Electric vehicle charging schedule for a car sharing system considering real traffic condition

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Abstract:

With application of sharing economy and severe environmental problems, electric vehicle (EV) sharing has become significant for transportation in urban life. However, among operations in EV sharing system, how to effectively schedule EV charging while considering realistic factors in traffic condition has become a critical issue. To tackle the problem, a charging scheduling model is proposed with estimation of charging power demand computed by traffic fluid model in this study. First of all, with the traffic fluid model, charging power demand is dynamically accessible for certain charging station in terms of number of vehicles, velocity and other factors. An EV charging schedule problem is formulated in order to achieve the charging schedule for nominated charging station. In intensive experimental analyses, the number of charging piles, estimated charging power demand, and required battery state-of-charge of EVs are investigated to examine their effectiveness and impact on system capability and availability. Relevant costs are analyzed in order to reveal traffic condition effectiveness along with its impact on EV charging operation system. Instantaneous electricity consumption is also studied to reveal crucial influence that proposed model can bring on energy consumption system application and maintenance. Finally, impact of traffic condition in different location and various time period on system performance is investigated and compared while effectiveness and significance of charging power estimation is emphasized.

Keywords: Electric vehicles, Charging scheduling, Car sharing system, Two-stage mechanism, Traffic fluid model

Notations:

Indices

t time index, $t \in T$

i EV index, $i \in I$

s charging pile index, $s \in S$

Parameters

$N_e(x,\ t)$ number of discharged EVs entering area Ω at t

$N_l(x,\ t)$ number of discharged EVs leaving area Ω at t

$N_o(x,\ t)$ number of discharged EVs from spatial origin to charging station at t

$N_p(x,\ t)$ number of discharged EVs that have already passed through charging station before t

$n_o(x,\ t)$ traffic density at charging station at t

$n_p(x,\ t)$ traffic flow at charging station at t

$v(x,\ t)$ velocity of EV at charging station at t [km/h]

$\beta(t)$ rate of EVs passing by charging station at t

$a(x,\ t)$ arrival rate of EVs at charging station at t

$\mu(t)$ charging completion rate at charging station at t

e unit electricity price [$/kWh]

$SOC_{arr}(i)$ arrival battery state-of-charge of ith EV [%]

$SOC_{req}(i)$ required battery state-of-charge of ith EV [%]

$t_{arr}(i)$ arrival time of ith EV

$t_{dep}(i)$ departure time of ith EV

$P_{max}(i)$ max charging power of ith EV [kW]

$P_{max}(s)$ max charging power of sth charging pile [kW]

$P_{av}(s)$ average charging power of sth charging pile [kW]

$P_d(x,\ t)$ estimated charging power demand for charging station at time t

$p(s,\ t)$ power provided by sth charging pile at t

cp_1 penalty cost occurs when $SOC_{dep}(i) \leq SOC_{req}(i)$ [$/kWh]

cp_2 penalty cost occurs when system capacity exceeds $P_d(x,\ t)$ [$/kWh]

Decision variables

$SOC_{dep}(i)$ departure battery state-of-charge of ith EV [%]

$z(x, t)$ = 1, sth charging pile is occupied at t

= 0, sth charging pile is unoccupied at t

$y(i, s, t)$ =*1*, ith EV is charging at sth charging pile at t

=*0*, ith EV is not charging at sth charging pile at t

1. Introduction

1.1 Research background

With the increasingly severe environmental problem all over the world, sustainable development is unprecedentedly drawing attention leads to exploration on clean and renewable energy [1]. Under this premise, the transportation sector in urban regions plays a significant role in air pollution resulting in climate change due to greenhouse gases emissions; this has necessitated road transport electrification, whereby replacing internal combustion vehicle with renewable energy vehicles like electric vehicles (EV) seems to be promising towards sustainable development. Nowadays, EV as an alternative to traditional internal combustion engine vehicle is widely perceived as a green solution to improve energy efficiency and reduce carbon emissions [2]. However, inner connection between transportation sector and EV energy consumption hasn't been discussed precisely in most prior works. As a matter of fact, large-scale adoption of moving EV loads significantly accelerates the integration of power and traffic systems [3]. There have been studies on EV loads in an integrated power and traffic system where the spatial-temporal variation of line congestion and voltage drop are evaluated at each transmission line and power system node [3-5]. What's more, the location and sizing of EV charging stations over consideration of traffic network is also discussed in some literature [6]. Nevertheless, researchers developed the approach aiming at determining jointly the traffic and the charging service assignment for a population of vehicles that partly need a battery charging during their trip. To put it differently, the problem chiefly tackled with planning the location and sizing of charging station in urban environment instead of demonstrate the essential relationship of EV charging energy demand and urban traffic condition. What's more, the universal resurgence of EVs revealed the adverse impact of the EV charging loads on the operating parameters of the power system. In order to provide an efficient charging service to EVs, it is important for the charging station to estimate its available capacity. The detrimental impact of EV charging station loads on the electricity distribution network cannot be neglected [7]. There are some existing studies considered charging station location and sizing along with energy consumption and distribution integrally [7-14]. Simultaneously, the limited drive range of EVs is regarded as one of the major challenges that EV manufacturers are attempting to overcome. Therefore, a simple, accurate and approach is needed to enhance the energy efficiency of EVs and thus extend their travel range [15]. Vehicle sharing is one of the possible answers to increasing demand of EV mobility [16]. EV sharing system is usually launched combining relocation of EVs and charging operation scheduling. For instance, optimizing charging and repositioning operation of EVs in a free-floating car-sharing system (FFCSS) is proposed in [17]. A novel mixed integer programming (MIP) model is developed to solve the problem. In addition to this, relationship between service pricing and charging schedule of EVs in sharing system is proposed in [18]. Nevertheless, even though mobility of EVs has been discussed in preceding research repeatedly, from simply EV repositioning to integration with human factor analysis such as user preference and service pricing. It has always been neglected that traffic condition of surroundings may also exert influences on EV charging station energy consumption as well as EV charging operation.

1.2 Research objective

The research is conducted to estimate charging power demand of EVs operated by a car sharing system within certain area. In the meantime, formulating EV charging schedule for EVs arriving at the charging station. Therefore, impact of urban traffic condition on EV charging power demand can be studied. Furthermore, EV sharing system operation, especially charging operation is also able to be tackled. The system is operated under assumption that charging operation of car sharing system is considered particularly. In other words, subsequent service phase is not included. Under the circumstances, system energy demand during single time interval will be computed in terms of certain information. For example, traffic flow in system including number of vehicles arriving and leaving the system, velocity of moving EVs and so on. Sequentially, estimated demand will be set as energy consumption constraint for the system when obtaining optimal charging schedule for EVs. Once the whole system energy consumption exceeds estimated demand, specific action will be taken in order to control the energy consumption. During the operation, not only the optimal charging schedule of the system will be formulated, relationship within urban traffic condition and EV energy consumption can also be revealed.

1.3 Organization

This paper is organized as following: introduction will be presented in the first place including research background, objective and organization. Following, literature review is depicted where previous research related to this paper will be discussed. Problem description and formulation will be third part of the paper where applied integrated model is illustrated as spatial-temporal traffic fluid model and EV charging operation model respectively. Section four conducted solution approach for nominated problem in general through implementation of two models. Section five is consist of experimental analysis and sensitivity analysis result. Last but not least, conclusions and discussion of future study are demonstrated in the last section accordingly.

2. Literature review

Although study and research about EV in traffic network is discussed in [19-22], they mainly focused on optimization of control strategy of energy consumption [19] and real road network adaptable controller of EV battery [20]. For example, a model of complex adaptive system including the electric vehicle group, traffic network and charging stations is developed in [21]. With the result of distribution of charging power obtained via the simulation with the multi-agent technique, it is illustrated that the effect on power system brought by the charging load of large-scale electric vehicle can be reduced. The problem of optimal locating and sizing of charging stations in smart grids has also become essential with development of EV technology. For instance, a battery capacity-constrained EV flow capturing location model is proposed in [22] to maximize the EV traffic flow that can be charged given a candidate construction plan of EV charging stations. However, research mentioned above chiefly focused on relation of charging station and traffic network information where specific charging operation for individual EVs is not considered.

Charging operation of EV has always been a crucial topic ever since EV constitutes a major mean of urban transportation. Hence, charging schedule of EVs is frequently considered comprehensively along with grid operation, charging station or parking lot operation, renewable energy application and so on. For instance, a real-time charging scheme is proposed in [19] to coordinate EV charging to accommodate demand response programs in the parking station. The charging scheduling is formulated as binary optimization problem to solve the problem more efficiently. Similarly, a two-stage admission and scheduling algorithm for EV charging is proposed in [20]. So that availability and capability of charging station are considered with EV charging schedule simultaneously. From methodology-wise point of view, quadratic programming (QP) and dynamic programming (DP) are also widely launched, for example in [21-23] and [24]. In the meantime, when considering EV charging with renewable energy sources such as photovoltaic system or wind energy system, energy storage system is generally deployed to achieve better utilization of energy for EV charging [26, 27]. Other researchers have also conducted studies on EV charging schedule tackled from perspective of parking station operator or EV owners using different linear programming (LP) formulation in [19] and [28]. Above all, EV charging scheduling involving renewable energy, user satisfaction level, coordination with smart grid and so on have been demonstrated significantly. Yet, in consideration of charging station energy consumption and mobility of EV, traffic condition of surround environment is necessary to take into account when formulating EV charging schedule. Nonetheless, in this paper, EV charging schedule problem will be solved compositely after estimating charging energy demand by means of traffic fluid mathematical model.

3. Problem description and formulation

3.1 Problem description

The problem of EV charging schedule in car sharing system mainly consists two parts. First of all, in order to restore the balance between electricity demand and supply, charging power estimation is in need for certain charging station operated by car sharing system. Recent research in EV operation illustrates the fact that demand response (DR) is becoming a crucial tool alleviating the electricity demand-supply mismatch issue [23]. In other word, DR allows the system operators shift the operation into a more efficient and advanced form which not only will increase the flexibility of power grid but also remission energy consumption. Moreover, although it was not explicitly mentioned, charging demand estimation may allow grid's distribution planners to anticipate a charging demand profile for a specific charging station. The charging demand profile may also facilitate to determine the size of energy storage systems in the charging station in order to charge EVs during the peak time by the extra energy saved from the off-peak time [24]. In the meantime, system dynamics and mobility on demand are two significant topics for car sharing system. It is demonstrated in [25], demographic factors and transportation considerations affect mobility on demand naturally. Recent car-sharing services, such as car2go have emerged which offer the added convenience of return a vehicle to any one of multiple stations throughout the city. However, what left unchecked is that, traffic condition, travel pattern would create a surplus of vehicles and their impact on car sharing operation. As a result, estimation of charging power demand is absolutely of vital importance for EV operation. In this paper, traffic fluid dynamic model is proposed to predict total charging demand for single charging station. Mathematical formulation of spatial and temporal model of electric vehicle charging demand for a charging station presented in [29] is applied. It has been proved in [29-31] that the fluid dynamic traffic model and the M/M/s queueing theory can be conjunctively interpreted when considering an EV charging station along with relatively known traffic data such as traffic velocities which can be accessed through global positioning system (GPSs) or closed-circuit televisions (CCTVs) [30]. Through acquisition of traffic data including number of vehicles, distance between spatial origin and charging station, vehicle entering and exit speed and so on, power charging demand estimation for the charging station will be achieved. Subsequently, charging schedule for EVs entering the certain charging station will be described. Namely, a rather conventional EV charging operation model will be formulated while eventually through final solution the specific charging schedule will be depicted. In the meantime, result of charging power demand estimation will be applied to restrict system capacity when solving EV charging operation model. Specifically speaking, penalty cost will occur accordingly when system charging power exceeding the demand estimated previously. In the following section formulation of nominated models will be introduced respectively.

3.2 Traffic fluid model for charging power demand estimation

The first step to calculate EV charging demand is to identify the arrival rate of discharged EVs at a charging station based on the fluid traffic theory [29-31]. A deterministic fluid dynamic model is presented which will be used to estimate the arrival rate of discharged EVs at a charging station along with the charging demand in this certain charging station. In addition, there are some assumptions need to be claimed in the study:

1) Previous zoning strategy is operated to make sure that there is only one charging station operated by the car sharing system in area Ω

2) Distance between spatial origin and charging station is x

3) Batteries for an already charged vehicle entering the area with a full battery state-of-charge

4) Fully charged batteries can last for the entire range of the trip, which means that fully charged EVs will not be considered in nominated problem

Therefore, in this study, only EVs in need of charging will visit charging station during a trip. In or words, only discharged EVs are focused. The definitions for the random variables used in the section are presented in Fig.1 and summarized as follows

$N_e(x,t)$: Number of discharged EVs entering area Ω during time t

$N_l(x,t)$: Number of discharged EVs leaving area Ω during time t

$N_o(x,t)$: Number of discharged EVs from spatial origin to charging station (x) at time t

$N_p(x,t)$: Number of discharged EVs that have already passed through charging station (x) before time t

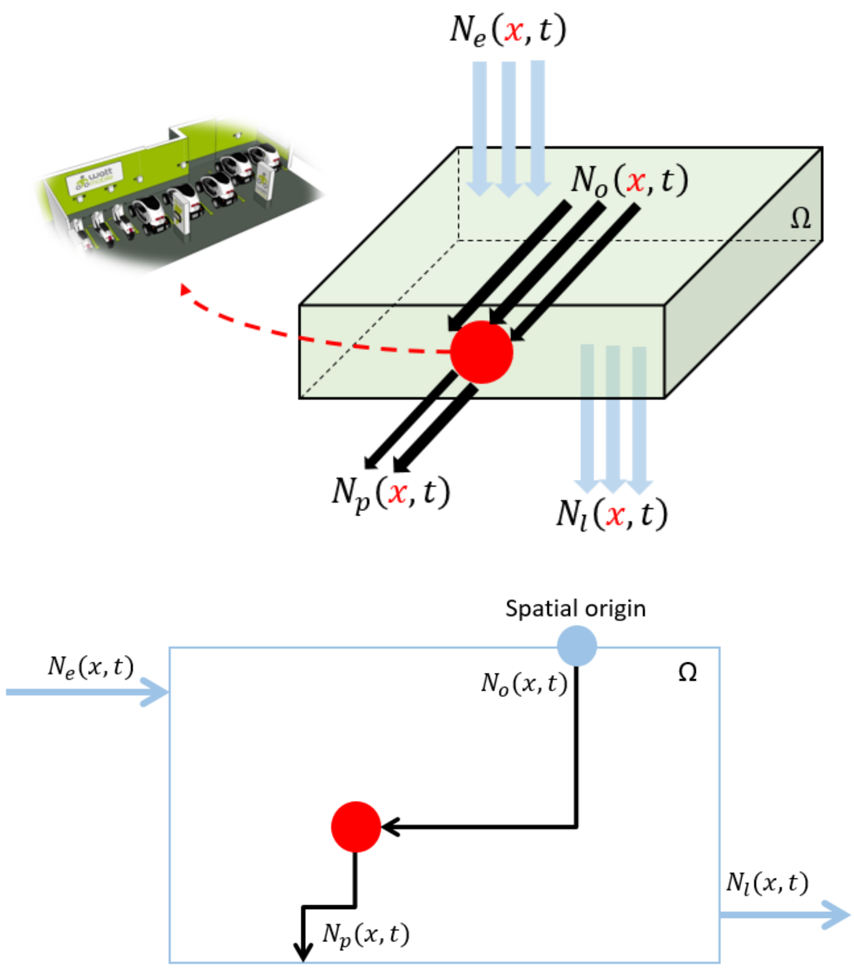

Fig. 1. Representation of four variables of discharged vehicles considered in the analysis

As demonstrated in Fig. 1, $N_e(x,t)$ represents number of discharged EVs entering area Ω during time t. Similarly, $N_l(x,t)$ depicts the number of discharged EVs leaving area Ω during time t. Therefore, value of difference between $N_e(x,t)$ and $N_l(x,t)$ refers to number of discharged EVs in area Ω at time t. Another interpretation is to measure number of discharged EVs from various direction. $N_o(x,t)$ and $N_p(x,t)$ in Fig. 1 indicate discharged EVs remaining on the way to from spatial origin to charging station (x) and those have already passed through charging station (x) at time t respectively. Hence, sum of $N_o(x,t)$ and $N_p(x,t)$ can also represent total discharged EVs remaining in area Ω at time t. Based on the illustration in Fig. 1, the sum of discharged EVs in area Ω at time t can be summarized as following equation, called the conservation equation [31]:

$$N_e(x,t) - N_l(x,t) = N_o(x,t) + N_p(x,t) \quad (1)$$

If all random variables in (1) are assumed to be finite and differentiable in both space and time, the density of discharged EVs at charging station location (x) and time to is:

$$n_o(x,t) = \frac{\partial N_o(x,t)}{\partial x} \quad (2)$$

Likewise, the traffic flow of discharged vehicles at charging station location (x) at time t is:

$$n_p(x,t) = \frac{\partial N_p(x,t)}{\partial t} \quad (3)$$

In the same way, the traffic flow of discharged vehicles at charging station location (x) at time t can be defined as:

$$n_e(x,t) = \frac{\partial^2 N_e(x,t)}{\partial x \partial t} \quad (4)$$

$$n_l(x,t) = \frac{\partial^2 N_l(x,t)}{\partial x \partial t} \quad (5)$$

According to definitions from (2)-(5), following PDE can be obtained by partially differentiating both sides of (1) in terms of x and t:

$$\frac{\partial n_o(x,t)}{\partial t} + \frac{\partial n_p(x,t)}{\partial x} = n_e(x,t) - n_l(x,t) \quad (6)$$

Based on the fundamental law of traffic flow in traffic theory [31], traffic flow can be defined as the multiplication of a traffic density by a vehicle's velocity. Consequently, the traffic flow of discharged EVs at charging station can be calculated as product of density of discharged

EVs and discharged EVs' velocity:

$$n_p(x,t) = n_o(x,t) \times v(x,t) \quad (7)$$

As a result, (6) can be reformulated as:

$$\frac{\partial n_o(x,t)}{\partial t} + \frac{\partial[n_o(x,t) \times v(x,t)]}{\partial x} = n_e(x,t) - n_l(x,t) \quad (8)$$

This partial differentiate equation is analogous to the law of conservation of mass in fluid dynamics [31]. In order to simplify (8), velocity of discharged EVs can be defined as the time derivative of charging station location (x):

$$v(x,t) = \frac{dx(t)}{dt} \quad (9)$$

Next, according to the chain rule:

$$\frac{dn_o(x,t)}{dt} = \frac{\partial n_o(x,t)}{\partial t} + \frac{\partial n_o(x,t)}{\partial x}\frac{dx(t)}{dt} \quad (10)$$

Therefore, equation (8) can be formulated as:

$$\frac{dn_o(x,t)}{dt} + \frac{\partial v(x,t)}{\partial x} n_o(x,t) = n_e(x,t) - n_l(x,t) \quad (11)$$

By substituting the right side, following simplified equation can be obtained sequentially:

$$\frac{dn_o(x,t)}{dt} = n_e(x,t) - n_l(x,t) - \frac{\partial v(x,t)}{\partial x} n_o(x,t) \quad (12)$$

The function above is considered as an ordinary differential equation. Consequently, density of discharged EVs at charging station location (x) $n_o(x,t)$ can be solved through numerical methods. Because of the partial derivative of $v(x,t)$ with respect to x, (12) is regard as an ordinary differential equation if and only if v(x, t) is not a function of $r(x,t)$. Therefore, (12) can be solved with numerical methods with the result of the density of discharged vehicles at charging station location (x) at time t. At the same time, $\beta(t)$ denotes rate of EVs passing by charging station x at time t. Therefore, arrival rate of discharged EVs at charging station can be calculated as:

$$a(x,t) = n_p(x,t) - \beta(t) = n_o(x,t) \times v(x,t) - \beta(t) \quad (13)$$

With the arrival rate of discharged EVs at charging station, the next step is to estimate charging power demand at charging station. Here $\mu(t)$ denotes charging completion rate at charging station. Therefore, minimum charging pile limit can be computed as follow:

$$s_{min} = \frac{a(x,t)}{\mu(t)} \quad (14)$$

Charging power demand of charging station can be estimated by the multiplication of the average charging power per charging pile $P_{av}(s)$ and s_{min},:

$$P_d(x,t) = P_{av}(s) \times \frac{a(x,t)}{\mu(t)} \quad (15)$$

3.3 EV charging operation model

In the proposed system, after estimating charging power demand in charging station located at *x*, a conventional EV charging schedule model will be formulated in order to depict charging schedule for individual EVs operated by car sharing system. The optimization problem can be solved using mixed integer programming presented. In order to provide customers with more efficient and reliable service, by mean of ensuring the condition of EVs in car sharing system, the requested energy level, arrival time and departure time of EVs are foreknown [24]. When an EV arrives at the charging station, it is required to fill up at least at required level of battery state-of-charge before its departure time. At the same time, the system is operated on the basis of first-come-first-serve principle. Which means the subsequent EV cannot be charged until one of the charging piles is unoccupied and EVs always select the earliest idle charging pile to charge. For instance, when *i*th EV arrives at charging station while there is only one charging pile s is unoccupied. Then the *i*th EV will have no choice but to charge at charging piles. On contrary, if all charging piles are occupied when *i*th EV arrives at charging station, then it has to wait until one of the charging pile finishes charging for previous EV.

The objective of the charging station is to minimize total cost for the charging operation by finding the optimal charging schedule for EVs. Therefore, the optimization problem can be formulated as:

$$\begin{aligned} min \qquad TC = \sum_t^T e(t) \times \sum_s^S p(s,t) \times z(s,t) + \sum_i^I \big(SOC_{req}(i) - SOC_{dep}(i)\big) \times c_{p1} \\ + \left(\sum_s^S p(s,t) \times z(s,t) - P_d(x,t)\right) \times c_{p2} \end{aligned} \qquad (16)$$

$$p(s,t) \times z(s,\ t) \leq P_{max}(s) \quad \forall s,t$$

$$s.t \tag{17}$$

$$p(s,t) \times y(i,s,t) \leq P_{max}(i) \quad \forall i, \mathrm{t} \tag{18}$$

$$SOC_{dep}(i) = \left(\sum_{t_{arr(i)}}^{t_{dep(i)}} p(s,t) \times y(i,s,\ t)\right)/P_{max}(i) + SOC_{arr} \quad \forall i, t \tag{19}$$

$$\sum_s^S \sum_t^T p(s,t) \times z(s,t) \leq P_{max}(sys) \quad \forall t \tag{20}$$

$$\sum_t^T \sum_i^I y(i,s,t) = \sum_t^T z(s,t) \quad \forall s \tag{21}$$

$$\sum_s^S p(s,t) \times z(s,t) - P_d(x,t) = max\left(0,\ \sum_s^S p(s,t) \times z(s,t) - P_d(x,t)\right) \ \forall t \tag{22}$$

$$SOC_{req}(i) - SOC_{dep}(i) = max\left(0,\ SOC_{req}(i) - SOC_{dep}(i)\right) \ \forall i \tag{23}$$

$$y(i,s,\ t)\begin{cases} = 1\ ith\ EV\ charging\ at\ charging\ pile\ s\ at\ t \\ = 0\ ith\ EV\ discharging\ at\ charging\ pile\ s\ at\ t \end{cases} \tag{24}$$

$$z(s,t)\ \begin{cases} = 1\ sth\ charging\ pile\ occupied\ at\ t \\ = 0\ sth\ charging\ pile\ unoccupied\ at\ t \end{cases} \tag{25}$$

Where (16) depicts objective of the model— minimizing system total cost. Total cost for the system is consist of three parts, electricity consumption cost, penalty cost occurred when required battery state-of-charge level is not reached within time period of EV arrival and departure and penalty cost when system capacity exceeds estimated charging power demand calculated in the previous section. c_{p1} relates to EV arrival and departure time while c_{p2} relates to instantaneity charging power amount offered by charging pile. Function (17) -(23) describe constraints appropriate for the system, including individual EV charging capacity, charging pile capacity and so on. (17) and (18) restrict that charging power at any time for any EV or charging pile should not exceed the charging capacity of neither EV or charging pile. (19) depicts battery state-of-charge level for *i*th EV when departing from charging station, it has been demonstrated in objective function (16) that penalty cost will occur accordingly if departure battery state-of-charge did not meet required state-of-charge for *i*th EV. Constraint (20) indicates that for all time intervals, charging power demand should not be exceeded. Following constraint (21) implies relationship between charging pile and EV. Since it has been set in assumption, EVs will be served according to first-come-first-serve principle. Therefore, one EV can only be charged if and only if there is unoccupied charging pile in the charging station. Meanwhile, after one EV completed charging operation, in other words, departure time has come for *i*th EV, the charging pile will be immediately open for *(i+1)*th EV. Above all, sum of EVs charged at charging pile s at all timeslots should equal to sum of charging pile operated at all timeslots. This constraint will make sure about the inner-connection for charging pile and

EV. Next, constraint (22) and (23) indicate non-negativity of two penalty costs. Finally constraint (24) and (25) are description of binary variable $y(i, s, t)$ and $z(s, t)$ which denote if sth charging pile is occupied or not and if *i*th EV is charging at *s*th charging pile respectively.

4. Two-stage mechanism

In order to solve the optimization problem formulated in previous section, a two-stage mechanism is proposed. First stage starts with input of actual traffic data, such as number of EVs, vehicle velocity and so on. With access towards prediction result of charging demand for certain charging station through traffic fluid model, second stage will focus on solving EV charging schedule problem through mixed integer linear programming (MILP) formulated as (16)- (22). In the MILP model, $y(i, s, t)$ and $z(s, t)$ represent whether ith EV is being charged at charging pile *s* at time *t*, and if sth charging pile is occupied at time *t* respectively. It is also noteworthy that both decision variables are binary variables. Therefore, charging schedule for EVs in the car sharing system can be conducted.

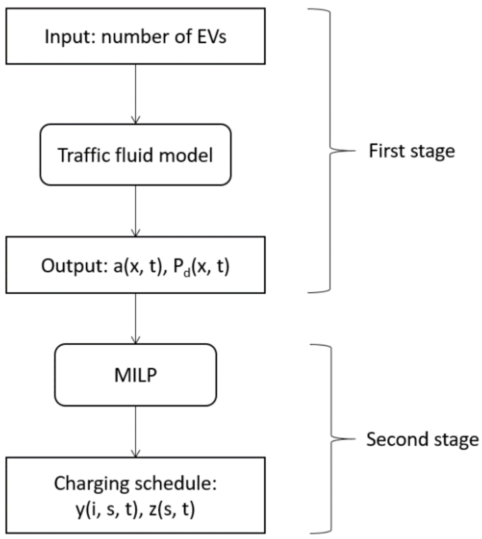

Fig. 2. Solution approach flow chart

4.1 EV charging power demand estimation

As discussed in section 3, charging energy demand is of vital importance when optimizing efficient and performance for electricity distribution system, especially with EV operation for car sharing system. Hence, EV charging power demand estimation will be determined by formulation (15). Suppose data reflecting actual traffic condition is collected as input for the charging station. Including number of discharged EVs entering and leaving area Ω at time t ($N_e(x,t)$, $N_l(x,t)$), along with number of discharged EVs from spatial origin to charging station location (x) and those who have already passed through charging station location (x) ($N_o(x,t)$, $N_p(x,t)$). By getting partial derivatives in terms of time and spatial, corresponding traffic density and traffic flow will be calculated for certain section of a path where charging station located. In the meantime, velocity data of EVs will also be gathered as input at the beginning of the algorithm. Therefore, through solving of original derivative equation, arrival rate for charging station location (x) at time t $a(x,t)$ can be achieved. Subsequently, charging power estimation for charging station located at x during t can be computed in terms of average charging power of charging piles ($Pav(s)$), arrival rate ($a(x,t)$) and service completion rate ($\mu(t)$).

4.2 Mixed integer linear programming

Second stage of nominated problem will be solved with optimization methodology. The proposed optimization model aims to minimize total cost for the system. Consequently, three parts of cost are included in the objective function, electricity consumption cost and two other penalty cost. Decision variables for the optimization model are $z(s,t)$ referring to whether charging pile s is occupied or not, *y(i, s, t)* representing charging condition of ith EV and $SOC_{dep}(i)$ implying departure battery state-of-charge of ith EV when leaving the charging station. Constraints (17)-(22) elaborated from perspective of system capacity, individual EV capacity and charging pile capacity. Due to the binary nature of decision variables and linearization of constraints, the model can be solved with MILP. As a matter of fact, three sectors of total cost not only represent components but also demonstrate three aspects closely associated with car sharing system operations. Although it has not been detailed discussed, penalty costs considered in the optimization model are closely linked to service level and operation level of the system. Penalty cost (c_{p1}) will occur when discharged EV is leaving the system without getting required battery state-of-charge which will directly influence EV service level during following trips. What's more, second penalty cost (c_{p2}) affects reaction of the system towards charging energy demand estimated by traffic fluid model. How the system will corporate with traffic condition surround by can be discovered through it. In the next section, we use numerical evaluations to show how the proposed two-stage mechanism is implanted to solve the charging station charging scheduling problem.

5. Experimental analysis and result

5.1 Case study

This section provides a numerical example in order to illustrate the spatial and temporal dynamics of charging station charging power demand and EV charging schedule accordingly. A numerical example of the model is presented here with acquisition of real traffic data in Seoul, South Korea.

Fig. 3. Considered urban road network and charging station

In this study, a road inside the metropolitan area of Seoul, South Korea is considered as shown in Fig. 3. The proposed analysis approach can also be applied to a larger scope without scalability issues. As depicted in Fig. 3, nominated area currently possesses with one charging station located at the center. This area Ω is chosen as the objective when predicting charging power demand for charging station. Red triangle on the map indicates the charging station.

Vary from previous studies, real-time CCTV data at the junctions of road segment in the area

[35] will be applied in this study in order to reveal the result in a more realistic perspective. Compared with previous researches which considered the problem mostly in private charging stations instead of public ones, EV arrival rate at the charging station is determined by number of EVs and velocity in certain road segment located in specified area. Real data at each time interval will be collected and processed through first stage computation so that charging power demand estimation for the charging station can be achieved.

For the sake of simplicity, the example provided here assumes:

1) Spatial origin is considered to be located at 5 km from the charging station, therefore $x = 5$ in following experiments.

2) Only one charging station is located in center of the area

3) Duo to the difficulties in collecting correct number of EVs through public data resource, number of EVs is implied according to ratio of conventional vehicles and EVs.

4) According to operation process in car sharing system, proportion of charged EVs and discharged EVs is determined as constant in experiment phase.

	Time-interval	Number of vehicles	Number of discharged EVs	Traffic density	Velocity
00:00-01:00	1	14	0.3	0.1	50.0
	2	12	0.2	0.0	50.0
	3	22	0.4	0.1	50.0
	4	21	0.4	0.1	50.0
	5	26	0.5	0.1	50.0
	6	41	0.8	0.2	50.0
01:00-02:00	7	36	0.7	0.1	50.0
	8	29	0.6	0.1	50.0
	9	14	0.3	0.1	50.0
	10	14	0.3	0.1	50.0
	11	23	0.5	0.1	50.0
	12	25	0.5	0.1	50.0
02:00-03:00	13	22	0.4	0.1	50.0
	14	31	0.6	0.1	50.0
	15	47	0.9	0.2	50.0
	16	35	0.7	0.1	50.0
	17	21	0.4	0.1	50.0
	18	11	0.2	0.0	50.0
03:00-04:00	19	17	0.3	0.1	47.0
	20	13	0.3	0.1	47.0
	21	12	0.2	0.0	47.0
	22	16	0.3	0.1	47.0
	23	18	0.4	0.1	47.0
	24	23	0.5	0.1	47.0

Table. 1. Data collection (partial)

With the achievement of arrival rate (a) and charging power demand (P_d) showed in Fig. 4 and Fig. 5, it is apparent that energy demand for the charging station has peak in morning time and evening time. Accordingly, maximum arrival rate of EVs is 14.5 and minimum is 0.2. Meanwhile, maximum charging energy demand is 277.7 and minimum is 3.8. Maximum number of charging piles in need is 5. With acquisition of charging schedule for EVs accessing the charging station, influence of traffic condition on system energy consumption will be revealed.

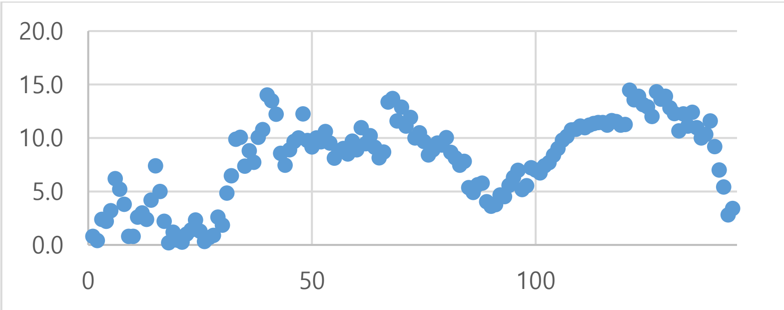

Fig. 4. Arrival rate of EVs

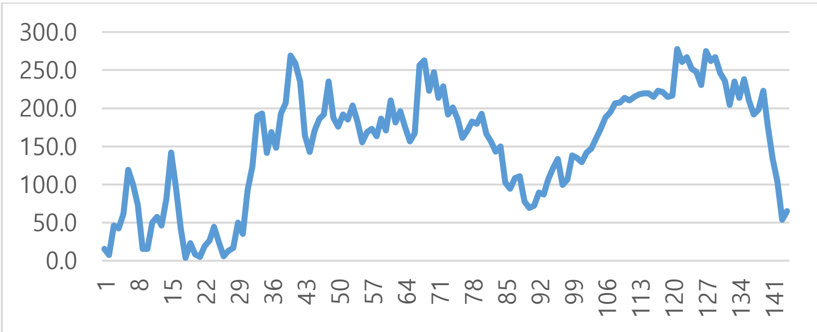

Fig. 5. Charging power demand for charging station

Before investigating the optimal charging schedule of charging station, parameters are set in table. 2 for following numerical analysis.

Parameter		Value
$P_{max}(sys)$	System capacity	500 [kW]
$P_{max}(s)$	Max charging power of sth charging pile	20 [kW]
$P_{max}(i)$	Max charging power of ith EV	100 [kW]
$SOC_{req}(i)$	Required battery state-of-charge of ith EV	80 [%]
$SOC_{arr}(i)$	Arrival battery state-of-charge of ith EV	N(0, 50) [%]
$p(s,t)$	Power provided by sth charging pile at t	20 [kWh]
cp_1	Penalty cost occurs when $SOC_{dep}(i) \leq SOC_{req}(i)$	0.5 [$/kWh]
cp_2	Penalty cost occurs when charging power exceeds $P_d(x,t)$	0.5 [$/kWh]
e	unit electricity price	N(2, 10) [$/kWh]
T	time index	144
S	charging pile index	5

Table. 2. Numerical analysis parameters

In table. 2, capacity of charging pile is considered as 20kW with optimal amount of charging pile obtained from stage 1, and EV charging power capacity is 100kW. Following, arrival battery state-of-charge of EVs is set to follow normal distribution between 0 to 50%, and all EVs will come to the charging station with battery state-of-charge requirement of 80%. Penalty costs are set to be equal for both penalties. However, electricity price for nominated system will be computed with normal distribution in order to reflect realistic situation due to price change at any time. Last but not least, each time interval will be set as 10 minutes, hence there will be 144 time intervals within one day.

The optimization problem formulated in case study is solved by Gurobi in python, and the optimal charging schedule is achieved by solving MILP formulation conducted in section 3.3.

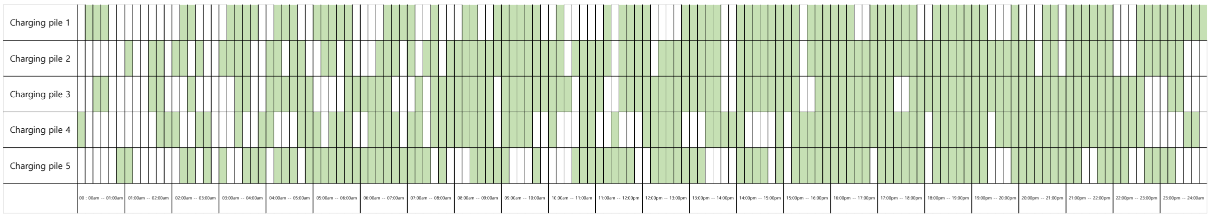

Fig. 6. charging schedule

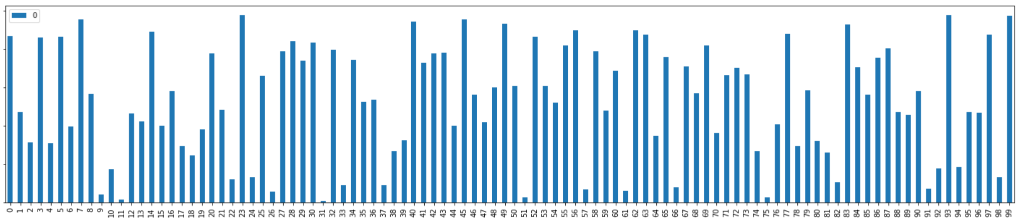

Fig. 7. Departure battery state-of-charge of EVs (partial)

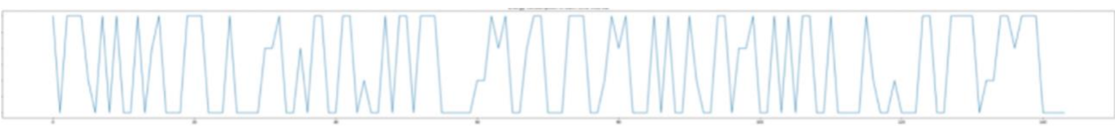

Fig. 8. Energy consumption in each time interval

Fig. 6-8 show the result of solving EV charging schedule problem. It can be found in Fig. 6 that the detailed charging process about how each charger provides energy to each EV has been established by the proposed solution approach. Due to the restriction for system capacity and system power demand, the balance between each charger is found accordingly. Consequently, in Fig. 7, departure battery state-of-charge for EVs charged in the charging station is revealed. Black line in the middle shows the battery state-of-charge requirement for EVs which is set to be 80% in this case study. Within 1146 EVs, number of vehicles met charging requirement is 962. In other words, more than 80% percent of EVs left with satisfaction within available charging time they possessed. Fig. 6 and Fig. 7 illustrate operational performance as well as service ability of the system which can be considered as the proof of the robustness of proposed model and solution. Fig. 8 illustrated energy consumption in each time interval.

5.2 Experimental analysis

In this section, experiments are conducted in order to demonstrate relationship between traffic condition and EV charging operation in-depth. Sensitivity analysis on factors which have a significant influence is conducted so that the availability and tolerance of the system can be revealed. Meanwhile, interactions between penalty costs and study on Instantaneity electricity consumption is proceeded to evaluate system performance on energy consumption perspective. The parameters used in this section will be the same with case study, only the values of factors involve with the experiment will be adjusted. Nevertheless, considering scale of the problem and computation complexity, number of EVs will be fixed on the basis of system availability.

5.2.1 Sensitivity analysis

First of all, sensitivity analysis is conducted within three aspects: number of charging piles, arrival rate of EVs and estimated charging energy demand. These three aspects are the result achieved from first stage—charging energy estimation through traffic fluid model. Therefore, they will be investigated primarily. The main purpose of sensitivity analysis is to see the impact that these factors bring to performance of the system. What’s more, Fig. 9 below reveals that relation between number of EVs arrive at the charging system and estimated charging energy demand. Due to the linearity attribute of the curve, the experiment will be conducted accordingly.

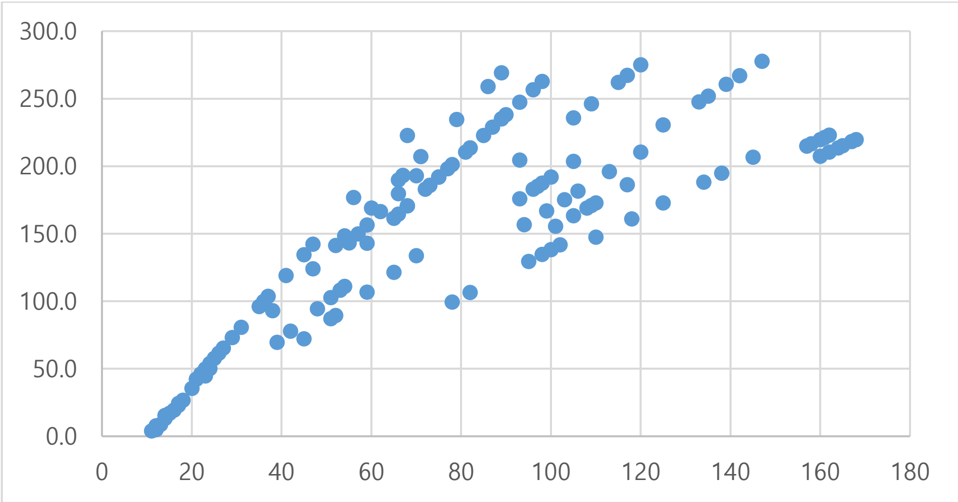

Fig. 9. Relation between number of EVs and charging power demand

5.2.1.1 Number of charging piles

Firstly, interaction between number of charging piles with total cost and total energy consumption is revealed. The experiment is conducted with scenarios from only one charging pile to possessing ten charging piles in the system. In order to elaborate system performance, we select total cost and total energy consumption as performance index for the experiment. The result is showed in Table. 3 and Fig. 10.

No. of charging piles	TC	Psum
s=1	13750	339
s=2	12698	391
s=3	11533	479
s=4	10263	473
s=5	9285	529
s=6	8617.73	614
s=7	5789.54	608
s=8	4991.15	672
s=9	4796.26	660
s=10	4369.6	725

Table. 3. Total cost and total energy consumption in scenarios with different number of charging piles

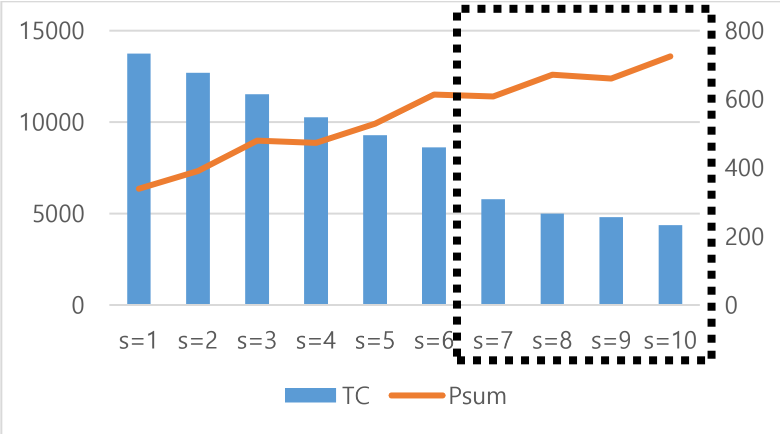

Fig. 10. Total cost and total energy consumption in scenarios with different number of charging piles

It can be concluded that, with number of charging piles increasing, total cost will decrease due to sufficient space for new arriving EVs. In other words, idleness for the whole system is significantly enhanced. The system possesses high viability and vitality. In the meantime, total energy consumption increase since there are more EVs get charged in the system, the amount of increase is approximate 50% which means that the system has the capability of accommodating 50% more EVs. However, total cost decrease range become less when there are more than 7 charging piles. With same vehicle arrival rate, once existing charging pile is enough for all EVs, even with more charging pile implemented, there will be no huge change in total cost. Nevertheless, subtle difference in total cost shows that, even when number of charging piles is enough for the system, more charging piles signifies reduction of penalty cost.

5.2.1.2 Estimated charging power demand

In this section, we conducted the experiment under assumption of different estimated charging power demand to check the relevance between system performance and charging power demand. Since P_d applied in case study is acquired from real traffic data, therefore, we take the maximum and minimum value of P_d and set 20 experiments within this range. All experiments are proceeded under assumption with 100 EVs and 5 charging piles. The only difference is estimated system energy demand value. The result is showed as Table. 5 and Fig. 12.

i=100 s=5	TC	Psum	Service performance
Pd = 2.00	infsb	infsb	infsb
Pd = 8.76	2891.11	94	56%
Pd = 15.52	2687.86	98	64%
Pd = 22.29	2776.99	124	73%
Pd = 29.05	2915.25	118	76%
Pd = 35.81	2094.28	178	75%
Pd = 42.57	1879.03	198	74%
Pd = 49.33	1505.53	190	74%
Pd = 56.10	1601.18	218	78%
Pd = 62.86	1637.19	210	78%
Pd = 69.62	1647.12	206	81%
Pd = 76.38	1594.8	196	85%
Pd = 83.14	1587.04	210	79%
Pd = 89.90	1253.82	200	86%
Pd = 96.67	1243.94	198	86%
Pd = 103.43	1370.85	228	82%
Pd = 110.19	1204.15	204	81%
Pd = 116.95	1269.57	208	88%
Pd = 123.71	1290.88	216	88%
Pd = 130.48	1166.74	202	92%
Pd = 137.24	904.38	196	90%
Pd = 144.00	1058.324	194	93%

Table. 5. Total cost, total energy consumption and service performance in cases with different charging energy demand estimation

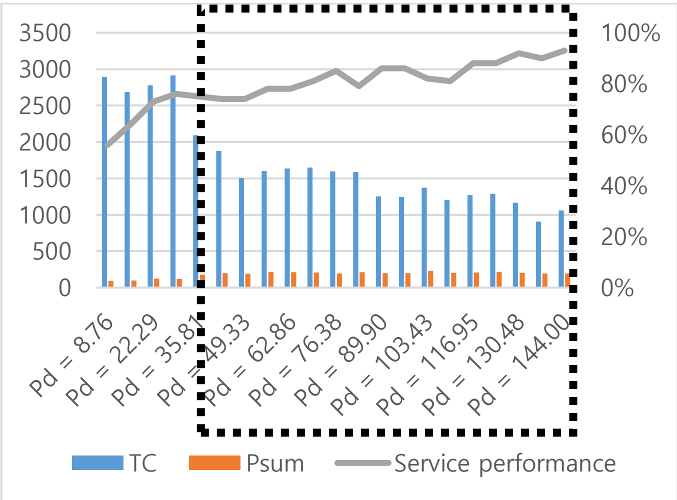

Fig. 12. Total cost, energy consumption, service ability of system with various estimated charging power demand

It can be observed that with increase of estimated charging energy demand, total cost decrease for about 70%. This change is mainly due to loosen of restriction for energy demand. In order words, within single time interval, more energy is allowed to use for the system. Thus, penalty cost is reduced and comes consequently total cost is also reduced. Nonetheless, there is no significant decrement in total cost after charging power demand P_d reach 49.33kW. Hence, it can be concluded that the system possesses the most preferable charging power demand more than 49.33kW, which also indicates that when planning energy distribution, the energy demand for nominated charging station can be foreseen. From another point of view, there is no significant change in total energy consumption amount. We can figure out the internal reason when consider service ability together. Gray line shows an obvious rising trend of service ability for the system. We can conclude that, more EVs arriving at the charging station are able to charge their vehicle to required battery state-of-charge level. With completion of this, along with almost same amount of energy consumption, total cost will decrease for sure.

5.2.1.3 Required battery state-of-charge

In this section, we assume that the required battery state-of-charge for the system is under different level. We conducted experiment under circumstances where required battery state-of-charge is set to be from 60% to 100%. System performance is investigated in different cases and summarized in table. 6 and fig. 13 below:

SOCreq	TC	Psum	Service performance
60%	11596	236	90%
65%	13249	243	88%
70%	14374	279	86%
75%	14965	288	84%
80%	15634	327	85%
85%	16247	350	79%
90%	20567	428	67%
95%	25045	502	52%
100%	infeasible	infeasible	infeasible

Table. 6. Total cost, energy consumption, service performance of system with various required battery state-of-charge

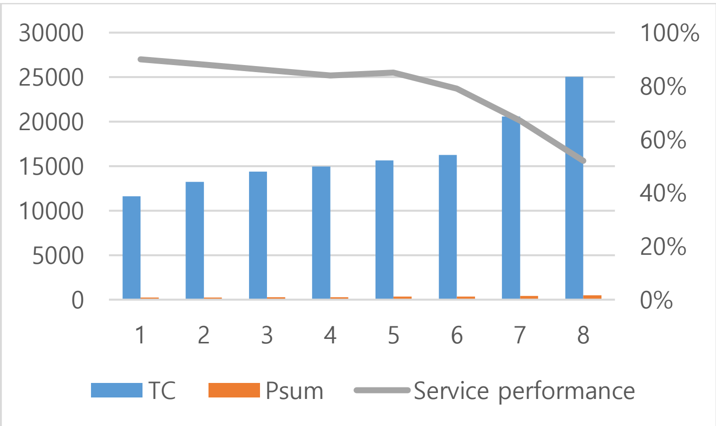

Fig. 13. Total cost, energy consumption, service performance of system with various required battery state-of-charge

What we can conclude from the result that, total cost and total energy consumption keep increasing when required battery state-of-charge increase. This is due to the charging power in need keeps increasing. Meanwhile, service performance keeps descending due to unavailability of arranging all EVs in the system and excessive situation of providing EVs with enough charging power to meet the requirement of battery state-of-charge. It is visible that while SOC_{req}rises from 60% to 95%, service performance has dropped almost 50%. If we set the standard to 100%, the model become infeasible implying breakdown of the system.

5.2.2 Interaction between penalty costs

We investigated influence of two penalty costs on the system total cost and total energy consumption. First of all, we considered the extreme case where both penalty cost is set as 0 respectively to eliminate impact. In other words, three scenarios were considered as showed below in Table. 7:

cp1+cp2	$TC = \sum_{t}^{T} e(t) \times \sum_{s}^{S} p(s,t) \times z(s,t) + \sum_{i}^{I} \left(SOC_{req}(i) - SOC_{dep}(i)\right) \times c_{p1} + \left(P_d(x,t) - \sum_{s}^{S} p(s,t) \times z(s,t)\right) \times c_{p2}$
cp1	$TC = \sum_{t}^{T} e(t) \times \sum_{s}^{S} p(s,t) \times z(s,t) + \sum_{i}^{I} \left(SOC_{req}(i) - SOC_{dep}(i)\right) \times c_{p1}$
cp2	$TC = \sum_{t}^{T} e(t) \times \sum_{s}^{S} p(s,t) \times z(s,t) + \left(P_d(x,t) - \sum_{s}^{S} p(s,t) \times z(s,t)\right) \times c_{p2}$

Table. 7. Objective functions for different scenarios

It is noteworthy that, when considering only first penalty cost—penalty cost for not meeting battery state-of-charge when leaving the charging station, then cost for exceeding system demand is overlooked. Thus, the problem became a typical EV charging operational problem and can be seen as benchmarking to compare with. Meanwhile, if only the second penalty cost is considered, then the impact of restriction to system demand is prominent. In the experiment, total costs calculated with diverse objective functions are showed in Table. 8. and Fig. 14.

TC	cp1+cp2	cp1	cp2	Psum	cp1+cp2	cp1	cp2
s=1	13750	3734.18	11034	s=1	339	155	209
s=2	12698	3511.06	11274	s=2	391	136	247
s=3	11533	3350.47	10465	s=3	479	136	256
s=4	10263	3364.61	10854	s=4	473	139	370
s=5	10285	3932.42	9188	s=5	529	142	415
s=6	9617.73	3887.1	8408	s=6	614	143	468
s=7	5789.54	3222.57	6002	s=7	608	127	457
s=8	2991.15	3147.8	5406	s=8	672	135	502
s=9	1796.26	3436	5364	s=9	660	135	466
s=10	1769.6	2985.6	2789	s=10	725	135	525

Table. 8. Penalty cost interaction experiment result

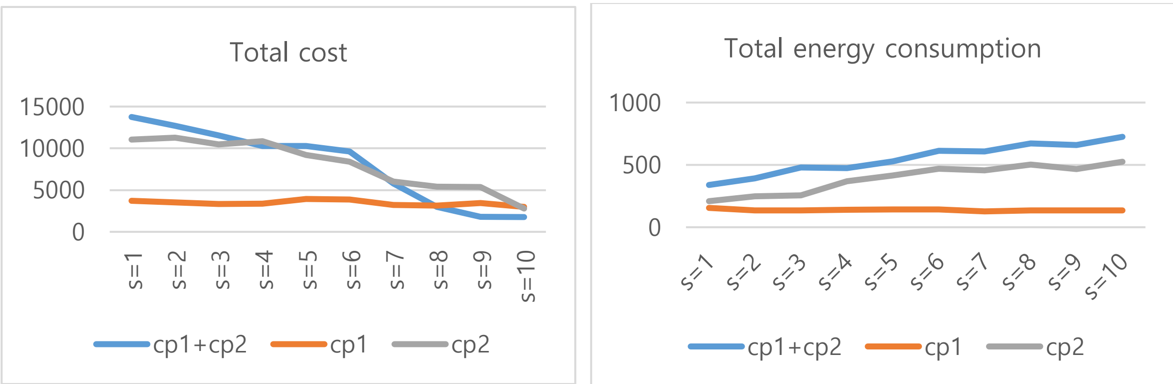

Fig. 14. Penalty cost interaction experiment result

When considering both penalty costs, with increment of charging piles, idleness of the system also increases. Consequently, total cost reduces due to decrement of both penalty cost. However, in cases considering first penalty cost and second penalty cost, total cost both increase while number of charging piles rise. This may be due to unreasonable planning of EV charging operation and congestion of the system. Nevertheless, curve for scenario $c_{p1} + c_{p2}$ and c_{p2} share similar trend while scenario c_{p1} seems quite smooth without significant change. Therefore, it can be summarized that in extreme situation, c_{p2} is more effective and critical to the system. Meanwhile, total energy consumption is also studied. Specifically, it is clearer to see that c_{p1} is the more effective to the system. Thus, when considering only c_{p1}, energy consumption is extremely low. However, in order to figure out the reason for that, we conducted another experiment in order to evaluate three cases from service performance.

In order to show the result more intuitive and precise, we simulated 24 scenarios showed in first column of Table 9:

Scenario	Number of EVs	Number of charging piles	cp1+cp2	cp1	cp2
1	50	5	0.81	0.44	0.63
2	50	10	0.82	0.36	0.64
3	50	15	0.9	0.64	0.81
4	100	5	0.8	0.35	0.67
5	100	10	0.9	0.5	0.69
6	100	15	0.92	0.57	0.76
7	150	5	0.86	0.47	0.57
8	150	10	0.89	0.52	0.62
9	150	15	0.93	0.56	0.72
10	200	5	0.81	0.4	0.57
11	200	10	0.88	0.42	0.61
12	200	15	0.92	0.56	0.7
13	250	5	0.79	0.45	0.56
14	250	10	0.84	0.51	0.62
15	250	15	0.91	0.52	0.67
16	300	5	0.73	0.39	0.53
17	300	10	0.82	0.42	0.62
18	300	15	0.85	0.48	0.64
19	500	5	0.79	0.32	0.57
20	500	10	0.83	0.34	0.63
21	500	15	0.82	0.58	0.65
22	1000	5	0.73	0.37	0.51
23	1000	10	0.76	0.42	0.58
24	1000	15	0.8	0.62	0.62

Table. 9. Service performance experiment result

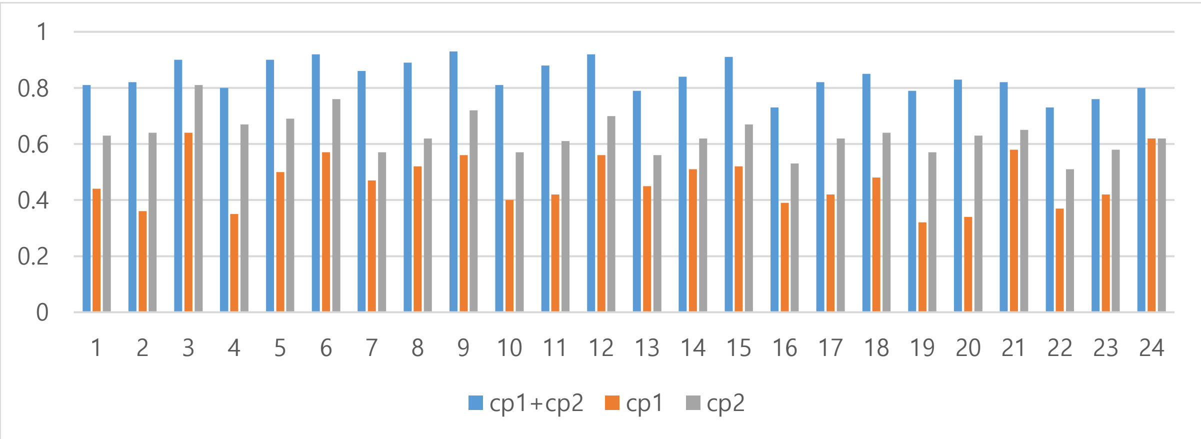

Fig. 15. Service performance experiment result

From the result showed in Fig. 15, proposed model obtained the best service level in all scenarios. However, when taking only first penalty cost into account, the service level is not very desirable which can also explain why it possesses minimum energy consumption amount. What is noteworthy is even when only considering second penalty cost, the service level is remarkably preferable.

5.2.3 Instantaneity electricity consumption

In the last part of experimental analysis, we are going to discuss instantaneity energy consumption in the system. The factor has a lot to do with sustainability and maintenance of energy system [34]. We compared instantaneity energy consumption before and after optimization of charging schedule, the result is showed below in Fig. 16:

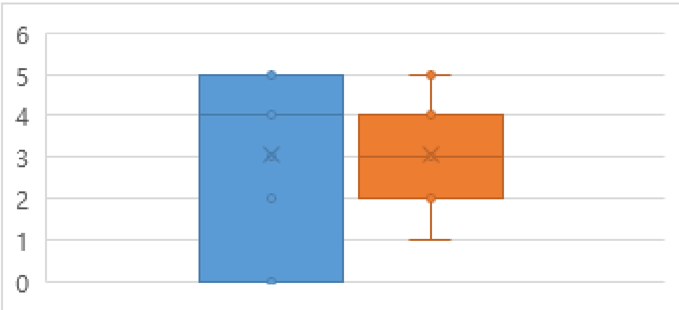

Fig. 16. Instantaneity electricity consumption comparison

It can be observed that with proposed charging schedule, instantaneity energy consumption altered with less peak power output and better stability in energy transmission. This means that, with consideration of estimated charging energy demand, the system possesses property of decentralization. In other words, the ability of distributing charging operation into all available time interval. This property has vital significance in balancing energy transmission and consumption as well as maintenance of energy system.

5.2.4 Traffic condition impact

In order to reflect traffic condition, we investigated two other scenarios ($\Omega 1, \Omega 2$) in Seoul, South Korea beside case study mentioned above, indicating traffic condition downtown and suburb in Fig. 17 and Fig. 18.

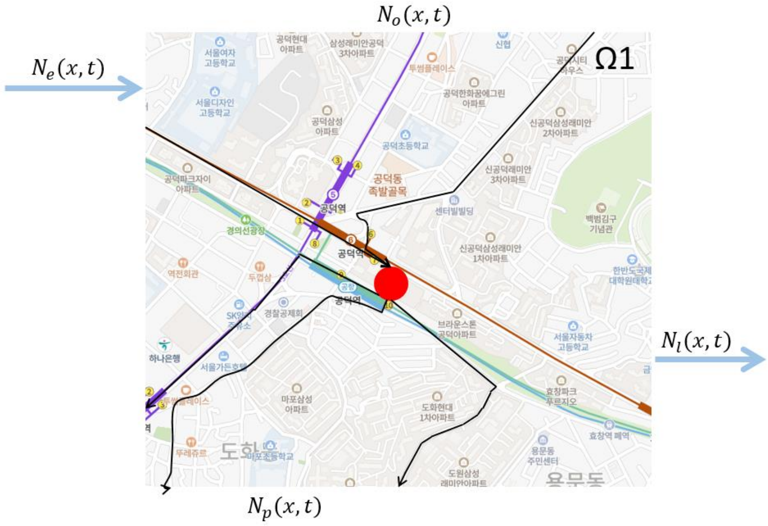

Fig. 17. Considered downtown road network and charging station

Fig. 18. Considered suburb road network and charging station

In the meantime, peak hour from 6:00am--10:00am and 15:00pm—10:00pm are also considered in the experiment showed in red. Through first stage of problem solving, charging power demand for three locations are showed as Fig. 19 below:

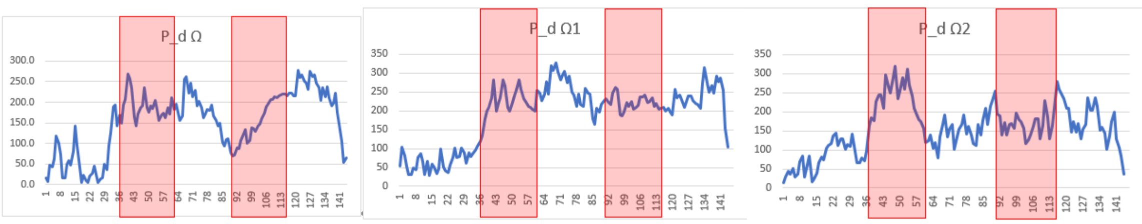

Fig. 19. Charging power demand for three traffic condition scenarios

Charging power demand in varies significantly to charging station location due to various traffic flow each scenario possesses. Under general considerations, peak hour is usually regard as charging power demand peak. Nevertheless, peak hour is but not always power demand peak. For instance, maximum charging power demand occurs beyond peak hour in Ω and Ω1. Therefore, it is necessary to estimate charging power demand according to traffic fluid in order to grasp demand pattern and adjust energy transmission and management.

Following, we solved the optimization problem formulated previously in order to compare performance of proposed model in three scenarios. Performance of the system is measured from perspective of cost, energy consumption, service performance and number of charged EVs. The result is showed as Table. 10 and Fig. 20:

Scenario	Peak hour	Cost	Energy consumption	Service performance	Number of charged EV
Ω	peak hour	4265	278	72%	430
	off-peak	5020	251	92%	715
	total	9285	529	82%	1145
Ω1	peak hour	6397	482	67%	561
	off-peak	4998	134	93%	885
	total	11395	616	81%	1446
Ω2	peak hour	3926	295	75%	299
	off-peak	3597	176	93%	396
	total	7523	471	87%	695

Table. 10. Experiment result for traffic condition scenarios

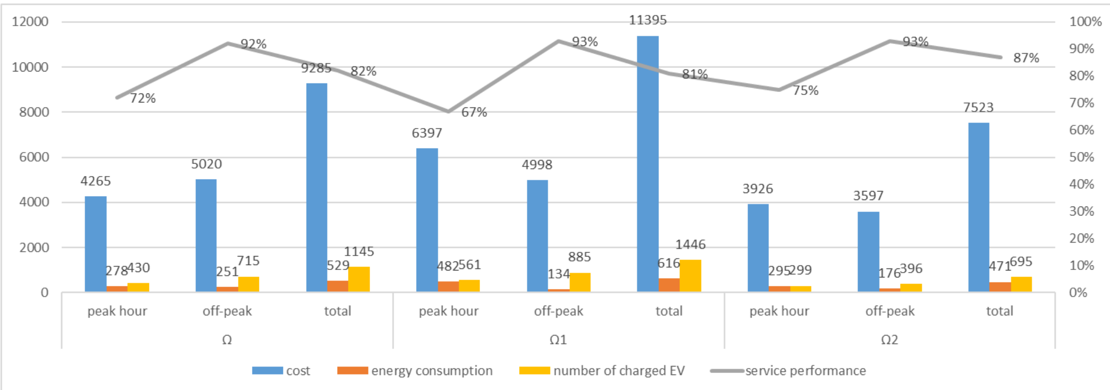

Fig. 20. Experiment result for traffic condition scenarios

Through internal comparison, peak hour consists 33% of time but 40% of number of charged EV and more than 50% of total cost. This may due to overload of traffic causing breakdown of the system along with increment of penalty cost. In addition, service performance of suburb area is significantly better than other two cases. This may due to less traffic jam and more precise estimation of power demand. Above all, it can be concluded that traffic condition has vital effectiveness to the system operation and performance.

6. Conclusions and future study

6.1 Conclusions

This research combined the problem of traffic fluid model and EV charging scheduling together. Estimation of charging power demand for certain charging station in a car sharing system is obtainable with application of traffic fluid model. Following, EV charging schedule is presented with estimated charging power demand restricting system capability. The nominated problem is solved with two-stage mechanism. Specifically speaking, in order to achieve estimation of charging power demand, number of vehicle, velocity of EVs and other data related to traffic condition is collected. Then, with estimated charging power demand, EV charging schedule model is conducted and solved as an MILP model. The model is solvable with optimization tool and the optimal charging schedule is accessible. In order to illustrate practical significance of proposed model, a case study in Seoul, South Korea is formulated in order to simultaneously evaluate accessibility of proposed model. Then, experimental analysis is operated to evaluate the model all-around. Primarily, sensitivity analysis among three aspects: number of charging piles, estimated charging energy demand and required battery state-of-charge are conducted. Evaluations were proceeded in terms of total cost, total energy consumption and service performance respectively. Secondly, interaction between two penalty costs is studied to check the impact which two penalty costs brought to the system. Mentioned experiments are solved with three scenarios possessing different objective functions. The result shows a promising consequence that introducing penalty cost on estimated charging power is promising in EV charging scheduling operation. Finally, we discussed instantaneity energy consumption before and after solving the model. It showed that proposed model helps energy consumption system by reducing peak energy output which has profound significance in energy distribution system and energy management operations.

6.2 Future study

The research studied the problem considering actual traffic condition and the impact it brought to EV charging scheduling problem. However, the problem is solved with MILP formulation, which can be regarded as limitation. Therefore, for future study, with access to diverse data, big data analysis approach might be applied in order to achieve more realistic result.

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