Delft University of Technology

Research project

A mathematical model for optimal fleet and usage price control of shared EVs with V2G

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1 Introduction

When entering 21st century, the environment issue is one of the key challenges that human beings are facing. It has been estimated that in Europe, around 72% of the carbon emissions are produced by road transportation, and most of these vehicles are powered by fossil fuel which is not eco-friendly[1]. According to the statistics of International energy agency, the ICE-based(internal combustion engine) vehicles would be phrased out by seventeen countries in the way of adopting more environmentally friendly vehicles and zero-emission vehicles by 2050 gradually[2]. Moreover, the European Commission also has set a goal of "no net emissions of greenhouse gases by 2050" which is commonly said as the European green deal[1].

To begin with, the shared mobility could be considered as one possible solution for the emission reduction. Based on the research conducted by Tikoudis[3], if the shared mobility service is operated in urban area, it could contribute to the average elimination of 6.3% of passenger transport emissions. Additionally, it also helps to improve the efficiency and quality of residence's life in cities[4]. In the literature, a huge amount of papers regarding this service can be found, and the majority of existing applications are car-sharing system(CSSs)systems (CSSs), electric CSSs (eCSSs), bike sharing systems (BSSs) and autonomous connected electric vehicle (ACEV)-based CSSs and electric light vehicles. The station-based(one-way and round-way), free floating and hybrid system are the three main categories of the CSSs. The station-based CSSs means picking up and dropping off cars are only allowed in stations. For one-way station-based, the users are required to use shared mobility at the predefined stations provided by the car-sharing providers and the drop-off station could be different from the pick-up station while the round-way station-based CSSs requires the drop-off and pick-up stations must be the same[5]. The free floating is the most flexible one as the shared mobility can be accessed by users in any place of the service area and return it at the any idle parking area under the control of car-sharing providers. The last one is the hybrid system which is the combination of the first two kinds of station-based CSSs. Most car-sharing companies choose the one-way CSSs in which the customers could pick up and drop off vehicles at the specific charging stations, but this leads to a challenging system operation problem: how can we balance the distribution of vehicles?, which has widely aroused the researchers' concern[6][7].

For the initial stage, car-sharing companies mainly used the ICE-based vehicles to operate the CSSs, but recently the concept of CSSs with EVs is one of the hottest topics in transportation research field as it has the potential to create a more sustainable and greener urban transport system. In 2019, the total GHG emission produced by the ICE-based vehicles was twice the amount emitted due to the electricity generation for consumption by the same number of EVs in that year[2], which shows its high potential of reduction in emission. Thanks to the favourable policies, investment, and subsidies from the authority, increasing level of public acceptance, lower cost of EV production and better battery, and well-developed infrastructure such as charging stations to support EVs, the global mobility market split is shitting from other ways to EVs[8]. However, considering the explosive market growth and large-scale adoption of EVs, finding the way of balancing the supply and demand in energy system is crucial otherwise some problems like risk of grid overload[9] could be triggered. A smart grid system can help handle the large-scale EVs integration and control to minimize the pressure of energy system[10]. What's more, only 5% of average duration(EVs working life cycle) has been chosen as a transportation mode, which is mainly used for weekdays commuting and weekends traveling[11]. For the rest of their time(95% remaining), or in other words, the idle time, they are parked in the parking.Therefore, other secondary applications of EVs are needed to be developed through appropriate management and control when they are not demanded by users, particularly the EVs are connected with the grid, ie., when the power demand is high, the EVs can provide the energy back to the grid; and use the excess power to recharge the EVs battery. It is going to say that the EV battery is treated as a kind of power storage, which forms the basic concept of Vehicle-to-Grid technology. Moreover, the V2G technology has been proved it could bring about various benefits. It creates a new business way of involving the EVs owners and power grid together and makes revenues for both.

Furthermore, the objective of the integration of V2G technology is to make profits when the demand is high and price is also high, the EVs sell the power back to the grid while the demand and price are low, they buy the power in. This means in our case there would be a volatile electricity price during operation. Therefore, a dynamic usage price suggestion fluctuating with the electricity price(or based on the fixed reference EV usage price obtained from electricity price) could be made which helps maximize the syetem profits.

Based on the authors' knowledge, there is limited number of researchers focusing on the V2G and CSSs especially combined with the dynamic usage price scheme(DUPS). So this paper is going to propose an Mixed integer linear model(MILP) for a one-way electric cars sharing system considering V2G and DUPS. It will determine the optimal schedules of EVs charging and discharging, distribution of EVs at a certain location and find the suggested EV usage price per time step during defined operation period. Furthermore, maximizing the sum of car-sharing service revenues and V2G revenues is made as the objective function based on the providing service for customers and power sales/purchase. The electricity price variation and mean expected daily reference customer demand have been prepared and proposed as well as the relation between usage price and expected customer demand. In particular, the model can be used for V2G CSSs profits evaluation when the car fleet and system size are fixed.

The rest of paper is organized as follows: the next section will summarize the literature review about the concepts discussed in this paper. Section 3 introduces the proposed mathematical formulation. Section 4 focused on the model application and results analysis about a real-case network of Delft. The last part concludes the finding and work limitation.

2 Literature review

2.1 Car-sharing system key performance indicators

The first outputs of our model is the start-of-day distribution, so as I mentioned above, one of the main challenge is the one-way CSSs vehicle relocation. Because of the imbalanced demand-supply at various stations, there could be some cars accumulating at some stations where the trip demand is low while at the same time, other stations do not have enough cars available for users[12]. Therefore, the efficient rebalancing strategies to place the vehicles at the right places and right time are required. Previous research on car relocation challenge can be divided into two categories: the operator-based strategies and user-based strategies. For operator-based strategies, CSSs operators are responsible for the car relocation. [13] proposed a three-phase optimization-simulation model to balance the car relocation problem. This model finds the optimal vehicle relocation strategies in the first stage which was divided into a set of practical parameters like staff relocation, location threshold, etc. The last phrase would evaluate the performance of the strategies found. For user-based strategies, the users can decide where the vehicles will be relocated. [14] proposed an optimization model for the operation of one-way car-sharing system. In particular, it can determine the rejecting/accepting orders, relocations of EVs and staff movements.

In order to evaluate the performance of vehicle distribution among different locations, the key performance indicators are necessary. The first KPIs are 'zero vehicle time' or 'full port time', which represents a station without parked vehicles and the parking pot is full of reserved cars respectively[13]. Both KPIs reduce the attractiveness of CSSs, cause there is no service available for other users. What's more, some other KPIs introduced in the literature are "acceptance ratio", "average fleet usage", "number of trips" and "number of relocations". The "acceptance ratio"[15] is obtained from the completed reservation divided by the total reservations, which indicates the service quality of CSSs. The "average fleet usage"[16] got from the vehicles used in system divided by total fleet implies the service quality and efficiency of CSSs. Additionally, "number of trips"[17] provides the actual number of reservations that have been satisfied, which is a good indicator in evaluation of the service level for meeting customers' demand. The last one is the "number of relocations"[18] which helps to evaluate the performance of applying some relocation strategies.

For our proposed model, we use the "number of trips" to define the first KPI which is transferred to "CSSs revenues".

2.2 V2G technology concept

In 1992, the V2G concept was first introduced by Kempton and Letendre. This concept means the technology could make electricity to be transferred between EVs and grid bidirectionally. The EVs batteries are regarded as a kind of energy storage, when the energy demand is high, it sends the energy back to the grid to relieve the demand pressure of grid system. There is some literature proving that various benefits could be brought about by applying V2G technology on EVs, which can be classified into three parts. Firstly, they are technical advantages which include virtual power plant (VPP), frequency and voltage regulations, spinning reserve, peak shaving, load leveling, reduction of intermittence and renewable energy curtailment, renewable energy storage and congestion mitigation[19]. For environmental benefits, it reduces the carbon emissions when the technology combined with renewable power source[20] and CSSs. Finally, it leads to the social and economic benefits. For EV owners, V2G reduces the total ownership cost of EVs[12] and makes new revenues by selling/purchasing the energy stored in the batteries to/from the power grid according to the dynamic electricity price all the day. For grid operators, the EVs batteries serve as a new source for energy storage and it provides a great solution to the grid congestion and reduction in the risk of grid overload. What's more, the V2G can help office or estate owners manage the local peak shaving and load leveling.

Currently, the application of V2G technology is challenging and still at very initial stage, even though some pilot projects show the positive results by allowing the bidirectional power transformation between cars and grid. Some ongoing projects are Direct Solar DC V2G Hub @Lelystad[21] and V2G @ home Bidirektionales, Netherlands[22],etc.

2.3 Car-sharing system with V2G

In the literature, researchers[23] in 2012 first introduced the concept of Vehicle to grid combined with car-sharing system by developing a agent control architecture to achieve the goal of maximizing EVs charging involving the car-sharing operators, grid operators and renewable resources. A MPC model was proposed by[24] , and it optimizes the V2G charging/discharing, routing and relocation of automated electric cars at the same time. [25] introduced a static relocation strategies for CSSs considering vehicle-to-grid technology, which suggests the start-of-day distribution, use of V2G and meets the customers' demand simultaneously. Finally, a two-stage stochastic integer linear program was created[26] to assess the profitability of EVs CSSs considering V2G. The objective function was to minimize total cost solved by a linear-decision-rule-based method which optimizes the schedule of EVs fleet, battery charging, electricity selling together.

Therefore, what we understand from the literature is that the V2G profit is one of the important KPIs for V2G Car-sharing system performance evaluation. However, there is not doubt that it could lead to the reduction in the number of satisfied orders as if the shared EVs sell their energy back to the grid, the SOC of EVs would be lower, which means the EVs may be not available for users and the system is rejecting users. But according to the statistics mentioned above, around 95% of the working life cycle of one EV is spent in parking area, it is worthwhile to integrate V2G technology allowing the sales of power when the power price is high. So another KPI used in our objective function is "V2G profits" obtained by selling/purchase of power.

2.4 Dynamic usage price scheme

A price strategy can be divided into two parts, which are dynamic and static price strategy. The trip price determined by the trip characteristics (origin, distance and duration) and context like time of day, SOC, congestion, etc can be regarded as dynamic. If the price only depends on the trip characteristics or context, it is static[27].

When it comes to the customers in sharing service economy, the dynamic usage price (DUPS) is an essential element since the users are always price sensitive[28]. If the trip price is increasing, indeed there would be lower users' demand/intention to use. So the problem related to how to balance the usage price and users' intention to use needs a more intelligent solution to control so that it can optimize the profits. The previous study[29] developed a EVs routing optimization model that considers the transportation and power system while the electricity price is changing over time. The model minimizes the total distribution cost of EV route under the constrains of battery capacity, charging time and the influence of vehicle loading on the energy consumption per mile. Moreover, a Mixed integer nonlinear mathematical model is proposed by Jorge[30] which maximizes the profit in the way of finding optimal trip price in one-way CSSs and they pointed out that how the trip price strategies leading to reducing fleet imbalance can help to maximize the profit. Shuyun et al.[12] introduced a dynamic price scheme for a large-scale EV sharing network with the V2G technology, which solves the distribution of EVs imbalance problems and does the station-based users demand prediction.

In this paper, we took into account the dynamic usage price(DUP) scheme which makes the proper price suggestion for CSSs operators and balances trade-off between the users demand and usage price.

3 Proposed Optimization model

In this section, a mixed integer linear programming for smart start-of-day EVs distribution and schedules of charging and discharging of the one-way station-based eCSSs considering the optimal EV usage price and V2G technology has been proposed. Additionally, we introduced the detailed model description and assumption in the following section.

3.1 Model description and assumption

Sets	Definition
K = $(1, ..., i, ..., S)$	set of stations
T = $(1, ..., t_s, t_e, ...T)$	set of time steps
V = $(1, 2, ..V)$	set of EVs
$A = (1_1, 1_2, ..., i_1, ..i_t, ..., S_T)$	set of time-space network nodes, and the i_t represents station $i \in K$ at time step $t \in T$
$C^0_{i_tj}$	set of time-space aggregated expected demand where the element $C^0_{i_tj}$ represents the reference number of users leaving from station i at time step $t \in T$ with $i_t \in A$ to station $j \in K$
C_{i_tj}	after the price is varied, the estimated number of users leaving from station i at time step $t \in T$ with $i_t \in A$ to station $j \in K$
Z_i	element Z_i represents maximum parking places at each station $i \in K$
D_{ij}	travel time matrix with element D_{ij} representing the travel time from origin $i \in K$ to destination $j \in K$
e_t	estimated energy unit price sets with e_t representing the energy price at time step $t \in T$
Parameters	**Definition**
Q	Battery energy capacity(kWh)
I_c	energy charging rate(percentage): the amount of SOC increasing per time step during charging state
I_d	energy discharging rate(percentage): the amount of SOC decreasing per time step during discharging state
E_c	energy transfer efficiency of charging state(percentage)
E_d	energy transfer efficiency of discharging state(percentage)
a	consumption rate per time step of EV battery during a user trip (percentage)
SOC_{max}	the capacity of EV battery(percentage)
SOC_{min}	the lower bound of EV battery(percentage)
t_s	start of operating time
t_e	end of operating time
p_0	EV usage reference price per time step
u	upper bound of the dynamic suggested EV usage price
E_{demand}	Carsharing elasticity of demand
Decision variables	**Definition**
SOC^v_t	continuous variable(percentage) which represents the state of charging of vehicle $v \in V$ at time step $t \in T$
p_{i_tj}	continuous variable(€/time step) which represents the suggested EV usage fee for EV departing from station $i \in K$ to $j \in K$ at time step $t \in T$
$y^v_{i_tj}$	continuous variable which is the product of $p_t * x^v_{i_tj}$ by adding the constrains
$b^v_{i_t}$	binary variable; $b^v_{i_t} = 1$, when vehicle $v \in V$ is charging at station $i \in K$ during time step $t \in T$, and 0 otherwise
$w^v_{i_t}$	binary variable; $w^v_{i_t} = 1$, when vehicle $v \in V$ is on stand-by at station $i \in K$ during time step $t \in T$, and 0 otherwise
$s^v_{i_t}$	binary variable; $s^v_{i_t} = 1$, when vehicle $v \in V$ is discharging at station $i \in K$ during time step $t \in T$, and 0 otherwise
$x^v_{i_tj}$	binary variable; $s^v_{i_t} = 1$ when vehicle $v \in V$ is going from station $i \in K$ at time step $t \in T$ to station $j \in K$, and 0 otherwise

Table 3.1: *Definition of notations*

All the sets, decision variables and parameters used in the proposed model has been listed in table3.1 above.

There are a set of Car-sharing system stations K and a set of vehicles V in the system. Every station i has been assigned with limited number of parking places which is z_i, and it should be noted that this also means the number of V2G-enabled charging equipment equals to z_i. Additionally, the location and number of charging stations, capacity of each charging station and the available electric vehicles are constant in our case. The energy capacity of each EV is set to be Q and as required, the EVs only can be picked up and dropped off at a predefined station based on the reservation. Furthermore, for the operation time, we divide the entire time of one day into 2 parts which are "operating time from t_s to t_e" and "non-operating time". The EVs only can be used by users during the operation time. Therefore, the states "working" and "inactivation" are used to define the EVs and the state of EVs must be one of them. For inactivation, the EVs are plugged in or just on stand-by, while working means the EVs are serving the users. During the working state, our CSSs is making one of our KPIs "CSS revenues" by getting revenues from users. The time-space network is represented by a set of time-space nodes $i_t \in A$(statin i and time step t) and time-space aggregated customer demand matrix C(reference demand before price varies) which is based on the real data where $C^0_{i_tj}$ represents the number of customers planning to reserve a EV going from station i to station j at time step t are used to generate the EV trips. According to the customers demand, the reserved vehicle v will be travelling through the time-space network arc(i_t,j) when the value of decision variable $x^v_{i_tj}$ equals to one, while zero indicates no EVs have been reserved to traverse a specific arc. So the first optimal output of our model is the EVs distribution at the start of operation, which is on the basis of the static relocation. What is more, when the EVs are being used by customers, we consider a fixed battery energy discharging rate a to describe the reducing rate of SOC per time step due to trips. Last but not least, the travel time is represented by the element D_{ij} meaning the number of time steps are needed for EV to travel from origin i to destination j(or traverse the arc(i_t,j)). Finally, in our case, because of the energy price variation, we consider finding the optimal dynamic usage price per time step(p_t) which means it suggests the optimal usage price at a specific time step for EV that is reserved to travel from i to j within the operation period so that the model could optimize our total profits. Note: Only when there exists car-sharing demand, the DUP scheme will be activated. The suggested usage price per time step(p_{i_tj}) is the second model output. However, the users are usually price sensitive, we assume that if the price is higher/lower than a reference price(p_0) , the customers' demand in using EV would be reduced/increased. This relation between demand C_{i_tj} and usage price p_t will be explained by a mathematical formulation by introducing a car-sharing demand elasticity(E_{demand}). Then the CSS revenues can be obtained by getting the summation of travel time of each trip multiplied by its specific p_{i_tj}.

The state "inactivation" consisting of 3 possible phases: charging, discharging and stand-by would lead to the V2G revenues. Firstly, it is the fact that EV battery charging and discharging process should be a non-linear pattern, and in some previous study like vehicle routing problem, the charging/discharging process is always explained by mathematical formulations which are fixed-rate, linear or non-linear charging patterns. Considering the high requirements for linear or non-linear function in computation time and their application in a real large-scale network and limitation of computation equipment, it would be reasonable to only analyse the constant charging function in our case. Therefore, by taking the transfer efficiency into account, we can easily get the the exact amount of energy purchased/sold from/to grid which are $Q * E_c * I_c$ and $E_d * Q * I_d$ during time step t with the estimated electricity unit pricee_t. And the SOC^v_t of vehicle v at time step t demonstrating the battery charging state will be increased or decreased by the charging/discharging rate(I_c and I_d) during inactivation state. For the stand-by phase, EVs are not going to do anything and their SOC keeps constant. The EVs discharging, charging and stand-by states would be controlled by our model, so a detailed schedule about these three phases of each EV at each time step within the operation period is the third output of our model. The state of EVs in the system at each time step is represented by the binary variables$s^v_{i_t}$, $w^v_{i_t}$ and $b^v_{i_t}$. The difference between the energy purchase cost and sales revenues is the V2G profits.

3.2 Model formulation

$$max \sum_{v\in V}\sum_{i_t\in A}\sum_{j\in k} y^v_{i_tj} * D_{ij} + \sum_{v\in V}\sum_{i_t\in A}(e_t * E_d * s^v_{i_t} - e_t * b^v_{i_t}) \tag{3.1}$$

subject to:

$$y^v_{i_tj} \le u * x^v_{i_tj}, \forall i_t \in A, j \in K, v \in V \tag{3.2}$$

$$y^v_{i_tj} \le p_{i_tj}, \forall i_t \in A, j \in K, v \in V \tag{3.3}$$

$$y^v_{i_tj} \ge p_{i_tj} - u * (1 - x^v_{i_tj}), \forall i_t \in A, j \in K, v \in V \tag{3.4}$$

$$y^v_{i_tj} \ge 0, \forall i_t \in A, j \in K, v \in V \tag{3.5}$$

$$C_{i_tj} \ge C^0_{i_tj} + \frac{E_{Demand} * C^0_{i_tj} * (p_{i_tj} - p_0)}{p_0} - 0.5, \forall i_t \in A, j \in K \tag{3.6}$$

$$C_{i_tj} \le C^0_{i_tj} + \frac{E_{Demand} * C^0_{i_tj} * (p_{i_tj} - p_0)}{p_0} + 0.5, \forall i_t \in A, j \in K \tag{3.7}$$

$$C^0_{i_tj} + \frac{E_{Demand} * C^0_{i_tj} * (p_{i_tj} - p_0)}{p_0} \ge 0, \forall i_t \in A, j \in K \tag{3.8}$$

$$C_{i_tj} = 0, \forall i_t \in A, j \in K, C^0_{i_tj} = 0 \tag{3.9}$$

$$\sum_{v\in V} x^v_{i_tj} \le c_{i_tj}, \forall i_t \in A, \forall j \in K, i \ne j \tag{3.10}$$

$$\sum_{i\in K}\sum_{j\in K} x^v_{i_1j} = 1 \tag{3.11}$$

$$\sum_{j\in K} x^v_{i_tj} = \sum_{j_{t-D_{ji}}\in A|j\ne i} x^v_{j_{t-D_{ji}}i} + x^v_{i_{t-1}i}, \forall v \in V, \forall i_t \in A, t \ge 2 \tag{3.12}$$

$$SOC^v_{t-1} + E_c * I_c \sum_{i\in K|i_t\in A} b^v_{i_t} - I_d \sum_{i\in K|i_t\in A} s^v_{i_t} - a \sum_{i\in K|i_t\in A}\sum_{j\in K|j\ne i} x^v_{i_tj} * D_ij = SOC^v_t, \forall v \in V, t \in T, t \ge 2 \tag{3.13}$$

$$\sum_{v\in V}\sum_{j\in K} x^v_{i_tj} \le z_i, \forall i_t \in A \tag{3.14}$$

$$b^v_{i_t} + s^v_{i_t} + w^v_{i_t} = x^v_{i_ti}, \forall v \in V, i_t \in A \tag{3.15}$$

$$SOC^v_1 \le SOC^v_T, \forall v \in V \tag{3.16}$$

$$SOC_{min} \le SOC^v_t \le SOC_{max}, \forall v \in V, \forall t \in T \tag{3.17}$$

$$b^v_{i_t}, s^v_{i_t}, w^v_{i_t} \in 0, 1, \forall v \in V, \forall i_t \in A \tag{3.18}$$

$$x^v_{i_tj} \in 0, 1, \forall i_t \in A, \forall j \in K, \forall v \in V \tag{3.19}$$

The formulations(3.1-3.19) above are the proposed optimization model to maximize the total profits, taking into consideration the "V2G profits" and "Car-sharing system revenues" which are the revenues from 1)energy purchase and sales; 2)serving customers' trips introduced in section 2. It should be noted that when the EVs are selling or buying the energy to/from grid, the EV owners need to cover the cost of energy transfer loss, which means during sale process, we consider the transfer efficiency E_d in the second term(energy sales revenues) of our objective function while no transfer efficiency used in the third term(energy purchase cost). Moreover, a varied energy price of a day and EV dynamic usage price(DUP) are considered in our model. In particular, the varied energy price is an important influential factor when trying to maximize the V2G profits while the dynamic usage price would affect the CSSs service revenues obtained from customers.

The formulations(3.2-3.19) are the constrains that our objective function is subject to. Equations(3.2-3.5) are essential for adding the new continuous variable y_{itj}^v to replace the product of $x_{itj}^v * p_t$ which are a binary variable and a continuous variable in objective function to represent a reserved trip of vehicle v travelling from station i to j at time step t with suggested EV usage price p_{itj}, if $x_{itj}^v * p_{itj}$ is directly used in objective function, it would become a non-linear problem which hugely enhances the complexity in the process of finding solutions. Constrains (3.6) and (3.7) compute the new estimated demand C_{itj} resulting from the EV usage price change based on the mean expected reference customers' demand C_{itj}^0. We assume that the demand is the continuous function of EV usage price with a known car-sharing price elasticity to the mean expected demand E_{demand}, and these two formulations also ensure the calculated demand is always integer. The calculated demand should be positive or none, and that is why we use constrain (3.8) and (3.9). Constrain (3.10) assigns the EVs on the basis of customers demand C_{itj} that is planning to travel from station i to j at time step t. And it should be noted that the users' demand only occurs during the operation time from starting time t_s to ending time t_e. Additionally, the situation when $i = j$ is excluded as there is no user demand for travelling at the same station ($C_{iti} = 0$). Constrain (3.11) guarantees that a arc(i_1,j) has been chosen by a vehicle v to transverse at the start of the day(t=1) leading to the start-of-day EV distribution. And as noted, i could equal to j if the vehicle stays at the same parking station. Constrain (3.12) ensures the continuous conservation of vehicle flows at each node of time-space network. Constrain (3.13) defines the SOC of each vehicle v at each time step, which is calculated by residual SOC at previous time step (SOC_{t-1}^v and sum of other three terms representing the energy change during two possible EV states. The inactivation state is represented by the first and second term which are energy purchase from the power grid and energy sales of EV batteries back to the power grid, while the third term indicates the working state in which the energy of EVs batteries is consumed by serving customers. Constrain (3.14) defines the maximum number of parking places at each station i, and the number of EVs assigned at each station should not exceed the capacity of this station z_i. Constrain (3.15) makes sure that during inactivation state, there is only one phase can be selected by the vehicle v. These phases are charging, discharging and stand-by when $x_{iti}^v = 1$ the EVs are parked in parking lot and not used by users. Constrain (3.16) ensures that the SOC of the EV at the start of operation(t=1) should not exceed the SOC of the same EV at the end of operation(t=T). Since this condition guarantees that with the goal of maximizing the V2G profits as much as possible, the system should avoid the situation that it always gives the capacity of battery defined(SOC_{max}) to the SOC_1^v at the start of operation and the lowest value(SOC_{min}) to the SOC_T^v at the end of operation time. Constrain (3.17) limits the SOC of each vehicle v at any time step within the technology-allowed range which has lower and upper bound (SOC_{min} and SOC_{max}). Finally, the domain of each decision variable is defined by the constrains (3.18,3.19).

4 Case study

4.1 Numerical experiment with small-size case

Before starting to apply my model to the real case-study network, I tested the proposed model under three different scenarios with a small-size dataset to understand if it works well and evaluate its performance and computation time.

Parameters	Selected values	Literature
p_0	0.3€/min	[31]
E_{demand}	-1.5	[30]
u(upper bound of EV usage price)	30€/h	-
Z	6	-
a	4%/h	[32]
I_c/I_d	0.444/h	-
E_c/E_d	0.9	-

Table 4.1: *Parameters used in experiment case*

The data used for the small size test are set as follow (or see table 4.1 above): I assume there are 5 parking stations in the network and its parking capacity Z is 6 each. Then for test only, non-operation time is not taken into account while the operation period is divided into 10 time steps(1h=1 time step). Moreover, the EV fleet size are fixed which are equal to 12. And the predefined mean energy price(see figure 4.2) fluctuates between 0.02€/kWh and 0.025€/kWh along the day (This is a assumed changing trend for test only). The reference EVs usage fee per time step p_0 is selected to be 18€/time step(h)[31]. What's more, as stated before, a dynamic EV usage price(DUP) strategy is considered in this model to help increase the profitability of CSSs. Considering the model complexity and computation time, the static price scheme is applied, which means the price only depends on the trip context. For our case, the price is only related to the time of day and expected demand and its value is restricted within range from 0 to u=30€/time step(h) . And the estimated travel demand after varies usage price in this model, is explained by a elastic formulation by applying a price elasticity E_{demand} which is set equal to -1.5[30] to reference demand D_0. Last but not least, all the parking stations in our system are installed with fast-charging CHAdeMO connectors supporting V2G technology which is a DC charging protocol. It can be used for charging E-bus and EVs[33] with power varying from 6 to 400kW. The EV battery, Nissan Leaf 2020, is selected in this simulation with a energy capacity of 40 kWh as it has a quite consistent performance in bi-directional charging. Furthermore, based on the capabilities of Nissan Lear 2020 EV battery[32], the maximum kilometers that can be reached by the EVs are 270km. And I assumed that the type(size) of EV that will be used in test is in a small size with a low running-speed. The average EV speed is set equal to be 10km/h, which means the energy consumption rate per time step when they are serving users is a=4%. Additionally, since there is no reference regarding the charging and discharging rate of Nissan Leaf battery, the charging rate I_c and discharging rate I_d are both set to be 0.444 per time step with the same transfer efficiency E_c=0.9(since there would be energy loss during transformation). Finally, the assumed reference travel demand and travel time data are listed in following table 4.3 4.2.

Destination j	Origin i				
	1	2	3	4	5
1	0	2	1.5	2.6	3.15
2	2	0	1	1.25	2
3	1.5	1	0	1	1.5
4	2.6	1.25	1	0	1
5	3.15	2	1.5	1	0

Table 4.2: *Travel time for each pair of origin and destination*

origin i	**timestep t**	**destination j**	travel demand
1	2	2	5
2	5	5	5
3	8	5	5
3	9	1	5
3	9	4	5
2	9	1	5
4	1	5	5
5	5	1	5
5	4	1	5

Table 4.3: *Travel demand used for test*

Then I used software Gurobi Optimizer version 9.5.1 build v9.5.1rc2 (win64) to solve the proposed MILP model. For the test experiment, there is no time limit and gap limit had been set as I tried to get the most optimal solution. With these settings, the software finds the optimal solution with the tolerance gap equal to 0.50%, and the objective function value for V2G-DUP is 1025.7€ which is the sum of CSSs revenues(1013.5€) and V2G profits(12.2€).

For the purpose of seeing any existing improvements, the obtained results have been compared with a scenario(V2G) only with V2G technology and a scenario(Base) without V2G technology and dynamic EV usage price scheme(DUP). The "Base" is set up by making all the decision variable s_{it}^{v} to be 0 which indicates that during inactivate state, there is no energy transferred back to grid. All the results are shown in following table 4.4 4.6 4.5.

	CSSs revenues	Energy purchase	Energy sale	Objective value	V2G profits
Base	787.5	7.2	0	780.3	-7.2
V2G	787.5	28	48	807.5	20
V2G-DUP	1017.12	29.44	41.6	1029.28	12.16

Table 4.4: *Profitability comparison*

timestep t	from station i	to station j	suggested usage price	estimated demand
2	1	2	19.2	5
5	2	5	24	3
9	2	1	26.4	2
8	3	5	28.8	1
9	3	1	28.8	1
9	3	4	28.8	1
1	4	5	19.2	5
4	5	1	26.4	2
5	5	1	24	3

Table 4.5: *Suggested EV usage fee per time step at a specific time step t from station i to j for V2G-DUP*

Based on the tables above, the ranks for the optimal values of 3 objective functions are V2G-DUP, V2G and Base where the highest value generated by V2G-DUP is 1025.68€ which is the sum of CSSs revenues obtained from serving users and V2G profits calculated by the difference between energy purchase and energy sale. Except the base scenario where V2G is not integrated, V2G and V2G-DUP both produce the positive V2G profits, which means for these two scenarios, the energy sale would cover the cost of charging during operation time and even improve the profit for EV owners. Moreover, one important output of my model is the suggested EV usage price at a specific time step. As we can see from table4.5, it should be noted that the suggested scheme is only activated when there is demand existing at a certain time step, so they are time step 1,2,4,5,8,9 in test case. The new suggested prices are all higher than the reference price which is 18€ but lead to reducing (45-23)/45=48% of travel demand while enhancing 27.5% of total profits compared with that of V2G. And after varied demand, all travel requests have been satisfied while for V2G and Base, only 22 of 45 total demand has been served. Therefore, the results seem to be acceptable as our goal is to earn total profits as many as possible.

Base		V2G		V2G-DUP	
vehicle v	assignment at start of day	vehicle v	assignment at start of day	vehicle v	assignment at start of day(station i)
1	4	1	1	1	3
2	1	2	4	2	1
3	1	3	1	3	4
4	1	4	3	4	1
5	4	5	4	5	1
6	3	6	3	6	1
7	4	7	4	7	4
8	1	8	1	8	1
9	4	9	4	9	4
10	1	10	1	10	3
11	4	11	1	11	4
12	3	12	4	12	4

Table 4.6: *EV assignment at start of day*

Table4.6 listed the EV assignment at start of the operation time for three scenarios and its main goal is to meet the users demand.

The solution of "V2G-DUP" can be represented by the EV movements in the time-space network(see table 4.7),which shows the location of each vehicle v at a certain time step. Each cell in the table represents the parking station i at a time step t and the number inside the cell means the vehicle orders. As stated in section 3.2, constrains (3.10-3.12) guarantee that the EV must go through the time-space network based on the value of decision variable $x^v_{i_t j}$. For instance, if $x^9_{1_2 2} = 1$, the vehicle 9 transverses arc(1,2) at time step 2(can be seen in table4.7) which also means one travel demand has been satisfied by vehicle 9. What is more, by checking table4.7 and 4.5, we find that almost all the estimated demand has been satisfied and all EVs are used at least once during operation.

	time step									
Station i	1	2	3	4	5	6	7	8	9	10
1	3,5,8, 9,10	3,5,8, 9,10			4,6,11	1,2,4, 6,11	1,2,4, 6,11	1,2,4, 6,11	1,2,4, 6,11	1,2,4,6,8,12
2			3,5,8, 9,10	3,5,8, 9,10	3,5,8, 9,10	8,10	8,10	8,10	8,10	11
3	7,12	7,12	7,12	7,12	7,12	7,12	7,12	7,12	7,12	10
4	1,2,4,6,11									
5		1,2,4, 6,11	1,2,4, 6,11	1,2,5,6,11	1,2	3,5,9	3,5,9	3,5,9	3,5,7,9	3,5,7,9

Table 4.7: *EV movements in the time-space network during operation for "V2G-DUP"*

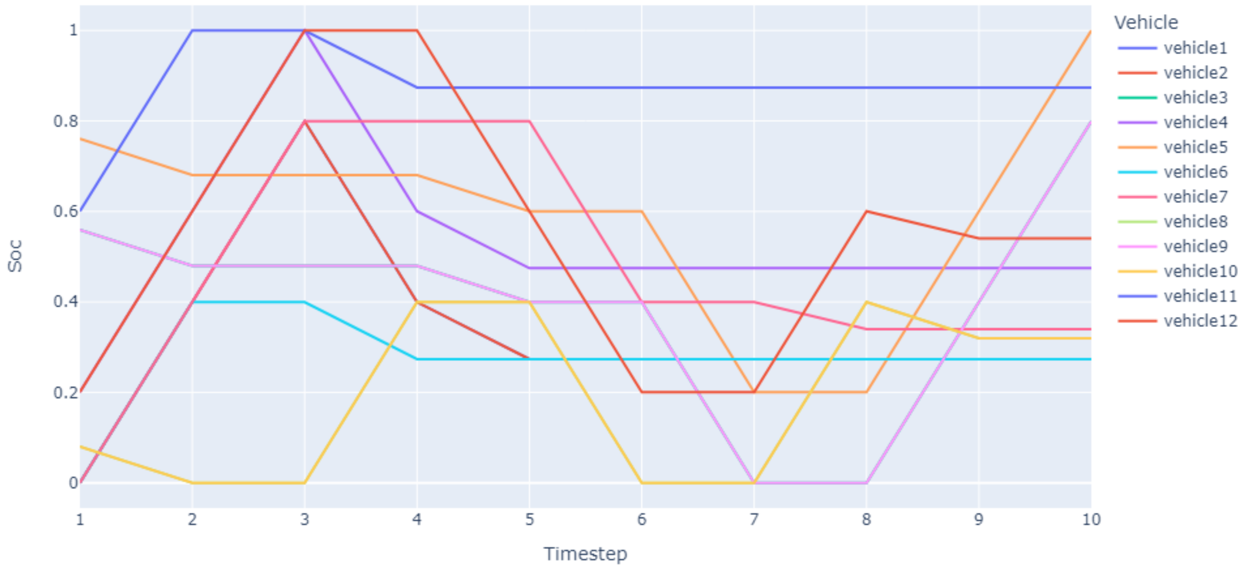

Figure 4.1: *SOC variation of each EV at each time step*

Another output of my model is the smart schedule of EV energy purchase/sale on the basis of electricity price variation and I present the SOC of each EV at each time step within the operation time. This smart scheduling can be found easily in figure 4.1 and 4.2: almost all the charging phases are taking place between time step 2 and time step 4 or 5 where the energy price is low while the discharging phases mostly occur at time step 5 to 7 with a high energy price. This is reasonable as one of our goal is to propose a smart charging/discharging operation to control the energy purchase and energy sale when the energy price e_t is low and high, respectively.

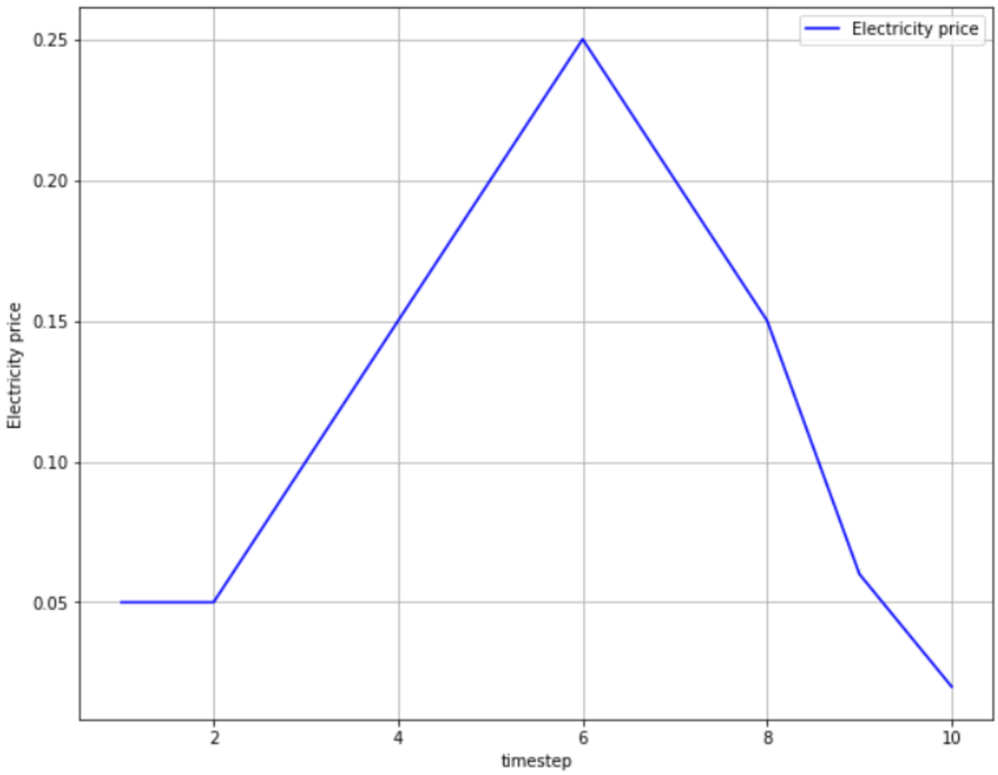

Figure 4.2: *Predefined energy price variation along the time step*

4.2 Application to real case: the city of Delft

4.2.1 Generating extra cuts to the problem

When finishing the test experiment in section 4.1, we found the computation time of the proposed mathematical model is quite long with such a small size of data. Therefore, considering the potential high computation time, the following constrains are imposed to accelerate the Branch and bound search.

$$\sum_{j \in K | i \neq j} x_{i_t j}^{v} \leq 1, \forall i_t \in A, v \in V \tag{4.1}$$

The constrain (4.1) is used to generate the extra cuts to the problem, and it should be noted that this does not change the solution space but helps tight the feasible domains by removing the non-integer solutions during the process of branch-and-bound relaxation method, which would reduce the computation time of finding optimal solution. It imposes that there is always only one variable representing the movement of vehicle v going through arc(i,j) serving one traveler can be selected to equal to 1. Even though the constrain(3.12) has been defined to maintain the flow conservation, the sum of left hand side of it is the same as the sum of the right side. But it may happen that each variable is within its domain but the value of sum on two sides exceeds one during the brand-and-bound search process. By adding this bound constrain(4.1), the relaxation process can avoid that situation and accelerate computation.

4.2.2 Symmetry breaking constrains

Another technique applied to reduce the computation time is the symmetry breaking valid inequalities, which has been proved in lots of literature that inputting variables' orders can have a good influence on the computation performance in solving the vehicle routing problem. Since for my case, all the EVs are homogeneous, giving orders indeed could help avoid the situation of searching some branches which are the same but only differ in vehicle orders. The symmetry breaking constrains are defined as follow:

$$\sum_{i_t \in A} \sum_{j \in K} x_{i_t j}^{v} * D_{ij} \leq \sum_{i_t \in A} \sum_{j \in K} x_{i_t j}^{v-1} * D_{ij}, \forall v \in V, v \geq 2 \tag{4.2}$$

This set of constrains breaks the symmetry by arranging the vehicle order based on the total travel time it would spend in satisfying travel demand ensuring that vehicle v that is going to travel for a longer time will be ordered first. This gives an order to our decision variables.

It should be noted that there must be some more techniques about the valid inequalities that will help accelerate the computation process, but talking about that seems to be out of scope of our research.

4.2.3 Setting up the real case

The proposed model is applied to the Delft city in the province of South Holland, Netherlands. Because of the limitation of data availability, a quasi-real case-study is applied. The goal of the case study is to test the model's performance and to get a rough understanding of the effects that may be induced by the application of V2G and Dynamic EV usage price in urban CSSs. The mobility dataset(2007/2008) is obtained from the Dutch mobility database which is collected by Dutch government and used for mobility behaviour research. The data consists of the individual daily movements on the basis of household with personal information regarding departure and arrival time, trip purpose, transport mode, trip dates(day, month and year), and origin and destination(post code). Until 2008, the trips of each household in delft were recorded, which are around 69635 in total on one day.

Then the dataset needs to be filtered and aggregated to obtain the daily mean expected reference travel demand C^0 of Delft city since it is not possible to analyze 69635 trips. The assumption is that a mobility-sharing company is operating shared EVs in Delft with operation period from 7:00am - 21:00pm and all the travel demand is expected to be satisfied. Furthermore, only trips by cars and taxi are considered leading to the current total number of trips are reduced to 16,140 which is still a big number. According to the previous research, actually in survey, each surveyed household represented 20 real households where an expansion coefficient of $\mu_h = 20$ is applied. Therefore, to derive the actual expected car-sharing demand in Delft, the real 16,140 trips are divided by 20 which means only 807 trips have been taken into account in my model. What is more, the assumed time step is 1 hour, so our demand is aggregated based on 1h intervals. Figure 4.3 shows the final filtered expected car-sharing reference demand of one day in Delft (The number represents the potential total car-sharing requests at a certain time step, but single request may differ in origin and destination).

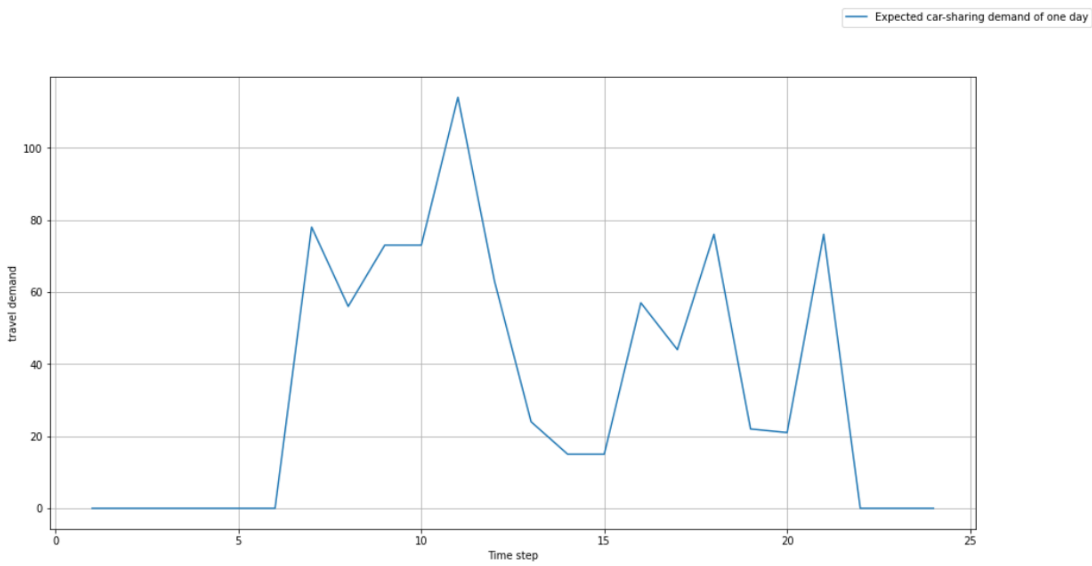

Figure 4.3: *Number of car-sharing requests per time step*

Figure 4.4: *Satellite map of Delft[34]*

The transport network of Delft has been simplified into 61 road links and 46 centroids based on the satellite map of Delft, see figure 4.4(used by Correia and van Arem[34]). Our hypothesis is that all EVs and charging stations have been equipped with V2G technology. Furthermore, the entire administrative region of Delft is divided into 13 boroughs officially which are 1: Delftse Hout, 2: Vrijenban, 3: Binnenstad, 4: Hof van Delft, 5: Voordijkshoorn, 6: Wippolder, 7: Voorhof, 8: Buitenhof, 9: Schieweg, 10: Tanthof-Oost, 11: Ruiven, 12: Tanthof-West, 13: Abtswoude[35] (figure 4.5), so I assume each centroid of borough would have a CSSs parking station with bi-directional charging columns.

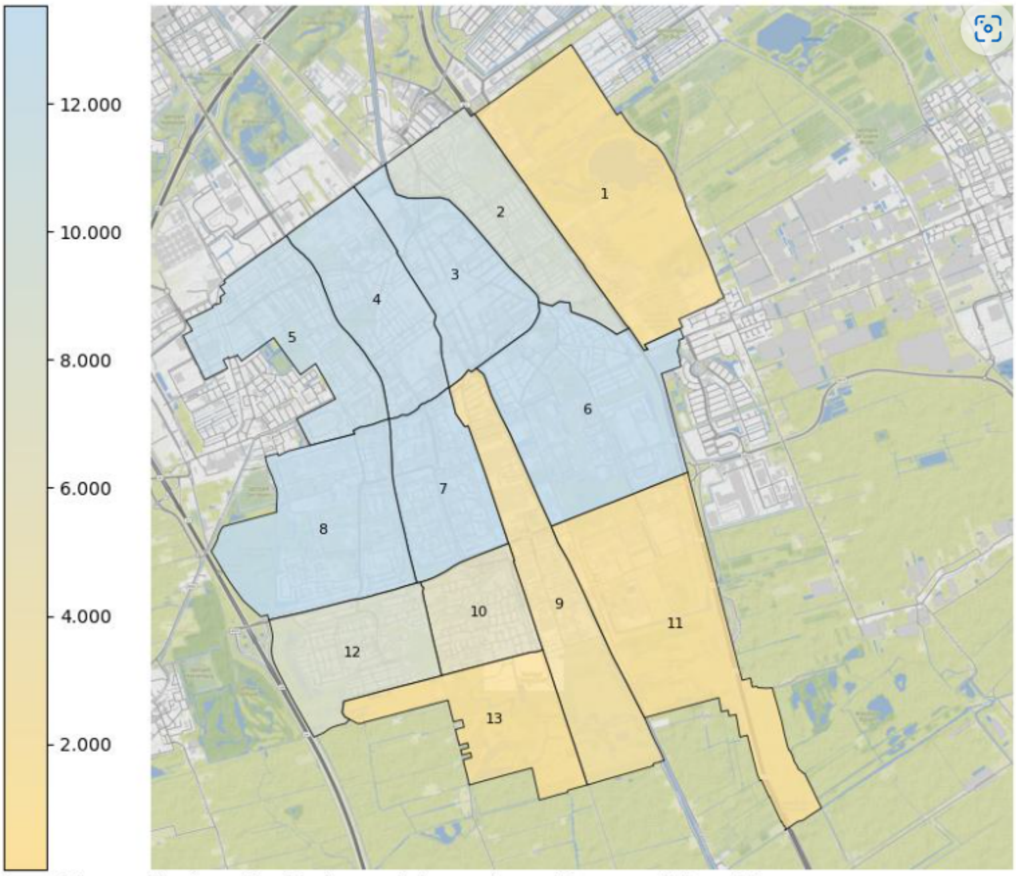

Figure 4.5: *13 Boroughs of Delft[35]*

The filtered dataset is classified on the basis of the origin/destination OD travel demand matrix. Each pair of OD among 46 centroids in simplified network in figure 4.4at a certain time step with number of expected requests has been well-specified. Then assignment of the location of centriod of 46 centriods on the official segregation map is done according to their geographical coordinates, in other words each borough will have some origins/destinations assigned based on the real location. For more detailed information, you can check figure4.6 and table4.8 showing the assignment of ODs where the black nodes indicate the origin or destinations of my filtered dataset. It is assumed that the expected car-sharing customers departing within the specific borough will use the CSSs parking station located in the center of that borough. So based on these assumptions, the dataset was finally aggregated to derive the expected car-sharing reference demand matrix C^0 among 13 boroughs in Delft at each time step. For instance, the car-sharing requests of borough 1:Delftse Hout should be the sum of centroid 24 and 1 requests. It should be noted that all our shared EVs are reserved in advance by users.

	Assigned centroids at each borough
1: Delftse Hout	1, 24
2: Vrijenban	2, 17
3: Binnenstad	25, 19
4: Hof van Delft	46, 28, 3
5: Voordijkshoorn	39, 4
6: Wippolder	29, 2, 10
7: Voorhof	44, 9, 23
8: Buitenhof	40, 43, 42
9: Schieweg	16, 34, 32, 8, 14, 33
10: Tanthof-Oost	38, 37, 22
11: Ruiven	30, 31, 41
12: Tanthof-West	20, 21, 27, 45
13: Abtswoude	26, 5, 6, 36, 35, 11, 7, 12, 13, 15

Table 4.8: *Assignment of centroids in each borough of Delft*

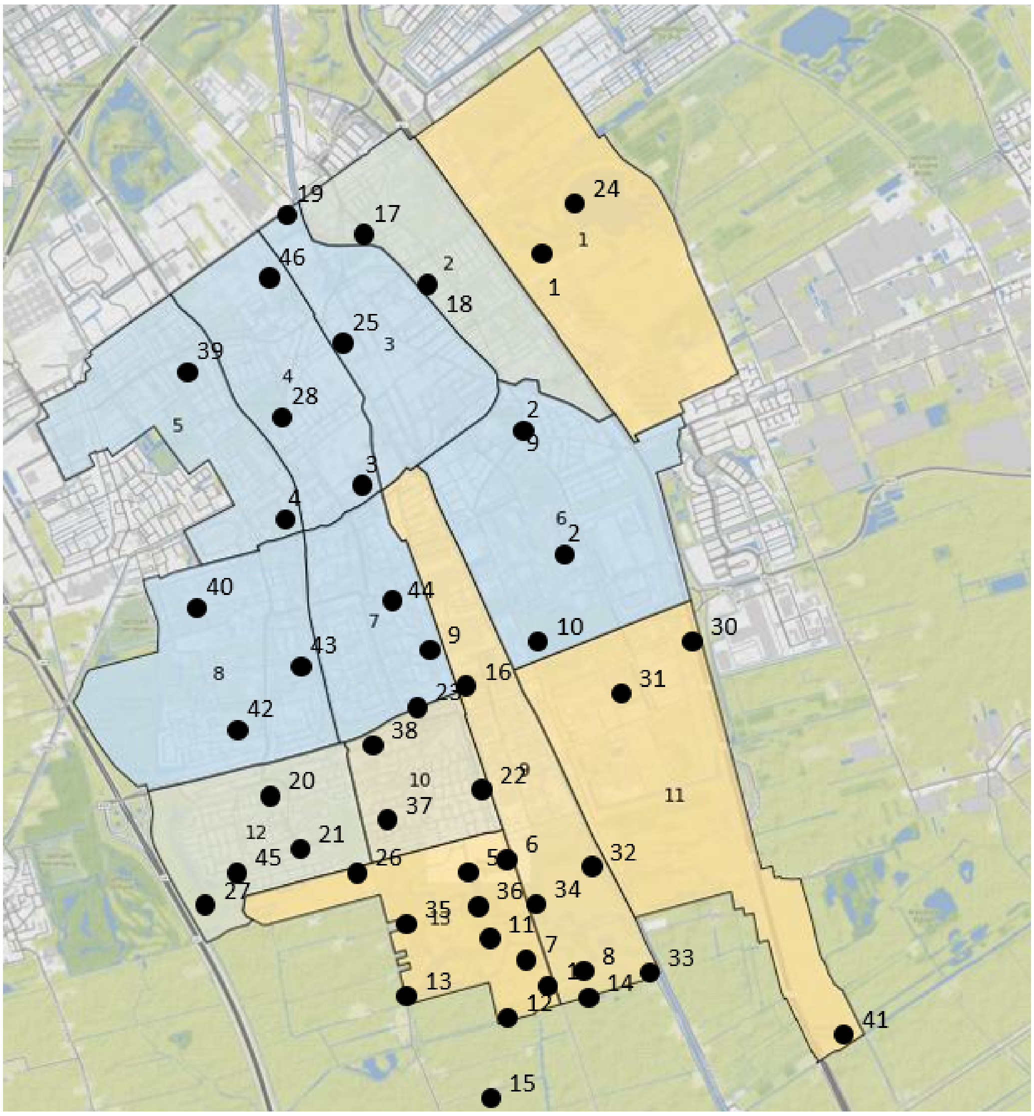

Figure 4.6: *The assignment of ODs and potential location of stations of Delft*

Since the assumed parking station location is at the centoid of each borough, the coordinates of them are known which can be used for minimum distance calculation by applying Dijkstra's algorithm in the real network. Then I divide the minimum distance between two stations by the assumed EV average speed and by 1 hour which is the duration of one time step in our case to get the pairs of travel time among different stations(travel time matrix D).

Some other assumptions and considerations used in our application are listed as follow:

1. The capacity of parking places at each station is 10, $Z = 10$
2. The EV battery model used in this case study is the same as the setting in test experiment such as parameters $a, E_d, E_c, etc.$ Readers can check table4.1
3. For my case, the whole day is divided into 24 time steps with duration of 1h each. The operation time is chosen to last from time step 7 to time step 21, and the rest of day is the non-operation period.
4. Other parameters like reference EV usage fee and its upper bound remain the same as Small-size test

The last important part that should be introduced in our model is the variation of electricity price model along the day. My assumption is that the expected electricity prices can be estimated from the average energy market in Germany. Therefore, a estimated hourly electricity prices model was proposed based on the German energy web[36]. The figure4.7 shows the fluctuations of energy unit prices e_t along the day which varies between 0.039 and 0.068 Kwh per Euro.

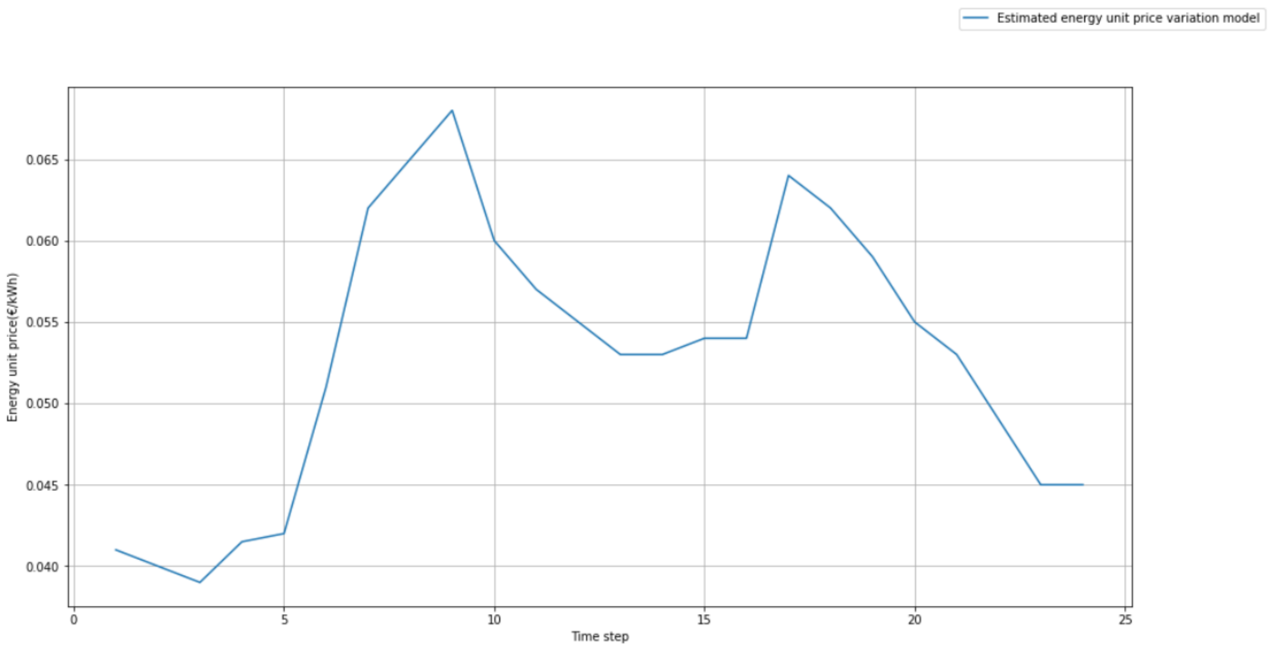

Figure 4.7: *Estimated electricity unit price variation along the day*

4.2.4 Perform the sensitivity analysis

Regarding the sensitivity analysis, I am going to set up several scenarios under different conditions. So 2 values of Demand elasticity(E_{demand}) and 2 types of vehicle fleet coefficients have been taken into account. We define a new parameter vehicle fleet coefficient N here, which means the number of trips that one EV needs to serve in the system to help reach the goal of our objective function. Firstly, 2 different fleet coefficients N_1, N_2 would be combined with the same three scenarios as small-case study which are Base-N1, Base-N2, V2G-N1, V2G-N2, V2G-DUP-N1 and V2G-DUP-N2 as there is no E_{demand} considered in Base and V2G. Then from the combination of N1, N2 and E^1_{demand}, E^2_{demand}, four scenarios would be evaluated for V2G-DUP only(V2G-DUP-N1-E^1_{demand}, V2G-DUP-N2-E^1_{demand}, V2G-DUP-N2-E^1_{demand} and V2G-DUP-N2-E^2_{demand}. The scenarios with corresponding parameters are illustrated in table4.9 .

	N(trips/vehicle)	Demand Elasticity
Base-N1	16	-
Base-N2	20	-
V2G-N1	16	-
V2G-N2	20	-
V2G-DUP-N1	16	-1.5
V2G-DUP-N2	20	-1.5
V2G-DUP-N1-E2	16	-2
V2G-DUP-N2-E2	20	-2

Table 4.9: *Parameters values used in different scenarios*

Because of the limitation of the computation ability of my computer, the tolerance gap is set equal to 0.1 and time limit is equal to 10h.

4.2.5 Results analysis

The computation process has been finished in the same equipment as the one in test experiment, and all the scenarios will be conducted under the same reference car-sharing demand. However, it should be noted that for one-way station-based CSSs, a huge number of shared cars are needed for fully satisfying the total demand, if there is no vehicle relocation operation during operation time[37]. That is why we choose the fleet coefficients as the sensitivity parameters to see if fleet size has any impact on the performance of our proposed model. Moreover, we assume that the unsatisfied travel demand will be served by other transport modes like public transport, other car-sharing system or private cars. The following tables and figures will show the outputs of my proposed model:

and from different perspective of view, we can make various observations.

	CSSs revenues	Energy purchase	Energy sale	V2G Profits	Objective value
Base-N1	649.8	12.48	0	-12.48	637.32
Base-N2	948.6	18.72	0	-18.72	929.88
V2G-N1	626.94	134.128	246.896	112.768	739.708
V2G-N2	891	217.352	410.48	193.128	1084.128
V2G-DUP-N1	1001.958	124.416	158.352	33.93601	1035.894
V2G-DUP-N2	1445.148	194.4	246.656	52.25601	1497.404
V2G-DUP-N1-E2	907.8046	116.912	151.376	34.464	942.2686
V2G-DUP-N2-E2	1319.275	191.024	243.088	52.064	1371.339

Table 4.10: *The results of defined scenarios*

From the table4.10, some findings could be made as follow. Firstly, from an total profit point of view, by comparing the Base scenarios with all other scenarios, an obvious increasing in objective revenues could be found. In particular, applying V2G technology only could increase total profits a bit than baseline while applying V2G and dynamic usage price scheme performs better in maximizing profitability of car-sharing company than Base and V2G. And the biggest improvement on total profits is 1497.404-637.32=860.084€ by comparing results of Base N1 and V2G-DUP-N2, which increased around 135%. Therefore, as a car-sharing company, increasing fleet size and deployment of DUP seems to be good at resulting in greater profitability. The best performance appears to be the scenario V2G-DUP-N2 with the highest objective revenues among 8 scenarios. But it doesn't mean it is the best solution of the operation strategy for the car-sharing company in Delft as they have two different sensitivity parameters, and one of them(fleet size) will undoubtedly lead to higher initial investment in EVs purchase. Furthermore, taking out the the scenarios with the same parameters like Base-N1, V2G-N1, V2G-DUP-N1, V2G-DUP-N1-E2(or Base-N2, V2G-N2, V2G-DUP-N2, V2G-DUP-N2-E2) and making comparisons, we found that indeed increasing the fleet size(N) would improve the total profits as it always leads to more CSSs revenues, but lower total profits will be made after decreasing the demand elasticity from -1.5($E1$) to -2.0(E2). This is true and easy to be interpreted since more EVs in the system can satisfy more travel requests and higher E would have a higher penalty in balancing demand loss and usage price increase, which also means the $E = -1.5$ performs better in our proposed model.

Secondly, we are going to talk about the V2G profits. For the first four scenarios(without DUP scheme), the obtained CSSs revenues are always higher than the V2G Profits. This is because the parameter reference EV usage price p_0 is set higher than the biggest difference between two varied electricity prices along the day, which means the priority of our CSSs always focuses on serving travel requests and the energy sale state should occur only if there is no refused demand increase. But when DUP is applied(for last four scenarios), the same situation take places: CSSs revenues are greater than V2G Profits. This implies the application of DUP in our model doesn't change the service priority of our system. What is more, we found that the energy purchase of Base costs much less than any other scenarios. Since two Base doesn't allow the energy sale, there would be no energy purchase happening when the energy price is low and then energy sale back to the grid when energy price is high. The most interesting observation is that the V2G Profits are all positive for the scenarios with V2G, which means the V2G technology can fully cover the charging costs of the EVs on that day and it will not be negatively influenced by the application of DUP.

	Energy bought from grid(operation)	Energy sold back to grid(operation)	Net energy transfer(operation)
V2G-N1	1744	3136	1392
V2G-N2	2800	5232	2432
V2G-DUP-N1	1136	1936	800
V2G-DUP-N2	1712	3008	1296
V2G-DUP-N1-E2	1008	1808	800
V2G-DUP-N2-E2	1664	2944	1280

Table 4.11: *Net energy transfer during operation time(kWh)*

Based on the table 4.11 above, some observations can be made. To start with, by comparing net energy transfer of all scenarios, we found the V2G-N2 leads to the highest value which is 2432kWh while the lowest net energy transfer(800kWh) is made by V2G-DUP-N1 and V2G-DUP-N1-E2. This net energy transfer during operation is a very significant value as the electricity demand is always high at the same time, sending the power stored in the EVs battery back to the grid when the EVs are not reserved by the users indeed helps release the pressure of electricity supply during peak hour. Sorting out the scenarios with similar parameters(V2G-N1, V2G-DUP-N1 and V2G-DUP-N1-E2; V2G-N2, V2G-DUP-N2 and V2G-DUP-N2-E2) and making comparisons, we observed that for scenario with V2G only, increasing net energy transfer can be realized by expanding fleet size. But after deployment of DUP scheme, a sharp decrease in net energy transfer is found. For instance, the results of V2G-DUP-N2 and V2G-DUP-N2-E2, which are 1296 and 1280, were reduced by around 50% compared with that of V2G-N2(2432kWh). Moreover, another finding is that after applying DUP, increasing the fleet size(N) doesn't make much sense in improving net energy transfer while enhancing the demand elasticity nearly shows no impact on the net energy transfer. This can be explained by the fact that because the flexibility of usage price and varied demand, more cars would be used for serving travel requests with higher potential profits instead of energy purchase and sale, leading to less energy transferred back to grid. According to the reference[38], the average energy consumption per household per day in EU would be about 16kWh. This means considering the EV fleet in each scenario, one EV probably could meet at least one(V2G-DUP-N1 and V2G-DUP-N1-E2) households' energy demand during peak hour while for V2G-N2, this number ups to 2. Therefore, from the perspective of local government, if they want a more constant energy supply and to release the pressure of energy supply during peak hour which would also help extend the life cycle of energy grid, they'd better consider V2G-N2 regardless of EVs purchase costs.

		V2G-DUP-N1		V2G-DUP-N2	
(Origin,time, destination)	Reference demand	Estimated demand	Suggested EV usage price	Estimated demand	Suggested EV usage price
(1, 8, 9)	26	1	29.76923077	6	27.46153846
(4, 13, 11)	24	2	29.25	4	28.25
(5, 17, 6)	44	0.5	30	8	27.95454545
(6, 20, 12)	21	2	29.14285714	6	26.85714286
(10, 8, 7)	30	0.5	30	75.5	0
(4, 10, 11)	33	2	29.45454545	6	28
(4, 16, 12)	24	0.5	30	60.5	0
(4, 21, 12)	14	1	29.57142857	35.5	0
(13, 7, 11)	21	5	27.42857143	53	0
(13, 9, 2)	40	10	27.15	10	27.15
(13, 15, 8)	15	38	0	38	0
(2, 10, 13)	40	6	28.35	6	28.35
(2, 18, 12)	31	4	28.64516129	4	28.64516129
(2, 19, 3)	22	51	2.454545455	55.5	0
(3, 18, 12)	31	8	27.09677419	10	26.32258065
(11, 9, 4)	33	2	29.45454545	5	28.36363636
(11, 11, 4)	33	3	29.09090909	5	28.36363636
(11, 12, 13)	21	51	1.142857143	53	0
(11, 16, 12)	33	2	29.45454545	0.5	30
(9, 11, 12)	39	51	14.46153846	0.5	30
(9, 12, 12)	42	51	15.57142857	81	7
(8, 14, 13)	15	1	29.6	4	27.2
(12, 7, 4)	24	51	4.75	60.5	0
(12, 7, 11)	33	51	11.63636364	81	0.727272727
(12, 11, 9)	42	51	15.57142857	81	7
(12, 18, 4)	14	1	29.57142857	1	29.57142857
(12, 21, 2)	62	10	28.16129032	10	28.16129032
Sum	807	456.5		760.5	

Table 4.12: *Suggested usage price and estimated demand 1*

Note: Because the limitation of computation ability of the equipment, the optimal solutions are not reached. The calculated values of estimated demand could be float instead of integer.

In this section, the observations are made on the basis of table4.12 4.13 and table4.10. First of all, nearly all scenarios with DUP and fleet size increase would have a lower value of demand except V2G-DUP-N1-E2, which indicates that the proposed model is at the expense of reduction in car-sharing demand (market share(mode split)) by increasing the average usage price to achieve the goal of reach the maximum total profits for the car-sharing company. The results show that our model performs well in increasing total profits: the average usage prices(€/timestep) of each scenario are 22.8(V2G-DUP-N1), 17.2(V2G-DUP-N2), 14.9(V2G-DUP-N1-E2) and 26.4(V2G-DUP-N2-E2) with decrease in demand by 43.4%, 5.7%, -15.6% and 90% respectively compared with reference values, but leading to improvement in total profits in all scenarios with maximum increase of 1497.404-929.88=567.524€(61%) for comparison of scenario V2G-DUP-N2 and Base-N2. Therefore, regardless of other market pitfalls of low market share, under the objective of maximizing total profits, adjusting EV usage price to cater the specific conditions(travel time, energy prices, etc) on the expense of travel demand seems to be acceptable for our case. Moreover, comparing the results of V2G-DUP-N2 and V2G-DUP-N2-E2 with the same fleet size(N) but differing in demand elasticity(E) to V2G-DUP-N1 and V2G-DUP-N1-E2, we found the scenario with high fleet size(N) and lower E would focus more on the maximizing the EV usage price, and vice versa. Lower demand elasticity means there is high level of demand loss penalty in usage price increasing, so when the fleet size is high and there is always unsatisfied demand existing, the system would maximize the usage price as much as possible to adjust the estimated demand to get close to the service ability of our system(fleet size). Meanwhile, it indeed helps increase the total profits.

		V2G-DUP-N1-E2		V2G-DUP-N2-E2	
(Origin,time, destination)	Reference demand	Estimated demand	Suggested EV usage price	Estimated demand	Suggested EV usage price
(1, 8, 9)	26	50	9.865384615	6	25.09615385
(4, 13, 11)	24	50	8.4375	4	25.6875
(5, 17, 6)	44	50	16.875	8	25.46590909
(6, 20, 12)	21	4	25.5	6	24.64285714
(10, 8, 7)	30	50	12.15	1.42E-14	27.15
(4, 10, 11)	33	2	26.59090909	6	25.5
(4, 16, 12)	24	50	8.4375	0	27.1875
(4, 21, 12)	14	0	27.32142857	0	27.32142857
(13, 7, 11)	21	50	5.785714286	1	26.78571429
(13, 9, 2)	40	10	24.8625	10	24.8625
(13, 15, 8)	15	45.5	0	0	27.3
(2, 10, 13)	40	7	25.5375	7	25.5375
(2, 18, 12)	31	3	26.27419355	3	26.27419355
(2, 19, 3)	22	50	6.75	0	27.20454545
(3, 18, 12)	31	10	24.24193548	10	24.24193548
(11, 9, 4)	33	50	13.5	4	26.04545455
(11, 11, 4)	33	4	26.04545455	5	25.77272727
(11, 12, 13)	21	50	5.785714286	1	26.78571429
(11, 16, 12)	33	50	13.5	1.42E-14	27.13636364
(9, 11, 12)	39	50	15.57692308	0	27.11538462
(9, 12, 12)	42	50	16.39285714	2.84E-14	27.10714286
(8, 14, 13)	15	45.5	0	0	27.3
(12, 7, 4)	24	50	8.4375	0	27.1875
(12, 7, 11)	33	50	13.5	1.42E-14	27.13636364
(12, 11, 9)	42	50	16.39285714	2.84E-14	27.10714286
(12, 18, 4)	14	42.5	0	0	27.32142857
(12, 21, 2)	62	10	25.62096774	10	25.62096774
Sum	807	933.5		81	

Table 4.13: *Suggested usage price and estimated demand 2*

Finally, I'd say the best performance of combination of N and E in our case is V2G-DUP-N2 as it leads to the highest total profits which are the objective of our proposed model. However, if we consider it from other points of view, the one(V2G-DUP-N1-E2) with highest potential demand would be the most suitable strategy. For example, from local policy point of view, the government wants to achieve their goals of less congestion or emissions, the more people are willing to use shared EVs the better the goal could be reached; or from the perspective of new car-sharing company in Delft, at the initial stage of operation of shared cars, they indeed want to get as higher market share as possible.

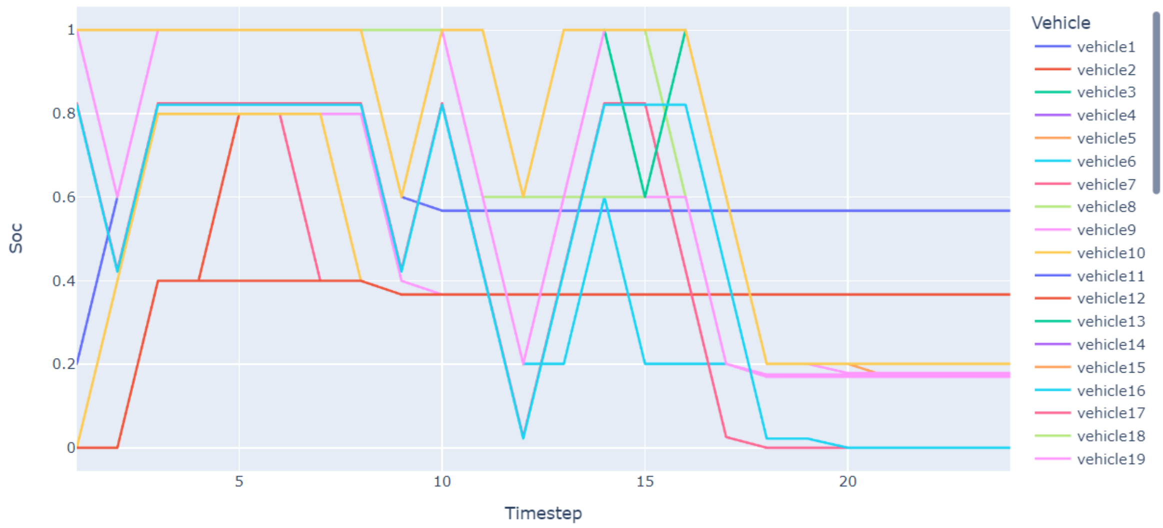

Figure 4.8: *SOC of V2G-N1*

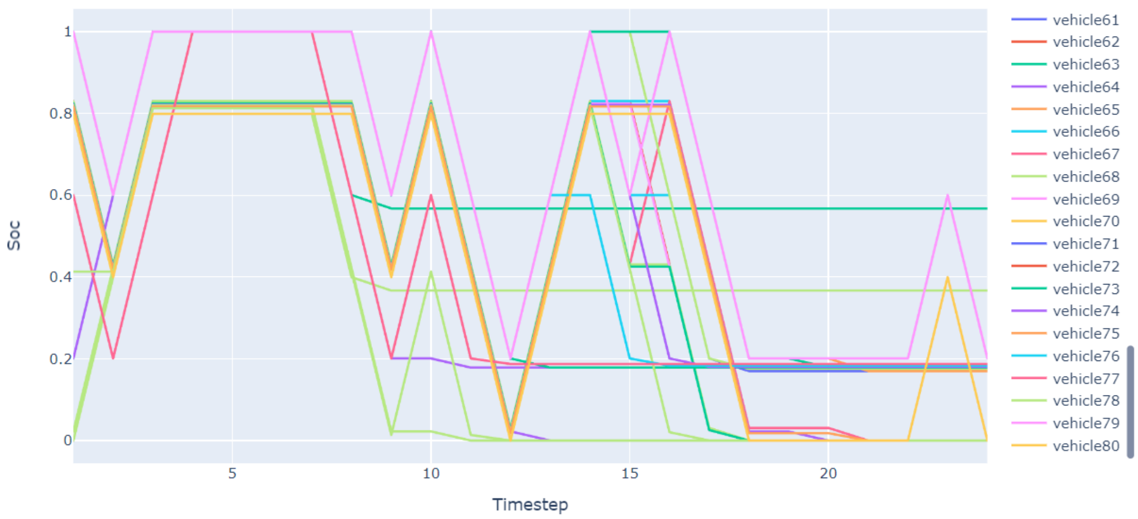

Figure 4.9: *SOC of V2G-N2*

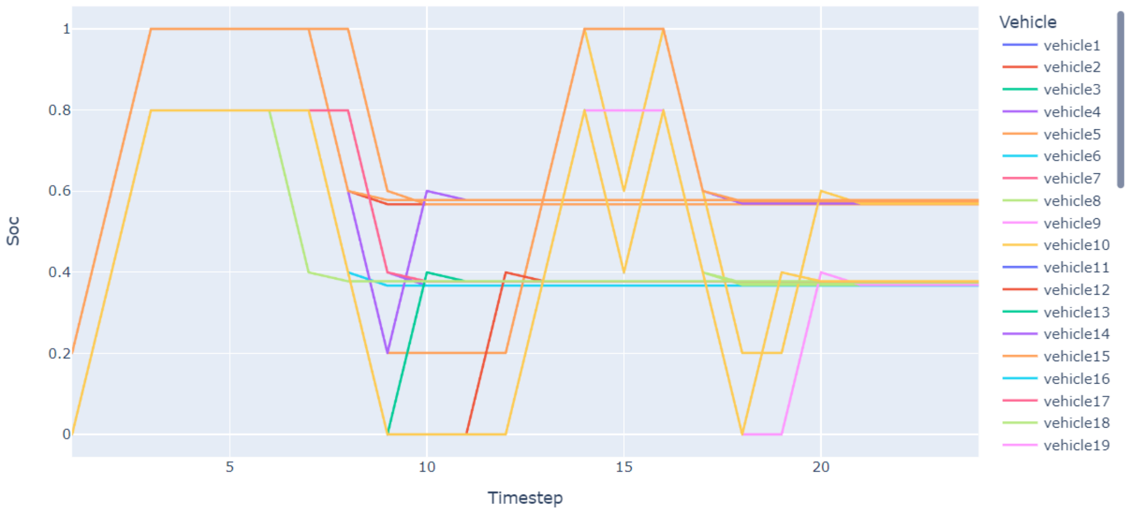

Figure 4.10: *SOC of V2G-DUP-N1*

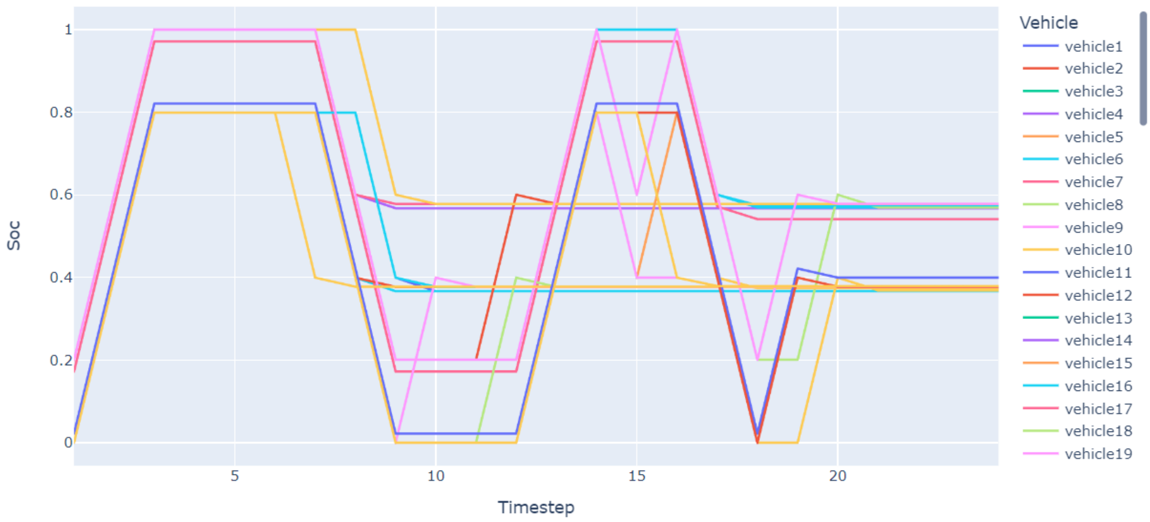

Figure 4.11: *SOC of V2G-DUP-N2*

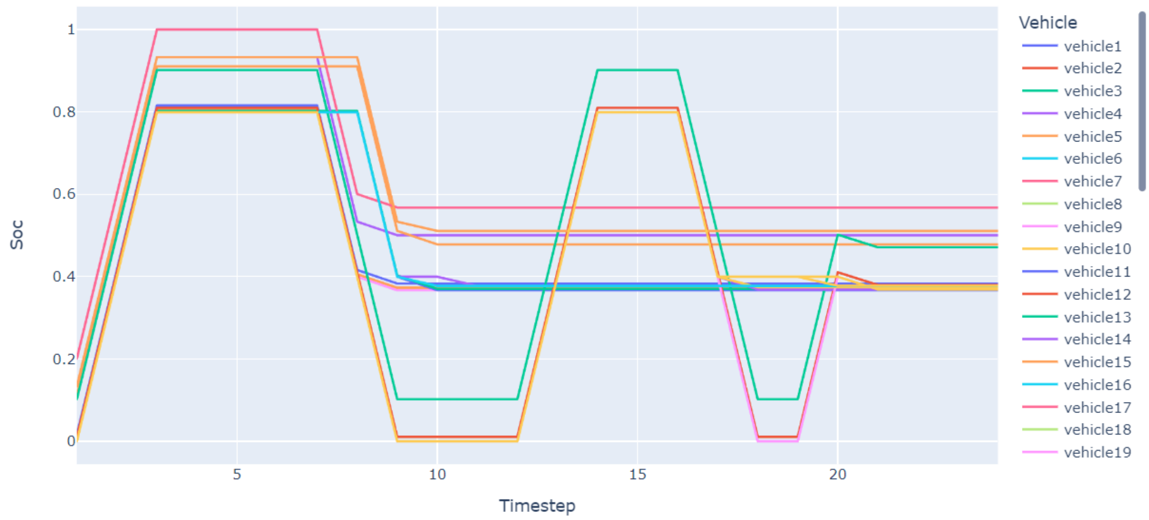

Figure 4.12: *SOC of V2G-DUP-N1-E2*

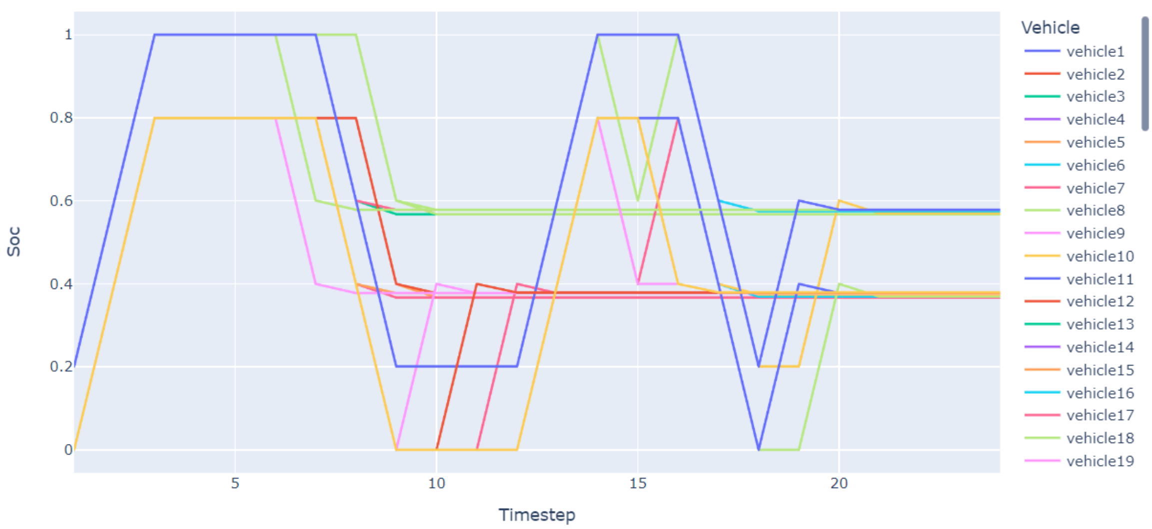

Figure 4.13: *SOC of V2G-DUP-N2-E2*

From figure 4.8 to 4.13, some considerations are made. These are one of the outputs of our model which is smart charging and discharging phases control according to the variation of energy price along the day thanks to the V2G technology. And for all the scenarios, the trend of charging and discharging looks the same. The results are in line with our hypothesis: the EV batteries charging phases mostly take place three times a day when the electricity is low based on the estimated electricity price variation(figure 4.7), These three charging periods are from timestep 0 to 5, 12 to 14 and 18 to 20. Regarding the impact of fleet size N on discharging and charging, the SOC of scenarios with higher N fluctuates more between maximum and minimum value for more times while lower N1 leads to more stable charging and discharging phases during the day.

	1	**2**		**4**	**5**		**7**	**8**	**9**	**10**	**11**	**12**	**13**
Base-N1	0	10	10	1	0	0	0	0	0	0	9	10	10
Base N2	10	10	10	10	0	10	0	0	0	0	10	10	10
V2G-N1	0	10	10	0	0	10	1	0	0	0	0	10	9
V2G-N2	0	10	10	10	10	10	0	0	3	0	8	10	9
V2G-DUP-N1	1	10	8	4	0	2	0	0	0	0	5	10	10
V2G-DUP-N1	1	10	8	4	0	2	0	0	0	0	5	10	10
V2G-DUP-N1-E2	0	10	10	2	0	4	0	0	0	0	4	10	10
V2G-DUP-N2-E2	6	10	10	10	8	6	0	0	0	0	10	10	10

Table 4.14: *The optimal assginment of EV at the start of day for each scenario*

The last outputs of my proposed model is the optimal EV assignment at the start of the day, which may be helpful for us to manage the fleet distribution. For all the scenarios with the same fleet coefficients(N), the EV assignment looks almost the same as the reference demand pattern is fixed for them. Therefore, the optimal EV assignment seems not to be affected by the deployment DUP or increasing the fleet size as well as the V2G technology.

5 Conclusion and limitation

The proposed model in the paper is the first kind of this report that is trying to combine the V2G technology and dynamic EV usage price in EV sharing system to maximize the total profits for shared-mobility company, although there are already some literature starting to talk about the profitability of integration of V2G combined with CSSs. My mathematical model which is a mixed integer linear programming helps determine the optimal EV assignment at the start of day, suggested usage price for each time step when there exists the car-sharing requests and the smart control for shared EVs discharging and charging phases. The total profits as my objective function consists of CSSs revenues and V2G profits which are got from serving travelers and energy purchase and sale based on the electricity price variation along the day. So this model could probably be used to assess the profitability of daily EV-sharing system operation with fixed fleet considering V2G and dynamic usage price. The model was applied to a test experiment and a real case of Delft city in the Netherlands with the estimated energy price variation model, mean expected reference car-sharing demand and EV batteries charging model. Additionally, I set up different scenarios to conduct a sensitivity analysis by varying the fleet size(N) and demand elasticity(E) applied in the DUP. Moreover, the scenarios with CSSs(only energy purchase allowed) only and with CSSs and V2G are also included in the analysis to help me understand any improvement caused by the deployment of DUP and impacts of varying parameters.

We found that deployment of DUP combined with V2G would significantly improve the total profitability of electric vehicles owners and benefit the local energy supply infrastructure with some degrees of car-sharing demand loss. In particular, the higher demand elasticity(E) performs better in balancing the demand loss and usage price increase to maximize the total profits in our case. From the profitability point of view, thanks to the V2G and DUP, V2G profit from difference between energy purchase at high price and sale at low price and better CSSs revenues are made. And the bigger the difference is, the better the V2G profits would be. For the local energy supply infrastructure(power grid) point of view, the net energy transfer during energy consumption peak hour indeed releases the pressure of power grid since some energy would be provided by EV which helps extend the life cycle of power grid. But the best results of the net energy transfer was found in scenario without DUP. Furthermore, I observe the combination of demand elasticity (E) and fleet coefficients (N) determines the focusing attention of my model, which indicates the scenario with higher E and higher N would focus more on maximizing the usage price while lower E and lower N would lead to the maximum varied estimated demand under the objective of maximizing the total profits. The DUP will also adjust the reference demand to some degree to approach the service ability of our CSSs system by avoiding or reducing some trips with very short travel distance(in our case, it is the short travel time) that do not make many CSSs revenues compared with the long distance trips. Therefore, it is possible to conclude that in the future, the shared EV company can design such a mobile application that will gather the total demand and make proper usage price so that the real amount of demand is getting closer to the service ability to maximize the total profits.

However, because the limitation of the project time, during the process of research, I also found a lot of limitations and problems that need to be addressed. Firstly, more cost terms maybe need to be considered in the model like emissions, costs for EV purchase and etc, as for my case, I used different fleet size to conduct the simulation, which will indeed increase the fixed investments. Moreover, the optimal combination of fleet coefficient(N) and demand elasticity(E) is not found, even though we get the considered parameters that lead to best performance on total profits, that is not the optimal combination of E and N. So, one of the future work could be to adjust my model into a multi-objective function to find both total profits and best combination of N and E with fixed travel demand. In addition, the dynamic usage price used in my model is only associated with the fixed reference demand. But in fact, it can be related with more influential factors such as time of day, SOC, congestion, etc. The travel time among stations can also be varied because of the congestion or queuing at station. The model could also be improved by combining shared EVs with the operation of other transport modes, since the DUP scheme could reduce the users' willingness to use shared EVs, but the actual total travel demand still exists. The reduced car-sharing demand can be potentially satisfied by other transport modes such as PT, E-bike and etc. The enhanced model will consider the bigger mobility system in the city which possibly would lead to more benefits for more stakeholders.

Appendices

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