+1}]$, which are known before the planning horizon. For i-th request with r_i loads, the corresponding pickup and delivery points are denoted as $\{i\} \in P = \{1, 2, \ldots, n\}$ and $\{i + n\} \in D = \{1 + n, 2 + n, \ldots, 2n\}$ respectively. There are s charging stations $S \subset P \cup D$ in service vertices where electric vehicles can partially charge the battery during the delivery tour. Fleet operators and their customers have different concerns in practice. The former focuses on improving the efficiency of delivery service and rapid charging with a more expensive price c_c at a charging station is considered as a temporary expedient. Therefore, detouring to a charging station and not providing delivery service is not allowed in this problem, i.e., vehicles can only charge at vertices where they visit and provide transportation service. The latter concerns the reliability of arriving on time and a soft time window (e_v, l_v) is assigned to each pickup and delivery node $v \in P \cup D$. The problem assumes the delivery service can start before or after the time windows but violating these time windows leads to customer dissatisfaction and additional penalty costs. For i-th pickup and delivery vertex $i \in P \cup D$, the specific unit penalty costs of earliness and delay are given as c_i^e, c_i^l respectively. Besides, arriving at the depot outside the planning horizon is allowed, but overtime salary should be paid to the vehicle driver with a unit cost of c_o. Moreover, service time se_v is considered in each customer node $v \in P \cup D$.

The problem assumes that energy consumption only has a linear positive correlation with travel distance. Given the constant energy consumption rate ϵ and travel distance d_{ij}, the energy consumption for travelling through arc $(i, j) \in A$ is calculated as $\epsilon \cdot d_{ij}$. The battery charging function is based on the nonlinear function applied by Montoya et al. (2017), who showed that the nonlinear function can be accurately approximated by piece-wise linear functions. The problem assumes rapid charging technique is applied in charging stations, which allows electric trucks to fast charge to 80% state of charge (SoC). Based on Montoya et al.'s charging function, this segment can be approximated as a linear increase with a known charge rate δ_c. Given the time u of the vehicle charges at the charging station and unit cost c_c, the charging cost is calculated as $c_c \cdot \delta_c \cdot u$. Each electric truck has to back the depot with a minimum SoC of 20%. The problem also assumes that the depot charging during the night has a lower off-peak electricity price $c_{night} < c_c$. After returning to the depot, trucks will be fully charged overnight to ensure that next-day services start with fully charged batteries.

Each arc $(i, j) \in A$ connecting vertices i and j is weighted by a travel distance d_{ij}. The corresponding travel time τ_{ij} is uncertain in this problem with a known probability distribution. Based on the research of Tas et al. (2013), the problem scales the travel time τ_{ij} with respect to corresponding arc distance d_{ij} and assumes it follows Gamma distributed with shape parameter αd_{ij} and scale parameter θ. Denote the realization of τ with a probability of occurrence $p(\omega)$ as $\omega \in \Omega$.

The research aims to develop a stochastic programming model considering the uncertainty of travel time and find an optimal vehicle routing plan and charging schedule for a planning horizon with known customer demand. The objective is to determine the minimum operational cost for satisfying all customer requests. Therefore, the problem can be modelled as a two-stage stochastic programming considering the possibility of violating time windows and related penalty costs. The fleet size, vehicle routes and charging decisions will be determined in the first stage. In the second stage, the specific charging times will be decided after realizing the random variables of travel times. The correction costs of violating time windows will be calculated based on vehicle routing and charging schedules.

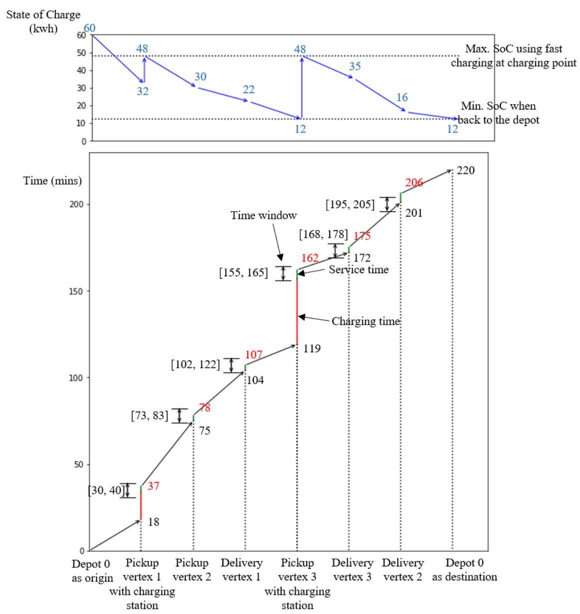


Figure 1: Illustration Example of A Deterministic Case

Table 1: Notation of parameters and decision variables used in the model

Notation	Description
$\mathbb{E}(..)$	The expected value of a random variable.
n	Number of pickup and delivery requests
s	Number of service vertices equipped with charging stations
k	Number of available electric trucks
Sets	
O	Set of depot, where $O = \{0, 2n+s+1\}$. Vertices $\{0\}$ and $\{2n+s+1\}$ denote this depot as route origin and route destination respectively.
P	Set of n demand origins, where $P = \{1, ..., n\}$.
D	Set of corresponding n demand destinations, where $D = \{n+1, ..., 2n\}$.
S	Set of demand vertices with charging stations, where $S \subset P \cup D$
V	Set of vertices, where $V = \{P \cup D \cup O\}$
A	Set of arcs connecting vertices in V, where $A = \{(i,j) \| i, j \in V, i \neq j\}$.
K	Set of electric trucks available at depot, where $K = \{1, ..., k\}$.
Ω	Set of scenarios for random variables, where $\omega \in \Omega$ refers to a realization with probability of occurrence $p(\omega)$
Parameters	
d_{ij}	Total distance between vertices i and j, where $(i,j) \in A$. (km)
τ_{ij}	Stochastic travel time between nodes i and j, where $(i,j) \in A$. These random variables follow Gamma distribution $\tau_{ij} \sim \Gamma(\alpha d_{ij}, \theta)$ with shape parameter αd_{ij} and scale parameter θ. The mean value is $\alpha\theta d_{ij}$ and the variance is $\alpha\theta^2 d_{ij}$. (minutes)
se_i	Service time for customer vertex i, where $i \in P \cup D$. (minutes)
(e_i, l_i)	Time window at node i where e_i is the earliest service time and l_i is the latest service time. The planning horizon is e_0, l_{2n+s+1}. (minutes)
c_e^i	Unit penalty cost of earliness at service vertex $i \in P \cup D$. (Euro/minute)
c_l^i	Unit penalty cost of delay at service vertex $i \in P \cup D$. (Euro/minute)
c_o	Unit cost paid by operators for working overtime. (Euro/minute)
Q	Capacity of electric truck.
r_i	The pickup/delivery load at point i, where $i \in P \cup D$. These parameters have positive values in pickup points and negative values in delivery points.
B	Battery capacity of electric vehicle. (kWh)
ϵ	Energy consumption rate related to travel distance. (kWh/km)
δ_c	Charge rate at charging station. (kW)
c_c	Unit charging price at planning horizon. (Euro/kWh)
c_n	Unit charging price at night. (Euro/kWh)
c_a	Unit fixed cost of electric truck used. (Euro/veh)
Decision Variables	
x_{ij}^k	Binary decision variables which take the value 1 if arc $(i,j) \in A$ is covered by electric truck k and 0, otherwise
y_i^k	Binary decision variables which take the value 1 if electric truck k charges at charging point $i \in S$ and 0, otherwise
z_k	Binary decision variables which take the value 1 if electric truck k is used for delivery service and 0, otherwise
q_i^k	Integer variable defines the vehicle load when electric truck k leaves vertex i
$u_i^k(\omega)$	Non-negative integer decision variables which means the charging time period of electric truck k at charging station $i \in S$ in scenario ω. (minutes)
$SoC_i^k(\omega)$	Continuous variable defines the state of charge when electric truck k arrives at vertex i in scenario ω (kWh)
$t_i^k(\omega)$	Continuous variable defines the arrival time when electric truck k visits vertex i in scenario ω. (minutes)
$ea_i^k(\omega)$	Continuous variable defines the earliness of truck k at node i in scenario ω. (minutes)
$de_i^k(\omega)$	Continuous variable defines the delay of truck k at node i in scenario ω. (minutes) $de_{2n+s+1}^k(\omega)$ refers to the overtime of the driver working on truck k in scenario ω. (minutes)

Figure 1 presents an illustration example of a pickup-and-delivery tour of an electric truck and the corresponding curve of SoC. The green line sections are fixed service times at service vertices. The red line sections are charging times at charging stations, which are determined in the second stage after the realization of uncertain travel times. Electric trucks could provide pickup-and-delivery service after finishing charging operations. The start time of service should be arranged within time windows and violating time windows leads to additional penalty costs of earliness or delay. The black line section refers to the vehicle trips between two vertices and the gradient is the average speed along this arc. The problem assumes uncertain travel times along delivery tours so average speeds vary in different arcs. The blue line graph illustrates the change in SoC along the delivery tour. Electric trucks are allowed to do partial charging operations at the charging stations, with an upper bound of a maximum of 80% SoC. Besides, electric trucks have to back to the depot with a minimum of 20% SoC.

Specifically, the following decision variables are introduced to define the first stage problem: x_{ij}^k is a binary decision variable that indicates whether arc (i, j) is travelled by vehicle k. The binary decision variables y_i^k characterize whether vehicle k charges at charging station i. The usage of electric vehicle k is characterized by binary decision variables z^k. Additionally, for any vertex $i \in V$, and integer variable q_i^k are used to define the vehicle load of vehicle k in this node. For a realization, $\omega \in \Omega$, the following second-stage variables can be defined. The continuous variable $SoC_i^k(\omega)$ define the state of charge along delivery tour. For the convenience of drivers operating the charging facility, the time vehicle k charges at station i is characterized by integer decision variables $u_i^k(\omega)$. The arrival time of vehicle k at node i is defined as a continuous variable $t_i^k(\omega)$. In addition, the earliness and delay of vehicle k at node i are denoted as $ea_i^k(\omega)$ and $de_i^k(\omega)$, respectively. Similarly, the expected overtime of the driver working on the route of vehicle k is denoted as $de_{2n+s+1}^k(\omega)$. The necessary notation of parameters and decision variables used in the assignment is given by Table 1. The problem is formulated as a two-stage stochastic programming. The first stage decides the fleet size, vehicle routing and intra-route charging decision. The second stage decides specific charging time after knowing the realization $\omega \in \Omega$. The development of the mathematical model is discussed in the next section.

4 Two-stage Stochastic Linear Programming

4.1 Objective Function

The assignment aims to investigate the trade-off between travel costs of vehicle usage and charging, and penalty costs of earliness, delay and overtime. This dilemma is described as minimizing the total cost in the objective function. The total cost consists of three components, respectively the fixed cost for EV usage, the charging cost for both intra-route charging and depot charging, and the expected penalty cost for violating time windows. Additionally, a weight factor ρ is assigned to travel costs and penalty costs to evaluate the importance of punctuality. In the first-stage problem, the routing decision $\boldsymbol{x}$, charging decision $\boldsymbol{y}$ and vehicle usage decision $\boldsymbol{z}$ are determined. Given the realization of travel times $\omega \in \Omega$, specific charging time $u_i^k(\omega)$ at each charging station can be decided at the second stage. Subsequently, earliness $ea_i^k(\omega)$, delay $de_i^k(\omega)$ and overtime $de_{2n+s+1}^k(\omega)$ can be calculated. The objective function of the two-stage stochastic program can be given as follows:

$$\min C = \rho \cdot c_a \cdot \sum_{k \in K} z_k + \mathbb{E}[Q(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{f}(\omega))] \tag{1}$$

$$= \rho \cdot c_a \cdot \sum_{k \in K} z_k + \sum_{\omega \in \Omega} p(\omega) \cdot Q(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{f}(\omega)) \tag{2}$$

Where $p(\omega)$ is the percentage of realization ω and $Q(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{f}(\omega))$ is the optimal value of the second-stage problem:

$$\min Q(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{u}, \boldsymbol{f}(\omega)) = \rho \cdot [c_c \cdot \sum_{k \in K} \sum_{i \in S} \delta_c \cdot u_i^k(\omega) + c_n \cdot \sum_{k \in K} (\sum_{i,j \in V} \epsilon \cdot d_{ij} \cdot x_{ij}^k - \sum_{i \in S} \delta_c \cdot u_i^k(\omega))] \tag{3}$$

$$+ (1-\rho) \cdot \sum_{k \in K} [\sum_{i \in P \cup D} c_e^i \cdot ea_i^k(\omega) + \sum_{i \in P \cup D} c_l^i \cdot de_i^k(\omega) + c_o \cdot de_{2n+s+1}^k(\omega)] \tag{4}$$

4.2 First-Stage Constraints

The constraints for the first stage ensure requirements of fleet size, flow, and vehicle capacity, i.e., all pickup and delivery demands are satisfied and each vehicle never overloads. The first-stage constraints are given by constraints (5)-(16). Constraint (5) associates electric truck usage with depot departure. The binary decision variable $x^k_{0,2n+1}$ takes the value 1 if the electric truck k is not selected for delivery service and stays at the depot during the planning horizon. Constraint (6) ensures each electric vehicle starts from and ends at the depot, where the source depot is denoted as {0} and the sink depot is {2n+s+1}. Constraint (7) ensures each pickup request is satisfied by one vehicle and constraint (8) forces each pair of pickup and delivery vertices to be visited by the same vehicle. Constraint (9) ensure the flow balance in pickup and delivery vertices. Constraint (10) ensures all vehicles are empty when departing from and arriving at the depot. Constraint (11) determines vehicles' onboard loads at nodes along their routes. Constraint (12) ensure capacity limitations of electric vehicles. The charging operation is not mandatory and constraint (13) ensures this consideration. The constraint (14) ensures the inaccessibility of arcs. As illustrated in Table 1, decision variables $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z})$ for vehicle routing, charging decisions, and vehicle usage are binary decision variables. Variables $\boldsymbol{q}$ for vehicle load are non-negative integer variables.

$$z_k = 1 - x^k_{0,2n+1}, \quad \forall k \in K \tag{5}$$

$$\sum_{i \in V} x^k_{0,i} = \sum_{i \in V} x^k_{i,2n+1} = 1, \quad \forall k \in K \tag{6}$$

$$\sum_{k \in K} \sum_{j \in V} x^k_{ij} = 1, \quad \forall i \in P \tag{7}$$

$$\sum_{j \in V} x^k_{ij} - \sum_{j \in V} x^k_{n+i,j} = 0, \quad \forall i \in P, k \in K \tag{8}$$

$$\sum_{i \in V} x^k_{iv} - \sum_{j \in V} x^k_{vj} = 0, \quad \forall v \in P \cup D, k \in K \tag{9}$$

$$q^k_i = 0, \quad \forall i \in O, k \in K \tag{10}$$

$$q^k_i + r_j \cdot x^k_{ij} - Q \cdot (1 - x^k_{ij}) \leq q^k_j, \quad \forall i, j \in V, k \in K \tag{11}$$

$$0 \leq q^k_i \leq Q \cdot z_k, \quad \forall i \in V, k \in K \tag{12}$$

$$y^k_i \leq \sum_{j \in V} x^k_{ji}, \quad i \in S, k \in K \tag{13}$$

$$x^k_{ii} = x^k_{i,0} = x^k_{2n+1,i} = 0, \quad \forall i \in V, k \in K \tag{14}$$

$$x^k_{ij}, y^k_{ij}, z_k \in \{0, 1\}, \quad \forall i, j \in V, k \in K \tag{15}$$

$$q^k_i \in \mathbb{N}, \quad \forall i \in V, k \in K \tag{16}$$

4.3 Second-Stage Constraints

Constraints in the second stage determine the specific charging time at charging stations after the realization of uncertain travel times. These constraints ensure all vehicles finish delivery tours without running out of battery. The constraint (17) ensures vehicles are fully charged at the beginning of tours. The constraint (18) ensures electric trucks are back to the depot with a minimum of 20% SoC. The constraints (19)-(20) calculate the state of charge at each vertex along routes. The constraint (21) ensures battery capacity limitations of electric vehicles. The constraints (22)-(23) ensure that electric trucks can partial charge at charging stations to a maximum of 80% SoC. As shown in Table 1, decision variables $\boldsymbol{u(\omega)}$ for intra-route charging times are non-negative integer variables, which are ensured by constraints (36).

Given the vehicle routing $\boldsymbol{x}$ and charging decisions $\boldsymbol{y}$ and vehicle usage $\boldsymbol{z}$ determined in the first stage and the specific charging times $\boldsymbol{u(\omega)}$ determined in the second stage, the following constraints can calculate arrival times $\boldsymbol{t(\omega)}$ at vertices along delivery tours and determine earliness, delay and overtime. The M is a constant larger than the planning horizon. Constraints (24)-(25) ensures vehicles leave the depot and visit other nodes after the beginning of the planning horizon. The arrival time of vertices outside the route of vehicle k is set to e_0. Constraints (26)-(29) calculate the arrival time of vertices in the network. The equation is converted into two inequalities using the big M technique. Constraint (30) ensures each pickup location i is visited before pickup location $n + i$. The calculation of earliness and delay at each node is realized by constraints (31)-(35). Since the objective function aims to minimize the expected penalty cost, these constraints only restricted the lower bound of earliness ea_i and delay de_i.

$$SoC_0^k(\omega) = B, \quad \forall k \in K, \omega \in \Omega \tag{17}$$
$$SoC_{2n+1}^k(\omega) \geq 0.2 \cdot B, \quad \forall k \in K, \omega \in \Omega \tag{18}$$
$$SoC_j^k(\omega) \leq SoC_i^k(\omega) - \epsilon \cdot d_{ij} \cdot x_{ij}^k + B(1 - x_{ij}^k), \quad \forall i \in V|S, j \in V, k \in K, \omega \in \Omega \tag{19}$$
$$SoC_j^k(\omega) \leq SoC_i^k(\omega) + \delta_c \cdot u_i^k(\omega) - \epsilon \cdot d_{ij} \cdot x_{ij}^k + B(1 - x_{ij}^k), \quad \forall i \in S, j \in V, k \in K, \omega \in \Omega \tag{20}$$
$$B \cdot (1 - z_k) \leq SoC_j^k(\omega) \leq B, \quad \forall j \in V, k \in K, \omega \in \Omega \tag{21}$$
$$0 \leq \delta_c \cdot u_i^k(\omega) \leq 0.8 \cdot B \cdot y_i^k, \quad \forall i \in S, k \in K, \omega \in \Omega \tag{22}$$
$$\delta_c \cdot u_i^k(\omega) \leq 0.8 \cdot B - SoC_i^k(\omega) + B \cdot (1 - y_i^k), \quad \forall i \in S, k \in K, \omega \in \Omega \tag{23}$$
$$t_0^k(\omega) = e_0, \quad \forall k \in K, \omega \in \Omega \tag{24}$$
$$e_0 \leq t_j^k(\omega) \leq e_0 + M \cdot \sum_{i \in V} x_{ij}^k, \quad \forall j \in V, k \in K, \omega \in \Omega \tag{25}$$
$$t_j^k(\omega) \geq t_i^k(\omega) + [\tau_{ij}(\omega) + se_i] \cdot x_{ij}^k - M \cdot (1 - x_{ij}^k), \quad \forall i \in V|S, j \in V, k \in K, \omega \in \Omega \tag{26}$$
$$t_j^k(\omega) \leq t_i^k(\omega) + [\tau_{ij}(\omega) + se_i] \cdot x_{ij}^k + M \cdot (1 - x_{ij}^k), \quad \forall i \in V|S, j \in V, k \in K, \omega \in \Omega \tag{27}$$
$$t_j^k(\omega) \geq t_i^k(\omega) + [\tau_{ij}(\omega) + se_i] \cdot x_{ij}^k + u_i^k - M \cdot (1 - x_{ij}^k), \quad \forall i \in S, j \in V, k \in K, \omega \in \Omega \tag{28}$$
$$t_j^k(\omega) \leq t_i^k(\omega) + [\tau_{ij}(\omega) + se_i] \cdot x_{ij}^k + u_i^k + M \cdot (1 - x_{ij}^k), \quad \forall i \in S, j \in V, k \in K, \omega \in \Omega \tag{29}$$
$$t_i^k(\omega) + se_i + \tau_{i,n+i}^k(\omega) - M \cdot (1 - \sum_{j \in V} x_{ij}^k) \leq t_{n+i}^k(\omega), \quad \forall i \in P, k \in K, \omega \in \Omega \tag{30}$$
$$ea_i^k(\omega) \geq e_i - t_i^k(\omega) - M \cdot (1 - \sum_{j \in V} x_{ji}^k), \quad \forall i \in V|S, k \in K, \omega \in \Omega \tag{31}$$
$$ea_i^k(\omega) \geq e_i - t_i^k(\omega) - u_i^k - M \cdot (1 - \sum_{j \in V} x_{ji}^k), \quad \forall i \in S, k \in K, \omega \in \Omega \tag{32}$$
$$ea_i^k(\omega) \geq 0, \quad \forall i \in V, k \in K, \omega \in \Omega \tag{33}$$
$$de_i^k(\omega) \geq t_i^k(\omega) - l_i, \quad \forall i \in V, k \in K, \omega \in \Omega \tag{34}$$
$$de_i^k(\omega) \geq 0, \quad \forall i \in V, k \in K, \omega \in \Omega \tag{35}$$
$$u_i^k(\omega) \in \mathbb{N}, \quad \forall i \in S, k \in K, \omega \in \Omega \tag{36}$$

5 Sample Average Approximation Method

The section 4 presents the development of a two-stage stochastic linear programming. To solve this model, the technique of sample average approximation is implemented to construct scenarios and model this stochastic programming to the deterministic equivalent. This deterministic equivalent is a large mixed integer programming and can be solved by Gurobi Optimizer. A large number N of sample scenarios $\Xi = \{\xi_1, \xi_2, ..., \xi_N\} \subset \Omega$ are generated from Ω through Monte Carlo sampling and each realization is treated as an individual deterministic sub-problem. The expectation of the second-stage objective value is approximated by the average value of these sample scenarios. The sample average approximation problem of the original objective function can be given as follows:

$$\min C_\Xi = \rho \cdot c_a \cdot \sum_{k \in K} z_k + \frac{1}{N} \sum_{n=1}^{N} Q(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{f}(\omega)) \tag{37}$$

With the number of scenarios considered in the sample average problem $|\Xi|$ approaches $|\Omega|$, the value of C_Ξ will approach the optimal solution C^*.

6 Computational Experiment

6.1 Test Instances and Parameter Setting

The computational experiments are conducted to illustrate the trade-off between fleet size and punctuality with uncertain travel time and to investigate the influence of different time windows and travel time uncertainties on optimal solutions. A small data set with one depot, 9 customers, 5 charging stations and 3 available electric trucks are used in the computational experiments. The geographic distribution of vertices is generated randomly and two sets of time windows are assigned to customers, respectively large and tight time windows. The travel distance is calculated as the Euclidean distance between two vertices. That is, for two vertices (x_1, y_1) and (x_2, y_2), the travel distance is $d_{12} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$. The experiment assumes travel time spent for one unit of distance follows the Gamma distribution, which is described by shape parameter α and scale parameter β. The Coefficient of Variation (CV) is the product of these two parameters $CV = \alpha \cdot \beta$. The planning horizon $[e_0, l_{2n+s+1}]$ is set to $[0, 480]$. Cost coefficients of earliness and delay (c_i^e, c_i^l) for all customers are set the same in this experiment, taking the values of $(4, 5)$ respectively. The rest cost coefficients of overtime, en-route charging and depot charging (c_o, c_c, c_n) are set to $(6, 1, 0.5)$. The vehicle characteristics are given as follows: The truckload Q is 3. The usable battery capacity B is 60 kWh. The energy consumption ϵ is estimated as 1 kWh/km. The average charging rate of chargers δ_c is 60kW. The number of scenarios used to obtain the SAA estimate is $N = 20$ for each instance. The mathematical formulations were implemented using the Python programming language, and Gurobi 9.5 was used as the underlying MILP solver. All calculations were performed by a laptop with an AMD Ryzen 7 5800H @ 3.20 GHz and 16GB RAM.

Table 2 illustrates the parameters of 12 instances tested in computational experiments. The experiment generated these instances by tunning three types of parameters, respectively time windows, Coefficient of Variation (CV), and weight parameter ρ. Each instance tuned one parameter to control variables. Two types of time windows were considered in experiments: large time windows and tight time windows. Besides, the experiments considered two types of traffic conditions, respectively smooth traffic and congested traffic condition. The CV of a smooth traffic condition takes a value of 1.5, which means trucks travel with a faster speed and a smaller variance. The congested traffic condition has a larger CV value, assuming trucks travel with a slower speed and a larger variance. Moreover, the experiment considered the importance of two cost components by tuning a weight factor ρ. Two cost components refer to travel costs consisting of fixed vehicle cost and charging cost, and penalty cost for violating time windows. A larger value of weight factor ρ means operators draw more importance to travel costs.

Instance	Time Windows	CV	α	β	ρ
1	Large	1.5	7.5	0.2	0.5
2	Large	1.5	7.5	0.2	0.7
3	Large	1.5	7.5	0.2	0.3
4	Tight	1.5	7.5	0.2	0.5
5	Tight	1.5	7.5	0.2	0.7
6	Tight	1.5	7.5	0.2	0.3
7	Large	2	8.5	4/17	0.5
8	Large	2	8.5	4/17	0.7
9	Large	2	8.5	4/17	0.3
10	Tight	2	8.5	4/17	0.5
11	Tight	2	8.5	4/17	0.7
12	Tight	2	8.5	4/17	0.3

Table 2: Parameters of Instances in Computational Experiments

The base instance is defined as follows: There are large time windows in service vertices. The travel time spent for one unit of distance is Gamma distributed where (α, β) are equal to $(7.5, 0.2)$. The Coefficient of Variation (CV) is, therefore, equal to 1.5. Set the weight factor ρ to 0.5, which gives the equal importance of two cost components. The vehicle routing of the SAA problem is given in Figure 2, where the red vertex refers to the depot, green vertices refer to service vertices with charging stations and purple vertices refer to service vertices without charging stations. Delivery tours between two vertices are represented by directed segments and routes for three vehicles will be distinguished by different colours, respectively orange, red, and blue. The vehicle routing of the optimal solution shows that two electric trucks with intra-route charging operations are enough to provide delivery service to all customers in the instance with large time windows and smooth traffic conditions. When it comes to tighter time windows, more congested traffic conditions or higher requirements of LoS, the fleet size and intra-route charging demand would change. The experiment results of 12 instances and findings will be discussed in the next subsection.

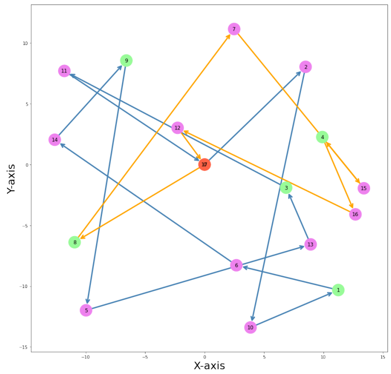


Figure 2: Optimal Solution of SAA Problem with Parameters in Instance 1

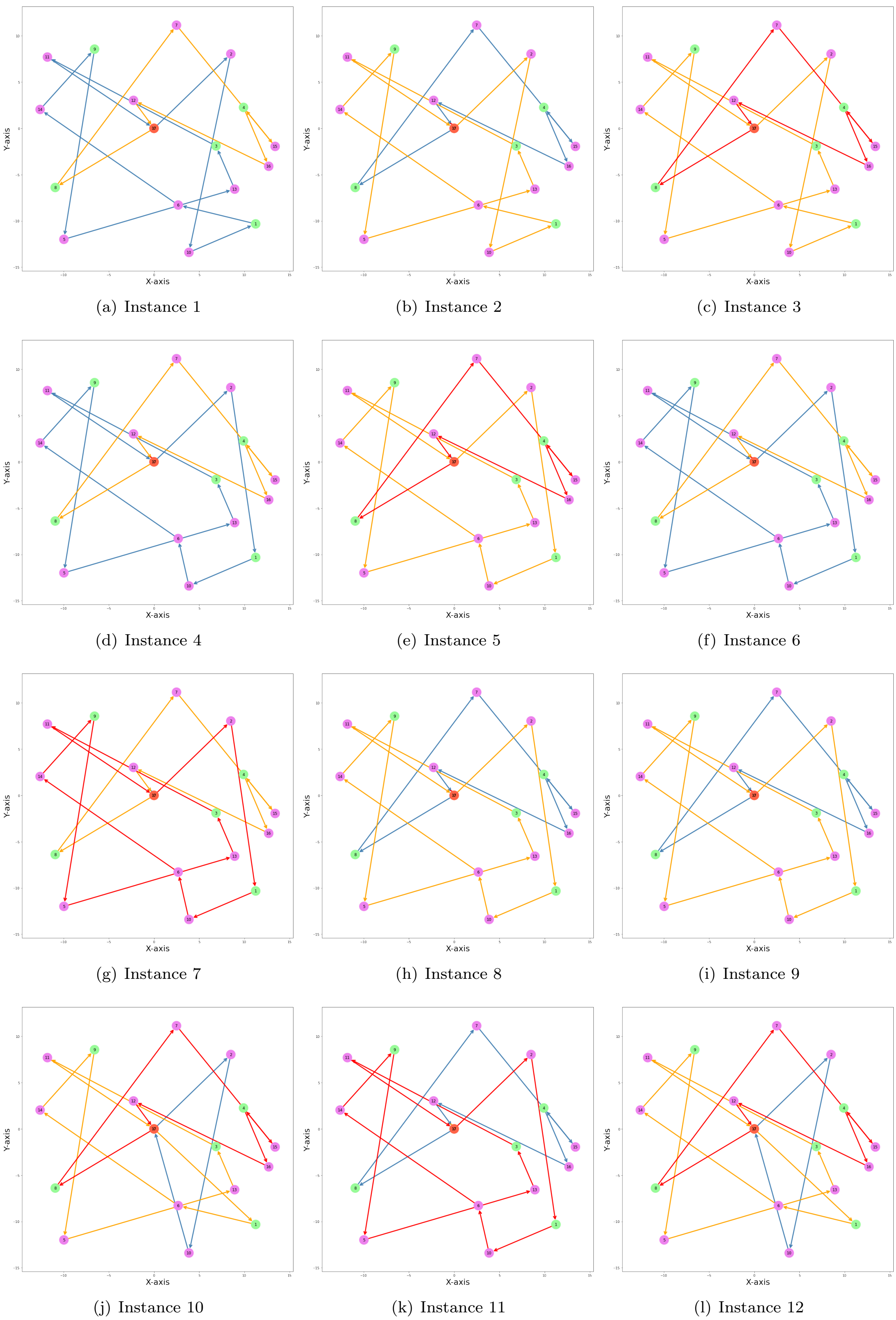
6.2 Results of Experiments

Instance	Fleet Size	Charging Time (min)	Earliness (min)	Delay (min)	Overtime (min)	Fixed Cost (Euro)	Charging Cost (Euro)	Penalty Cost (Euro)
1	2	185.60	1.98	0.09	0	240	214.29	8.37
2	2	182.00	4.04	0.55	0	240	212.49	18.92
3	2	185.80	1.93	0.20	0	240	214.39	8.70
4	2	207.60	0.71	0.29	0	240	221.82	4.27
5	2	206.80	1.82	1.06	0	240	221.42	12.57
6	2	210.00	0.58	0.20	0	240	223.02	3.34
7	2	150.20	0	13.50	0	240	193.12	67.48
8	2	148.20	0	14.20	0	240	192.12	71.00
9	2	151.80	0	7.48	0	240	193.92	37.40
10	3	171.00	27.44	0.43	0	360	217.59	111.90
11	2	156.40	1.74	46.06	0	240	196.22	237.29
12	3	167.40	21.09	0.14	0	360	215.79	85.06

Table 3: Details of Solutions Obtained by SAA

Table 3 reports the results of instances tested in the experiment and Figure 3 illustrates the optimal vehicle routing of each instance obtained in experiments. As shown by earliness, delay and overtime values in Table 3, uncertainties of travel time along delivery tours will lead to violation of time windows. Tighter time windows and more congested traffic conditions will increase the possibility of earliness and delay, which results in more undesired penalty costs. The experiment results show two measures to alleviate the negative impact of travel time uncertainties, respectively extending intra-route charging times and increasing fleet size.

The charging schedule is an important element which decides the actual cruise range of electric vehicles and impacts the arrival times at service vertices. As discussed in the parameter setting section, charging at charging stations is more expensive than depot charging. Since the studied problem assumes electric trucks will get fully charged after returning to the depot, intra-route charging with higher electricity prices could be regarded as an emergency measure to extend vehicle range and should be minimized to reduce charging costs. Vehicle routing of instances 4-9 in Figure 3 are the same and instances 7-9 have shorter charging time than that of instances 4-6. This result supports the argument that vehicles can finish delivery tours with shorter intra-routing charging times. Instances 4-6 with tight time windows have similar penalty costs as instances 1-3 and longer intra-route charging times. This comparison shows that charging longer at charging stations has the potential to adjust vehicle departure time at service vertices and provide pickup and delivery service on time. When it comes to congested traffic conditions where vehicles travel slower along delivery tours, the obtained solutions incline to reduce intra-route charging time and only ensure electric vehicles do not use up electricity along delivery tours. To sum up, charging at charging stations will occupy long time periods in the planning horizon, which impacts the start time for providing service. Operators could obtain a more reliable vehicle routing by adjusting the charging schedule and deciding departure time at each service vertex.



(a) Instance 1 (b) Instance 2 (c) Instance 3

(d) Instance 4 (e) Instance 5 (f) Instance 6

(g) Instance 7 (h) Instance 8 (i) Instance 9

(j) Instance 10 (k) Instance 11 (l) Instance 12

Figure 3: Optimal Vehicle Routing of 12 Instances

Increasing fleet size is another measure to ensure punctuality of delivery services. Compared with instance 11, instances 10 and 12 assign more importance on the level of service and their optimal solutions have larger fleet sizes with 3 vehicles and longer intra-route charging times. Penalty costs of these two costs are less than half of that in instance 11, showing that increasing fleet size has the potential to decrease the negative impact of travel time uncertainties and reduce the possibility of violating time windows. On the other hand, more fixed vehicle costs and charging costs raise when more electric vehicles are used. Therefore, the trade-off between fleet size and punctuality should be considered by operators.

As analyzed above, tuning values of weight factor ρ, i.e., assigning different importance to travel cost, also has an impact on charging times and fleet sizes selection. Solutions which place a high value on punctuality have the inclination to use more vehicles and charge longer at charging stations. Figure 3 shows that tuning in the first 9 instances does not impact the optimal fleet size and vehicle routing. Two vehicles are optimal for these instances and tuning the value of ρ only influences intra-route charging times. As for instances with tight time windows and congested traffic conditions, fleet size decisions and vehicle routing are sensitive to the operator's preference. By reducing the weight factor ρ from 0.7 to 0.5 and 0.3, i.e., attaching more importance to the level of service, the fleet sizes in instances 10 and 12 increase to 3 and the penalty cost decreases to half of that in instance 11.

7 Conclusion

In this assignment, an electric vehicle pickup-and-delivery problem with soft time window, partial charging policy and uncertain travel time is investigated. The studied problem is modelled as two-stage stochastic programming with first-stage costs to minimize the vehicle usage costs and second-stage recourse costs to charge EVs to complete the tour proposed by the first-stage and penalty for violating time windows. The sample average approximation (SAA) method is applied to model the stochastic programming to the deterministic equivalent. Specifically, the second-stage function is approximated by Monte Carlo sampling, whose objective value will converge to the optimal expected value with increasing instance size. By using the SAA method, the problem is approximated as a mixed integer programming and can be solved by optimization solver Gurobi.

A small set of 12 instances is used in the computational experiment, which involves the aspects of EV characteristics, time windows, travel time uncertainties, and operator preference. The experiment results indicate that larger vehicle fleet size and longer intra-route charging time have the potential to develop a more reliable vehicle routing with high punctuality. On the other hand, these measures increase the travel costs of vehicle usage and charging. The trade-off between travel costs and penalty costs of customer dissatisfaction should be carefully considered and is sensitive to operator preference in instances with tight time windows and congested traffic conditions.

There are limitations in the studied problem and can be extended in future research: (1) The experiment results show that staying longer at charging stations has the potential to enhance punctuality. But intra-route charging operations are expensive and overcharging is unnecessary for completing the delivery tour. The application of the Vehicle-2-Grid technique could be considered which allows EVs to utilize idle time at charging stations and sell excess electricity to the grid. Adopting a charging/discharging policy at charging stations can be an interesting direction for future study, which shows the potential to reduce charging costs and raise extra revenues. (2) The energy consumption used in this assignment is assumed to follow a linear function, which neglects the influence of vehicle speed, travel distance, traffic conditions and so on. Since the uncertainty of travel times is also related to these factors, applying a more realistic energy consumption function and associating travel time uncertainty with energy consumption uncertainty can be an interesting direction for future study. (3) In practice, travel times are time-dependent throughout the day. Travel speeds in peak hours have huge variances due to traffic congestion. Combining travel times stochasticity with time-dependent property can be also considered in future studies.

References

Abdulaal, A., Cintuglu, M. H., Asfour, S., & Mohammed, O. A. (2017). Solving the multivariant ev routing problem incorporating v2g and g2v options. *IEEE Transactions on Transportation Electrification*, *3*(1), 238-248. doi: 10.1109/TTE.2016.2614385

Cortes-Murcia, D. L., Prodhon, C., & Afsar, H. M. (2019). The electric vehicle routing problem with time windows, partial recharges and satellite customers. *Transportation Research Part E: Logistics and Transportation Review*, *130*, 184-206. Retrieved from https://www.sciencedirect.com/science/article/pii/S1366554518310597 doi: https://doi.org/10.1016/j.tre.2019.08.015

Council of European Union, E. (2021). Fit for 55. (https://www.consilium.europa.eu/en/policies/green-deal/fit-for-55-the-eu-plan-for-a-green-transition/)

Felipe, A., Ortuno, M. T., Righini, G., & Tirado, G. (2014). A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges. *Transportation Research Part E: Logistics and Transportation Review*, *71*, 111-128. Retrieved from https://www.sciencedirect.com/science/article/pii/S1366554514001574 doi: doi.org/10.1016/j.tre.2014.09.003

Froger, A., Jabali, O., Mendoza, J. E., & Laporte, G. (2021). The electric vehicle routing problem with capacitated charging stations. *Transportation Science*. Retrieved from https://hal.archives-ouvertes.fr/hal-02386167 doi: 10.1287/trsc.2021.1111

Guo, F., Zhang, J., Huang, Z., & Huang, W. (2022). Simultaneous charging station location-routing problem for electric vehicles: Effect of nonlinear partial charging and battery degradation. *Energy*, *250*, 123724. Retrieved from https://www.sciencedirect.com/science/article/pii/S0360544222006272 doi: https://doi.org/10.1016/j.energy.2022.123724

Keskin, M., & Catay, B. (2016). Partial recharge strategies for the electric vehicle routing problem with time windows. *Transportation Research Part C: Emerging Technologies*, *65*, 111-127. Retrieved from https://www.sciencedirect.com/science/article/pii/S0968090X16000322 doi: https://doi.org/10.1016/j.trc.2016.01.013

Lam, E., Desaulniers, G., & Stuckey, P. J. (2022). Branch-and-cut-and-price for the electric vehicle routing problem with time windows, piecewise-linear recharging and capacitated recharging stations. *Computers & Operations Research*, *145*, 105870. Retrieved from https://www.sciencedirect.com/science/article/pii/S0305054822001423 doi: https://doi.org/10.1016/j.cor.2022.105870

Lin, B., Ghaddar, B., & Nathwani, J. (2021). Electric vehicle routing with charging/discharging under time-variant electricity prices. *Transportation Research Part C: Emerging Technologies*, *130*, 103285. Retrieved from https://www.sciencedirect.com/science/article/pii/S0968090X21002965 doi: https://doi.org/10.1016/j.trc.2021.103285

Liu, X., Wang, D., Yin, Y., & Cheng, T. (2023). Robust optimization for the electric vehicle pickup and delivery problem with time windows and uncertain demands. *Computers & Operations Research*, *151*, 106119. Retrieved from https://www.sciencedirect.com/science/article/pii/S0305054822003495 doi: https://doi.org/10.1016/j.cor.2022.106119

Masmoudi, M. A., Hosny, M., Demir, E., Genikomsakis, K. N., & Cheikhrouhou, N. (2018). The dial-a-ride problem with electric vehicles and battery swapping stations. *Transportation Research Part E: Logistics and Transportation Review*, *118*, 392-420. Retrieved from https://www.sciencedirect.com/science/article/pii/S1366554517310086 doi: https://doi.org/10.1016/j.tre.2018.08.005

Montoya, A., Gueret, C., Mendoza, J. E., & Villegas, J. G. (2017). The electric vehicle routing problem with nonlinear charging function. *Transportation Research Part B: Methodological*, *103*, 87-110. Retrieved from https://www.sciencedirect.com/science/article/pii/S0191261516304556 (Green Urban Transportation) doi: https://doi.org/10.1016/j.trb.2017.02.004

Pelletier, S., Jabali, O., & Laporte, G. (2019). The electric vehicle routing problem with energy consumption uncertainty. *Transportation Research Part B: Methodological*, *126*, 225-255. Retrieved from https://www.sciencedirect.com/science/article/pii/S0191261519300153 doi: https://doi.org/10.1016/j.trb.2019.06.006

Schneider, M., Stenger, A., & Goeke, D. (2014). The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science*, *48*(4), 500-520. Retrieved from https://doi.org/10.1287/trsc.2013.0490 doi: 10.1287/trsc.2013.0490

Shao, S., Guan, W., & Bi, J. (2018). Electric vehicle-routing problem with charging demands and energy consumption. *IET Intelligent Transport Systems*, *12*(3), 202-212. Retrieved from https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-its.2017.0008 doi: https://doi.org/10.1049/iet-its.2017.0008

Soeffker, N., Ulmer, M. W., & Mattfeld, D. C. (2022). Stochastic dynamic vehicle routing in the light of prescriptive analytics: A review. *European Journal of Operational Research*, *298*(3), 801-820. Retrieved from https://www.sciencedirect.com/science/article/pii/S0377221721006093 doi: https://doi.org/10.1016/j.ejor.2021.07.014

Soysal, M., Cimen, M., & Belbag, S. (2020). Pickup and delivery with electric vehicles under stochastic battery depletion. *Computers Industrial Engineering*, *146*, 106512. Retrieved from https://www.sciencedirect.com/science/article/pii/S0360835220302461 doi: https://doi.org/10.1016/j.cie.2020.106512

Tas, D., Dellaert, N., van Woensel, T., & de Kok, T. (2013). Vehicle routing problem with stochastic travel times including soft time windows and service costs. *Computers & Operations Research*, *40*(1), 214-224. Retrieved from https://www.sciencedirect.com/science/article/pii/S0305054812001402 doi: https://doi.org/10.1016/j.cor.2012.06.008

Uhrig, M., WeiB, L., Suriyah, M., & Leibfried, T. (2015). E-mobility in car parks – guidelines for charging infrastructure expansion planning and operation based on stochastic simulations.

Wang, Z., Dessouky, M., Van Woensel, T., & Ioannou, P. (2023). Pickup and delivery problem with hard time windows considering stochastic and time-dependent travel times. *EURO Journal on Transportation and Logistics*, *12*, 100099. Retrieved from https://www.sciencedirect.com/science/article/pii/S2192437622000243 doi: https://doi.org/10.1016/j.ejtl.2022.100099

Zhang, L., Liu, Z., Yu, L., Fang, K., Yao, B., & Yu, B. (2022). Routing optimization of shared autonomous electric vehicles under uncertain travel time and uncertain service time. *Transportation Research Part E: Logistics and Transportation Review*, *157*, 102548. Retrieved from https://www.sciencedirect.com/science/article/pii/S1366554521003069 doi: https://doi.org/10.1016/j.tre.2021.102548

Zhang, S., Chen, M., & Zhang, W. (2019). A novel location-routing problem in electric vehicle transportation with stochastic demands. *Journal of Cleaner Production*, *221*, 567-581. Retrieved from https://www.sciencedirect.com/science/article/pii/S0959652619305669 doi: https://doi.org/10.1016/j.jclepro.2019.02.167