Spatial and Temporal Model of Electric Vehicle Charging Demand

Sungwoo Bae, *Student Member, IEEE*, and Alexis Kwasinski, *Member, IEEE*

***Abstract*—This paper presents a spatial and temporal model of electric vehicle charging demand for a rapid charging station located near a highway exit. Most previous studies have assumed a fixed charging location and fixed charging time during the off-peak hours for anticipating electric vehicle charging demand. Some other studies have based on limited charging scenarios at typical locations instead of a mathematical model. Therefore, from a distribution system perspective, electric vehicle charging demand is still unidentified quantity which may vary by space and time. In this context, this study proposes a mathematical model of electric vehicle charging demand for a rapid charging station. The mathematical model is based on the fluid dynamic traffic model and the M/M/s queueing theory. Firstly, the arrival rate of discharged vehicles at a charging station is predicted by the fluid dynamic model. Then, charging demand is forecasted by the M/M/s queueing theory with the arrival rate of discharged vehicles. This mathematical model of charging demand may allow grid's distribution planners to anticipate a charging demand profile at a charging station. A numerical example shows that the proposed model is able to capture the spatial and temporal dynamics of charging demand in a highway charging station.**

***Index Terms*—Charging demand, charging station, electric vehicle, energy management, modeling, planning, Poisson processes, power demand, power distribution planning, spatial and temporal model.**

I. Acronyms

EV	Electric vehicle.
PEV	Plug-in electric vehicle.
PHEV	Plug-in hybrid electric vehicle.
PALM	Poisson-arrival-location model.
GPS	Global positioning system.
CCTV	Closed-circuit television.
PDE	Partial differential equation.
ODE	Ordinary differential equation.

II. Introduction

This paper presents a spatial and temporal model of electric vehicle (EV) charging demand for a rapid charging station on a highway. Commercial plug-in electric vehicles (PEVs) have been produced by a few automakers such as Cooper, Nissan, and Tesla, and the first generation of plug-in hybrid electric vehicles (PHEVs) are emerging into the market in 2010 and 2011 [1]. This transportation electrification is expected to reduce gasoline consumption, thus decreasing greenhouse gas emissions [2]–[5]. However, [6] showed that uncontrolled daytime EV charging pattern may increase stress on the power system during the peak time, which may result in extensive grid outages. On the other hand, a recent study [7] concluded that the transportation electrification can fuel up to 84% of the U.S. light-duty vehicle fleet with the existing electricity infrastructure in the United States. However, since the analysis in [7] is based on a "valley-filling" approach, the "infrastructure" mentioned in [7] refers to the generation infrastructure. In fact, [7] also acknowledged that additional limitations may exist in distribution transformers. These limitations are aggravated by the uneven PEVs and PHEVs penetration favoring high-income areas [8], by the temporally and spatially changing nature of PEVs and PHEVs as loads [9], and by distribution planning difficulties caused by lack of historic data on PHEVs and PEVs behavior as loads. Reference [7] also acknowledged that high PEVs and PHEVs penetration may lead to higher electricity costs, lower reliability, and effects that could even worsen the impact of extreme events or grid emergencies to society. Thus, although PHEVs and PEVs are identified as one of smart grid motivating technologies [10], their highly disruptive impact if left unaddressed may hinder both smart grid development and PHEV adoption. Thus, it is critically important to understand how an increased electrification of the consumer's transportation sector will have on smart grids demand in order to avoid PHEVs and PEVs to become smart grid's "killer app" [10].

Despite the recognized importance of developing spatial and temporal EV charging demand, almost none of the studies seem to have explored the charging demand at a rapid charging station although it can severely increase electricity demand during the peak time. Most of previous studies [5], [7], [11]–[16] have postulated a fixed charging location—e.g., in a residential area—and fixed charging starting time, most of which occurs in the evening or at night. Although some studies [6], [9], [17], [18] suggested methods for anticipating temporal EV charging demand based on the Bass model [6], [19], Monte Carlo evaluations [9], [17], or based on a queueing theory [18], these studies are still limited to EV charging demand in residential areas. However, a PEV user may want to charge his/her vehicle at a rapid charging station when he/she forgets to charge it at night. This behavior is similar to that of a conventional gasoline vehicle user who can refuel the vehicle at any gas stations and any time. Some other precedent studies [20]–[22] have suggested EV charging demand at various locations such as residential areas, office areas, retail areas, and public parking

Manuscript received February 25, 2011; accepted May 25, 2011. Date of publication July 22, 2011; date of current version February 23, 2012. Paper no. TSG-00071-2011

The authors are with the Department of Electrical and Computer Engineering, University of Texas, Austin, TX 78712 USA (e-mail: sbae@mail.utexas.edu; akwasins@mail.utexas.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSG.2011.2159278

lots. Specifically, [20] anticipated EV charging demand in these areas through a survey from potential EV users. However, these studies [20]–[22] used limited charging scenarios at typical locations instead of a mathematical model of EV charging demand.

In contrast, this paper presents a mathematical model of rapid charging station's electricity demand which may vary both spatially and temporally. In order to limit the scope of the analysis to make its length suitable for this publication, this study only focuses on the charging station on a highway and not on urban or rural roads. Specifically, the methodology of this mathematical model is based on the fluid traffic model [23]–[25] and the M/M/s queueing theory [26]. Firstly, the arrival rate of discharged electric vehicles at a specific charging station is anticipated by the fluid traffic model proposed in wireless communication studies [23]–[25]. The idea of this fluid traffic model was introduced as the highway Poisson-arrival-location model (PALM) in [25] and expanded in [23] and [24]. This traffic model was called by the highway PALM since these studies assumed that a mobile user on a vehicle enters a highway with the Poisson distribution. The purpose of the highway PALM was to study the performance of wireless communication network on a highway such as calling and hand-off rates of mobiles [23]–[25]. Although the mobile user can initiate a call at any location on a highway, an EV user may only charge the vehicle at a specific location, generally a charging station near a highway exit. Therefore, the fluid traffic model here is modified from the highway PALM in [23]–[25]. Secondly, EV charging demand is predicted by the M/M/s queueing theory [26] once the arrival rate of discharged electric vehicles at a specific charging station is identified. The first letter M of M/M/s indicates that discharged vehicles arrive at a charging station with the Poisson distribution. The second letter M denotes that the time to charge each EV is exponentially distributed, and the third letter s means that there are s identical charging pumps at a charging station. Details of the M/M/s queueing theory [26] will be described in Section IV-B.

This mathematical model of charging demand 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. With this load shifting strategy, the charging station may participate in a demand response program [27]–[31] since the charging demand at the rapid charging station is expected to sharply increase during the day, although contrary to conventional demand response techniques, the charging station participation is based on actual, not virtual, energy storage. Energy storage systems at a charging station may also allow EVs to be charged by a diverse combination of energy sources, such as renewable energy sources in addition to the utility grid. Moreover, the mathematical model of charging demand requires relatively known traffic data such as traffic velocities which can be accessed through global positioning systems (GPSs) or closed-circuit televisions (CCTVs) on a highway without difficulties [32]–[35].

The rest of this paper is organized as follows. The detailed highway model in this study is described in Section III. The model formulations of a deterministic fluid model and a stochastic model are discussed in Section IV. A numerical example is included in Section V in order to illustrate spatial and temporal dynamics captured by the proposed charging demand model for a rapid charging station. Section VI concludes with a summary of findings.

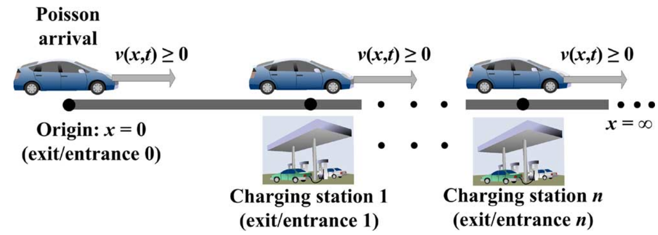

Fig. 1. Fundamental model of the highway EV PALM.

III. Highway Model Description

In order to provide the context for the analysis here, this section describes a highway for the fluid traffic model modified from the highway PALM [23]–[25]. This modified highway model here is called herein the highway EV PALM so as to differentiate it from the highway PALM [23]–[25] in wireless communication network studies. Fig. 1 depicts the basic highway model here based on a semi-infinite, one-way, single-lane freeway in the highway PALM [23]–[25]. The horizontal line of Fig. 1 represents a unidirectional single-lane highway, and a point x indicates a distance along the highway from the spatial origin which is the beginning point of the highway on the left side of Fig. 1. In addition, $v(x,t)$ and t represent the velocity field of each vehicle and time, respectively. Charging stations are located on each exit or entrance as illustrated in Fig. 1. Since the basic highway model is semi-infinite as shown in Fig. 1, the highway location space is defined as the interval $[0, \infty)$. In order to ensure that the basic highway is unidirectional, the velocity field of each vehicle is assumed to be greater than zero (i.e., $v(x,t) \geq 0$), for all x and t with $x \geq 0$ and $-\infty \leq t \leq \infty$ as depicted in Fig. 1. This study also postulates that a vehicle arrives at each entrance of the highway with the Poisson distribution; however, after the vehicle enters the highway, it is assumed to move according to the deterministic function of space and time based on its velocity field as the highway PALM [23]–[25] assumed. Despite this postulation, the highway model still captures stochastic behaviors as well as deterministic behaviors of vehicles according to the highway PALM [23]–[25].

This fundamental highway model can also be used as the building block for a multiple-lane highway in Fig. 2 and a bidirectional highway model in Fig. 3 as elucidated in [25]. As illustrated in Fig. 2, a multiple-lane highway traffic model is constructed by combining basic highway models in which vehicles have different velocities. As depicted in Fig. 3, a bidirectional highway traffic model is built by combining two independent unidirectional highway models with reverse-directional traffic flow; velocities of all vehicles on the bottom highway model in Fig. 3 are eastbound (i.e., $v_e(x,t) \geq 0$), while velocities of all vehicles on the top highway model in Fig. 3 are westbound (i.e., $v_{\mathrm{w}}(x,t) \geq 0$). Fig. 4 illustrates a more elaborate highway network which can be developed by superimposing groups of these multiple-lane and bidirectional highways according to [25].

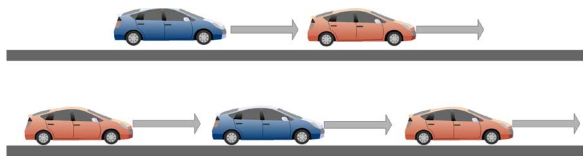

Fig. 2. Multiple-lane highway model of the highway EV PALM [25].

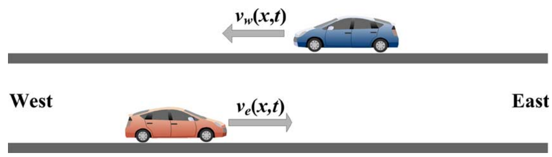

Fig. 3. Bidirectional highway model of the highway EV PALM [25].

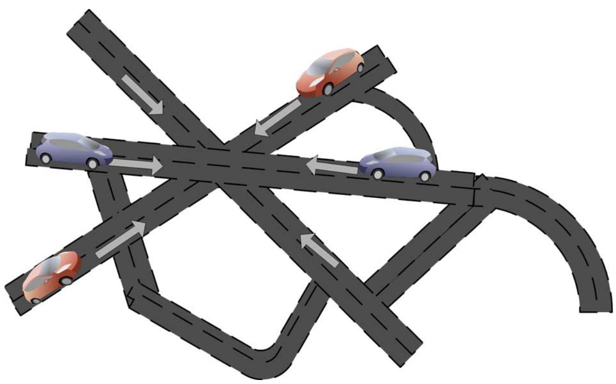

Fig. 4. Elaborate highway network model of the highway EV PALM [25].

IV. Model Formulations

As briefly discussed in the Introduction, 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 [23]–[25]. In Section IV-A, a deterministic fluid dynamic model is presented, which will be used to estimate the arrival rate of discharged EVs at a charging station. This deterministic fluid model is based on the conservation equation of traffic flow, which will be used for drawing partial differential equations (PDEs) whereby general engineering problems can be solved. In Section IV-B, EV charging demand will be calculated by the M/M/s queueing theory with the arrival rate of discharged EVs. In Section IV-C, a stochastic charging demand model is discussed, which illustrates the expected EV charging demand.

This study assumes that:

1) batteries for an already charged vehicle entering the highway have a full state-of-charge (e.g., due to the night-time charging at home) and
2) fully charged batteries can last for the entire range of the trip, which for typical trips it is a short one [12], [13]. Hence, the user of an EV that enters the highway fully charged EV may exit the highway not because the batteries are discharged but rather because he/she may require to rest.

Therefore, in this study it is considered that an already charged vehicle entering the highway does not require visiting a fast charging station during the trip. In contrast, a discharged vehicle on a highway denotes an EV of which batteries are almost drained, thus requiring charging at the closest charging station. In other words, this study focuses on the discharged EV's user who forgets to charge it at night, thus requiring visiting a charging station on a highway. Before elucidating the highway EV PALM, the definitions for the random variables used in this section and that are represented in Fig. 5(a) and 5(b) are summarized as follows.

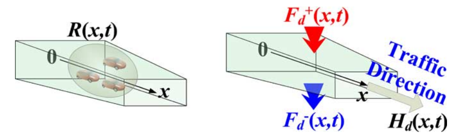

Fig. 5. Representation of the four variables of discharged vehicles considered in the analysis. (a) Left: $R(x,t)$. (b) Right: $H_d(x,t)$, $F_d^+(x,t)$, $F_d^-(x,t)$.

1) $R(x,t)$: The number of discharged EVs remaining in the interval $(0,x]$ at time t.
2) $H_d(x,t)$: The number of discharged EVs that have already passed through the position x before time t.
3) $F_d^+(x,t)$: The number of discharged EVs that have entered the highway along the interval $(0,x]$ before time t.
4) $F_d^-(x,t)$: The number of discharged EVs that have exited the highway along the interval $(0,x]$ before time t.

As illustrated in Fig. 5(a), $R(x,t)$ represents a static view of the highway status in terms of discharged vehicles within a location interval $(0,x]$ at a given time t. In contrast, Fig. 5(b) depicts traffic flow of discharged vehicles during the time interval $(-\infty,t]$. Specifically, $H_d(x,t)$ denotes the number of discharged vehicles which have already passed through the position x before the time t. $F_d^+(x,t)$ and $F_d^-(x,t)$ denote respectively the influx and efflux of discharged vehicles along the interval $(0,x]$ before the time t. In other words, $F_d^+(x,t)$ indicates the number of discharged vehicles which have entered the highway through any entrances between the highway starting point and a position indicated by x before time t. $F_d^-(x,t)$ is analogous to $F_d^+(x,t)$, but $F_d^-(x,t)$ indicates instead the number of discharged vehicles which have left the highway between those same highway markers before time t. In this context, discharged EVs leaving the system (i.e., $F_d^-(x,t)$) are divided into:

1) discharged EVs that permanently depart from the highway and that are recharged at their final destinations which are close to the highway exit and, of course, it is not the highway charging station; or
2) discharged EVs which temporarily leave the highway in order to recharge their batteries at the highway exit charging station. These discharged vehicles which will return to the highway after recharging their batteries at the highway charging station.

A. Deterministic Fluid Dynamic Model

Based on the illustration in Fig. 5 and the assumption that all vehicles only move toward the right side, the net flux of discharged vehicles in the interval $(0,x]$ before time t equals the sum of the following quantities: 1) all discharged EVs remaining in location $(0,x]$ at time t (i.e., $R(x,t)$) and 2) all discharged EVs which have passed through the position x before the time t (i.e., $H_d(x,t)$). This equality can be summarized as the following equation, called the conservation equation:

$$R(x,t) + H_d(x,t) = F_d^+(x,t) - F_d^-(x,t). \tag{1}$$

If all random variables in (1) are assumed to be finite and differentiable in both space and time, the density of discharged vehicles at location x and time t is $r(x,t)$, defined as follows:

$$r(x,t) \equiv \frac{\partial R(x,t)}{\partial x}. \tag{2}$$

In the same way, the traffic flow of discharged vehicles at location x and time t is $h_d(x,t)$, defined by

$$h_d(x,t) \equiv \frac{\partial H_d(x,t)}{\partial t}. \tag{3}$$

Similarly, the densities of discharged vehicles entering or leaving the highway at location x and time t are respectively $f_d^+(x,t)$ or $f_d^-(x,t)$. That is,

$$f_d^+(x,t) \equiv \frac{\partial^2 F_d^+(x,t)}{\partial x \partial t} \text{ and } f_d^-(x,t) \equiv \frac{\partial^2 F_d^-(x,t)}{\partial x \partial t}. \tag{4}$$

Based on the definitions in (2)–(4), the following PDE can be obtained by partially differentiating both sides of the conservation (1) with respect to the location x and time t:

$$\frac{\partial r(x,t)}{\partial t} + \frac{\partial h_d(x,t)}{\partial x} = f_d^+(x,t) - f_d^-(x,t). \tag{5}$$

According to the fundamental law of traffic flow in traffic theory [36], traffic flow can be defined as the multiplication of a traffic density by a vehicle's velocity. Thus, the traffic flow of discharged vehicles at location x and time t, $h_d(x,t)$, can be calculated with multiplying the density of discharged vehicles, $r(x,t)$, by the discharged EVs' velocity at location x and time t, $v(x,t)$. That is,

$$h_d(x,t) = r(x,t)v(x,t). \tag{6}$$

By substituting this traffic flow into (5), the differential form of the conservation equation can be obtained as follows:

$$\frac{\partial r(x,t)}{\partial t} + \frac{\partial}{\partial x}[r(x,t)v(x,t)] = f_d^+(x,t) - f_d^-(x,t). \tag{7}$$

This PDE (7) is analogous to the law of conservation of mass in fluid dynamics [37]. In order to simplify (7), it can be considered that the velocity field $v(x,t)$ is defined as the time derivative of the location $x(t)$ which is a function of time t as follows:

$$v(x,t) = \frac{dx(t)}{dt}. \tag{8}$$

Next, the following equation can be obtained based on the chain rule:

$$\frac{d[r(x,t)]}{dt} = \frac{\partial[r(x,t)]}{\partial t} + \frac{\partial[r(x,t)]}{\partial x}\frac{dx(t)}{dt}. \tag{9}$$

By replacing the first time partial derivative in (7) with (8) and (9), the following simplified equation can be obtained:

$$\frac{d[r(x,t)]}{dt} + \frac{\partial v(x,t)}{\partial x} r(x,t) = f_d^+(x,t) - f_d^-(x,t). \tag{10}$$

As briefly discussed at the beginning of this section, discharged EVs entering the highway (i.e., $F_d^+(x,t)$) denote discharged EVs which actually arrive at the highway. In contrast, discharged EVs leaving the highway (i.e., $F_d^-(x,t)$) are subdivided into discharged EVs which permanently depart from the system to their final destination different from the highway charging station, and discharged EVs which temporarily leave the highway for recharging their batteries at the highway charging station. Hence, the following notations are provided for further discussions.

1) $B_d^+(x,t)$: All discharged EVs actually arriving at the highway in the interval $(0,x]$ before time t. Thus, $F_d^+(x,t)$ and $B_d^+(x,t)$ are equivalent variables.
2) $B_d^-(x,t)$: All discharged EVs permanently departing from the highway in the interval $(0,x]$ before time t
3) $C_d^-(x,t)$: All discharged EVs temporarily leaving the highway in order to recharge their batteries in the interval $(0,x]$ before time t

In other words, $B_d^+(x,t)$ and $B_d^-(x,t)$ denote arriving and permanently departing discharged EVs, and their densities can be defined as follows:

$$b_d^+(x,t) \equiv \frac{\partial^2 B_d^+(x,t)}{\partial x \partial t} \text{ and } b_d^-(x,t) \equiv \frac{\partial^2 B_d^-(x,t)}{\partial x \partial t}. \tag{11}$$

These rate densities can be identified with the actual arrival rate (i.e., $\alpha_i(t)$) and the permanent departure rate (i.e., $\beta_i(t)$) of discharged EVs at the ith highway entrance/exit and at time t typically measured in the number of vehicles per minute. The condition, which discharged vehicles can only arrive at and depart from the highway through entrances/exits, can be expressed with a dirac delta function (i.e., $\delta(x)$) as follows [24]:

$$b_d^+(x,t) = f_d^+(x,t) = \sum_i \alpha_i(t)\delta(x-y_i), \tag{12}$$

$$b_d^-(x,t) = \sum_i \beta_i(t)\delta(x-y_i), \tag{13}$$

where y_i is a distance from the spatial origin to the ith highway entrance/exit. For simplicity, $\alpha_i(t)$ and $\beta_i(t)$ are assumed here to be constant values. However, in the future, as EV penetration increases and historical data of their use become available, more complex forms for $\alpha_i(t)$ and $\beta_i(t)$ can be considered.

On the other hand, $C_d^-(x,t)$ indicates discharged EVs that have temporarily left the highway for visiting the charging station in the interval $(0,x]$ before time t. The density associated to $C_d^-(x,t)$ can be defined by

$$c_d^-(x,t) \equiv \frac{\partial^2 C_d^-(x,t)}{\partial x \partial t}. \tag{14}$$

This temporarily departing discharged EVs' density can be characterized based on the temporarily departing rate per minute (i.e., $\lambda(x,t)$) and the density of discharged EVs (i.e., $r(x,t)$). If it is assumed that discharged EVs will return to the highway immediately after finishing to recharge their batteries, then,

$$c_d^-(x,t) = r(x,t)\lambda(x,t). \tag{15}$$

The temporary departing rate per minute (i.e., $\lambda(x,t)$), at which discharged vehicles temporarily leave the highway to recharge their batteries, can be defined with the dirac delta function as

$$\lambda(x,t) = \sum_i \mu_o(t)\delta(x-y_i). \tag{16}$$

Similar to the role played in (12) and (13), $b_d^+(x,t)$ and $b_d^-(x,t)$, the dirac delta function is included in the temporary departing rate in order to represent that discharged vehicles can only be recharged at a charging station located near the ith exit of the highway. The charging completion rate per minute (i.e., $\mu_o(t)$) can be approximated to a function of the average charging power per vehicle (i.e., $p_{\rm av}$[kW]) and the average recharged state-of-charge per vehicle at a charging station (i.e., $soc_{\rm av}$[kWh]), and that is

$$\mu_o(t) = k_1 \frac{p_{\rm av}}{soc_{\rm av}}. \tag{17}$$

where k_1 is a proportional constant that equals 1 over 60 [h/min]. The time to complete charging an EV can also be defined as the reciprocal of the charging completion rate.

In summary, the densities of discharged vehicles which enter or leave the system at exits between the origin and location x and at time t-that is, $f_d^+(x,t)$ and $f_d^-(x,t)$, respectively-can be expressed with (12) and (15) as follows:

$$f_d^+(x,t) = b_d^+(x,t) \tag{18}$$

$$\begin{aligned} f_d^-(x,t) &= b_d^-(x,t) + c_d^-(x,t) \\ &= b_d^-(x,t) + r(x,t)\lambda(x,t). \end{aligned} \tag{19}$$

By substituting the right sides of (10) with (18) and (19), the following simplified equation can be derived:

$$\frac{d[r(x,t)]}{dt} = b_d^+(x,t) - b_d^-(x,t) - \left[\frac{\partial v(x,t)}{\partial x} + \lambda(x,t)\right] r(x,t) \tag{20}$$

Because of the partial derivative of $v(x,t)$ with respect to x, (20) is considered an ordinary differential equation (ODE) if and only if $v(x,t)$ is not a function of $r(x,t)$. Therefore, (20) can be solved with numerical methods without many difficulties. The solution of (20) is the density of discharged vehicles at location x and time t, $r(x,t)$. In order to obtain the boundary condition for (20), the following points are considered:

1) There does not exist discharged EVs permanently leaving from the spatial origin of the highway but exist discharged EVs entering the spatial origin because the basic highway model is semi-infinite.
2) Since the arrival rate of discharged EVs at the spatial origin (i.e., $\alpha_0(t)$ [number of vehicles per minute]) can be considered the traffic flow at the spatial origin, $\alpha_0(t)$ can be estimated with (6). That is,

$$\alpha_0(t) = r(0,t)v(0,t). \tag{21}$$

Hence, the boundary condition for $r(0,t)$, for all $t > 0$, is given by

$$r(0,t) = \frac{\alpha_0(t)}{v(0,t)}. \tag{22}$$

Next, the solution of $r(x,t)$ from (20) can be used to calculate the exiting traffic flow of discharged EVs at the ith exit at time t (i.e., $h_d(y_i,t)$) based on (6). The exiting traffic at the ith exit at time t can be considered the sum of the permanent and temporary departing discharged EV. Thus, the arrival rate of discharged EVs at the ith highway charging station (i.e., $z(y_i,t)$) can be considered the difference between $h_d(y_i,t)$ and $\beta_i(t)$, that is,

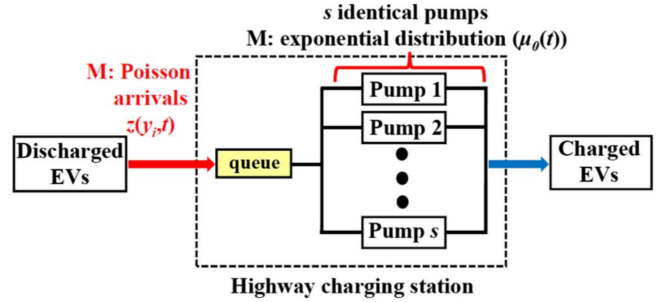

Fig. 6. M/M/s queueing system in the highway charging station.

$$z(y_i,t) = h_d(y_i,t) - \beta_i(t) = r(y_i,t)v(y_i,t) - \beta_i(t) \tag{23}$$

assuming that discharged EVs depart from the highway exit at the same velocities as were on the highway. Therefore, the arrival rate of discharged vehicles at a charging station can be obtained with the solution of (20) (i.e., $r(x,t)$), the exiting speed of discharged EVs at location y_i and time t (i.e., $v(y_i,t)$), and the permanent departing rate at ith exit (i.e., $\beta_i(t)$).

B. EVs' Charging Demand by the M/M/s Queueing Theory

The next step is to estimate the EVs' charging demand at a rapid charging station with (23) and the M/M/s queueing theory [26]. A queue is a waiting line which we may encounter at a bank, a post office, or a grocery store. In this case, EV users are customers in the charging station, and they may require waiting at a charging station in order to recharge their batteries. As illustrated in Fig. 6, the following conditions are assumed in the highway charging station:

1) Discharged vehicles arrive at a charging station based on the Poisson distribution whose mean is $z(y_i,t)$.
2) There are s identical charging pumps in the highway charging station under study.
3) The charging completion rate whose mean is $\mu_0(t)$ as described in (17) is independently and exponentially distributed.
4) The discharged vehicles form a single queue on their arrivals, which will be charged by the next available charging pump based on a first-come-first-served rule.

These assumptions allow an EV charging service at a fast charging station to follow the M/M/s queueing theory. According to the M/M/s queueing theory [26], the queueing system is stable if and only if the occupation rate of charging pumps (i.e., ρ) is less than 1. This occupation rate of charging pumps denotes the probability that a charging pump is not inactive (i.e., it is in use), and it can be obtained by dividing the arrival rate of discharged EVs at a charging station (i.e., $z(y_i,t)$) by the number of charging pumps in a charging station (i.e., s) and by the charging completion rate (i.e., $\mu_0(t)$). That is [26],

$$\rho = \frac{z(y_i,t)}{s\mu_0(t)}. \tag{24}$$

Based on the necessary and sufficient condition for the stability of the queueing system and (24), the minimum number of charging pumps should meet the following inequality in order to ensure that the queueing system of the highway charging station is stable [26]:

$$s > \frac{z(y_i,t)}{\mu_0(t)}. \tag{25}$$

Next, the limiting-state probability (i.e., $Q_n(t)$) that there are n numbers of discharged EVs in the highway charging station is required to determine the expected number of busy charging pumps. According to [26], the limiting-state probability that there are n number of customers-that is, the number of discharged EVs- in the M/M/s queueing system is given by

$$Q_n(t) = \begin{cases} \frac{1}{n!}\left(\frac{z(y_i,t)}{\mu_0(t)}\right)^n Q_0 & \text{if } 0 \le n \le s-1 \\ \frac{1}{s!s^{n-s}}\left(\frac{z(y_i,t)}{\mu_0(t)}\right)^n Q_0 & \text{if } n \ge s \end{cases}, \tag{26}$$

where Q_0 equals

$$Q_0 = \left[\sum_{n=0}^{s-1}\frac{1}{n!}\left(\frac{z(y_i,t)}{\mu_0(t)}\right)^n + \frac{1}{s!}\left(\frac{z(y_i,t)}{\mu_0(t)}\right)^s\left(\frac{s\mu_0(t)}{s\mu_0(t)-z(y_i,t)}\right)\right]^{-1}. \tag{27}$$

Since n and s are the number of discharged EVs and charging pumps in the highway charging station, respectively, the number of busy charging pumps is given by $\min(n,s)$. Then, the expected number of busy charging pumps (i.e., $B(t)$) is defined by [26] as

$$B(t) = \sum_{n=0}^{\infty}\min(n,s)Q_n(t) = \frac{z(y_i,t)}{\mu_0(t)}. \tag{28}$$

Derivation of (26) to (28) is out of the scope of this paper. However, a reader may refer to [26] for an explanation of such equations.

Now, the power demand of the ith exit charging station (i.e., $P_d(y_i,t)$) can be estimated by the multiplication of the average charging power per pump (i.e., p_{av}) and the expected number of busy charging pumps (i.e., $B(t)$). That is, the charging demand is

$$P_d(y_i,t) = p_{\mathrm{av}}B(t) = p_{\mathrm{av}}\frac{z(y_i,t)}{\mu_0(t)} \tag{29}$$

where y_i is a distance from the spatial origin to the ith exit on the highway.

C. Stochastic Model

The purpose of the stochastic highway EV PALM presented here is to identify the expected value of the stochastic EV charging demand. As the deterministic fluid dynamic model in Section IV-A, the same highway environment and notations are used here for the stochastic model unless stated otherwise. Thus, the same conservation equation can be applied to the stochastic highway EV PALM as follows:

$$R(x,t) + H_d(x,t) = F_d^+(x,t) - F_d^-(x,t). \tag{30}$$

Similar to the highway PALM [23]–[25], the density and traffic flow of discharged vehicles at location x and time t—that is, $\langle r(x,t)\rangle$ and $\langle h_d(x,t)\rangle$, respectively—in the stochastic model should be expressed with the expected values of discharged vehicles so that the model reflects stochastic behaviors of discharged vehicles on a highway. That is,

$$\langle r(x,t)\rangle \equiv \frac{\partial E[R(x,t)]}{\partial x} \text{ and}$$
$$\langle h_d(x,t)\rangle \equiv \frac{\partial E[H_d(x,t)]}{\partial t}. \tag{31}$$

where $E[\cdot]$ indicates the expectation of the operand. In order to capture stochastic behaviors, the densities, $\langle f_d^+(x,t)\rangle$, $\langle f_d^-(x,t)\rangle$, $\langle b_d^+(x,t)\rangle$, $\langle b_d^-(x,t)\rangle$, and $\langle c_d^-(x,t)\rangle$ should similarly be defined by

$$\begin{aligned}\left\langle f_d^+(x,t)\right\rangle &\equiv \frac{\partial^2 E[F_d^+(x,t)]}{\partial x\partial t},\\ \left\langle f_d^-(x,t)\right\rangle &\equiv \frac{\partial^2 E[F_d^-(x,t)]}{\partial x\partial t},\\ \left\langle b_d^+(x,t)\right\rangle &\equiv \frac{\partial^2 E[B_d^+(x,t)]}{\partial x\partial t},\\ \left\langle b_d^-(x,t)\right\rangle &\equiv \frac{\partial^2 E[B_d^-(x,t)]}{\partial x\partial t},\\ \text{and } \left\langle c_d^-(x,t)\right\rangle &\equiv \frac{\partial^2 E[C_d^-(x,t)]}{\partial x\partial t}.\end{aligned} \tag{32}$$

In the stochastic model, discharged EVs randomly enter the highway at location x and time t with the mean rate of $\langle \alpha_i(t)\rangle$, while discharged EVs randomly depart from and then never return to the highway with the mean rate of $\langle \beta_i(t)\rangle$. Then, similar to (12) and (13), $\langle f_d^+(x,t)\rangle$, $\langle b_d^+(x,t)\rangle$, and $\langle b_d^-(x,t)\rangle$ are expressed with $\langle \alpha_i(t)\rangle$ and $\langle \beta_i(t)\rangle$

$$\left\langle b_d^+(x,t)\right\rangle = \left\langle f_d^+(x,t)\right\rangle = \sum_i \langle \alpha_i(t)\rangle\,\delta(x-y_i) \tag{33}$$

$$\left\langle b_d^-(x,t)\right\rangle = \sum_i \langle \beta_i(t)\rangle\,\delta(x-y_i). \tag{34}$$

With the mean temporarily departing rate $\langle \lambda(x,t)\rangle$, discharged EVs randomly leave the highway to charge their batteries. Then, similar to (15) and (16), the associated density (i.e., $\langle c_d^-(x,t)\rangle$) is given by

$$\begin{aligned}\left\langle c_d^-(x,t)\right\rangle &= \langle r(x,t)\rangle\,\langle \lambda(x,t)\rangle\,,\\ &= \langle r(x,t)\rangle \sum_i \langle \mu_o(t)\rangle\,\delta(x-y_i)\end{aligned} \tag{35}$$

where $\langle \mu_o(t)\rangle$ is analogous to (17) and given by

$$\langle \mu_o(t)\rangle = k_1\frac{p_{\mathrm{av}}}{soc_{\mathrm{av}}}. \tag{36}$$

With these definitions, the mean density of discharged vehicles at location x and time t (i.e., $\langle r(x,t)\rangle$) can be obtained by solving the following ODE, similar to (20):

$$\frac{d\,\langle r(x,t)\rangle}{dt} = \left\langle b_d^+(x,t)\right\rangle - \left\langle b_d^-(x,t)\right\rangle - \left[\frac{\partial v(x,t)}{\partial x} + \langle \lambda(x,t)\rangle\right]\langle r(x,t)\rangle\,. \tag{37}$$

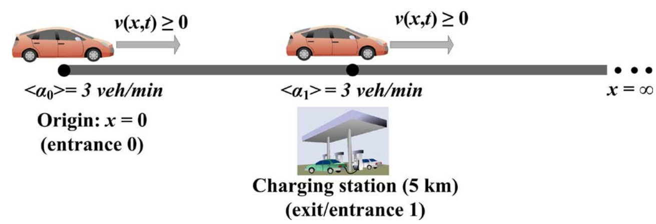

Fig. 7. Basic highway model for a numerical example.

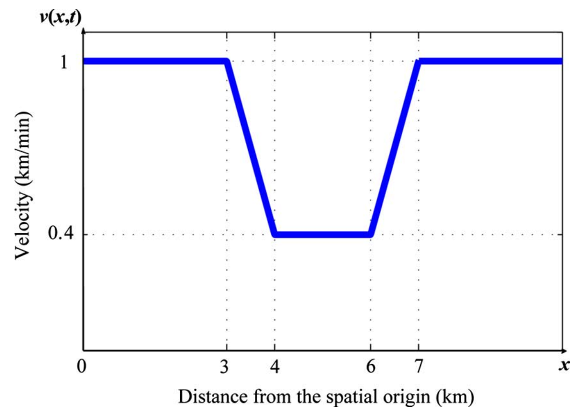

Fig. 8. Velocity fields of vehicles on a highway during the time interval $(40, 55]$ min.

In the same manner of (22), the boundary condition for $\langle r(0,t)\rangle$, for all $t > 0$, is given by

$$\langle r(0,t)\rangle = \frac{\langle \alpha_0(t)\rangle}{v(0,t)}. \tag{38}$$

Then, $\langle r(x,t)\rangle$ can be obtained by solving (37) with (38), and the mean arrival rate of discharged EVs at the ith exit charging station (i.e., $\langle z(y_i,t)\rangle$) can be considered the difference between the expected exiting traffic flow at location y_i and time t (i.e., $\langle h_d(y_i,t)\rangle$) and the mean rate of $\langle \beta_i(t)\rangle$, similar to (23). That is,

$$\begin{aligned}\langle z(y_i,t)\rangle &= \langle h_d(y_i,t)\rangle - \langle \beta_i(t)\rangle \\ &= \langle r(y_i,t)\rangle\, v(y_i,t) - \langle \beta_i(t)\rangle.\end{aligned} \tag{39}$$

By applying the mean arrival rate of discharged EVs into the M/M/s queueing theory [26], the expected charging demand of the ith exit charging station (i.e., $E[P_d(y_i,t)]$) can be estimated by

$$E[P_d(y_i,t)] = p_{\rm av}\frac{\langle z(y_i,t)\rangle}{\langle \mu_0(x)\rangle} \tag{40}$$

which is similar to (29).

V. Numerical Example and Discussions

This section provides a numerical example in order to illustrate the spatial and temporal dynamics of the highway EV PALM presented in Section IV. A numerical example of the stochastic model is presented here because planning activities will typically be based on such model. Nevertheless, extension into the deterministic model is straightforward because both models are analogous, as demonstrated by (20) and (37) showing the same form. Likewise, (29) and (40) show that the expected charging demand in the stochastic model and the charging demand in the deterministic model are also analogous.

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

1) that two entrances/exits are located one at the spatial origin and the other at 5 km from the spatial origin, respectively;
2) that discharged vehicles arrive to the spatial origin and to the 5 km entrance at the mean rate of 3 vehicles/min (indicated by $\langle \alpha_0(t)\rangle = \langle \alpha_1(t)\rangle = 3$); and
3) that only one rapid charging station is located near the exit at 5 km as shown in Fig. 7.

In addition, it is postulated that discharged vehicles only depart from the highway through the 5 km exit in order to recharge their batteries at a rapid charging station. Although standards of charging power for a rapid charging station have not been finalized yet, it is expected that an EV can be charged with 50 to 70 kW at a level 3 charging station [1]. In this example, it is assumed that an EV will be charged with 70 kW at the highway fast charging station (i.e., $p_{\rm av} = 70$ kW). The EV considered here is a PHEV33 compact sedan [7] whose electric mode driving range and battery size are 33 mile—that is, about 53 km—and 8.6 kWh, respectively. Since the EV user may also recharge it at the final destination (e.g., office), every user will not fully charge it at the highway charging station whose charging price may be more expensive than that of the slow charging station (e.g., home or office). Thus, it is assumed that the average charge per vehicle at the highway charging station (i.e., $soc_{\rm av}$) is 4 kWh which is about 50% of the battery capacity and can last for the one-way trip to the final destination. Then, the mean charging completion rate per minute (i.e., $\langle \mu_o(t)\rangle$) can be calculated by (36), which results equal to 0.3. Hence, it requires 3.4 min to charge 4 kWh with a 70 kW charging rate.

In order to mimic traffic congestion during rush hour, it is hypothesized in this example that the velocity fields of vehicles on the highway $v(x,t)$ is 1 km/min for all $x \geq 0$ when $t \leq 40$ or $t > 55$ min and that $v(x,t)$ during the time interval $(40, 55]$ min corresponding to rush hour is described as follows:

$$v(x,t) = \begin{cases} 1 & \text{if } x \leq 3 \\ 1 - 0.6(x-3) & \text{if } 3 < x \leq 4 \\ 0.4 & \text{if } 4 < x \leq 6. \\ 0.4 + 0.6(x-6) & \text{if } 6 < x \leq 7 \\ 1 & \text{if } x \geq 7 \end{cases} \tag{41}$$

Fig. 8 depicts the velocity fields of vehicles on a highway as a function of the distance from the spatial origin during the time interval $(40, 55]$ min representing rush hour. As can be seen in Fig. 8, vehicles on a highway reduce their velocities starting from 3 km and then recover their normal speeds at 7 km. The velocity drop in the interval $(3, 7]$ during the time interval $(40, 55]$ min in Fig. 8 can represent reduced speeds in a congested area during rush hour.

Under those aforementioned assumptions and parameters of this example, the mean traffic density of discharged vehicles on a highway is solved with numerical methods using (37) during normal hours and rush hour. The boundary condition for $\langle r(0,t)\rangle$ is $\langle \alpha_0(t)\rangle / v(0,t)$ for all $t > 0$ as obtained from (38). Figs. 9 and 10 illustrate the simulated mean densities of discharged vehicles on a highway at $t = 35$ min and $t = 45$ min

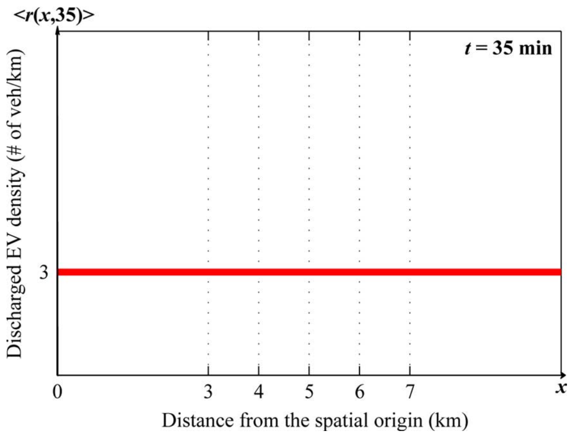

Fig. 9. Simulated mean density of discharged vehicles at $t = 35$ min.

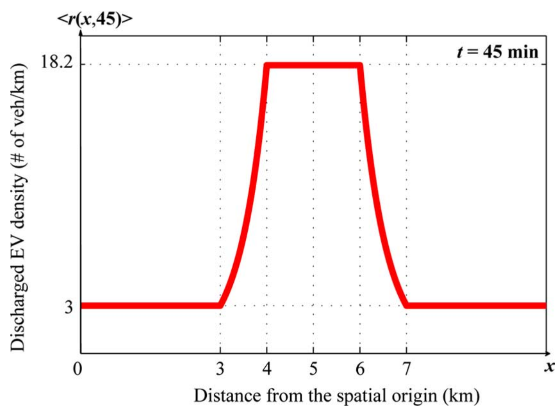

Fig. 10. Simulated mean density of discharged vehicles at $t = 45$ min.

respectively. As revealed by Fig. 9, the mean density of discharged vehicles is constant at 3 vehicles/min, which is the same than the boundary condition. This result indicates that during the normal hours if the mean rate of discharged vehicles entering the highway is constant the expected EV charging demand at a highway charging station is almost constant. In contrast, as attested in Fig. 10, the simulated mean density of discharged vehicles during the rush hour-the time interval $(40, 55]$ min-increases sharply starting from 3 km due to reduced velocities in the interval $(3, 7]$. This high mean traffic density in these locations implies that there is traffic congestion in this area and that the expected EV charging demand of a rapid charging station located near the 5 km exit increases due to the high mean density of discharged vehicles in this region. Figs. 11 and 12 obtained by (6) describe the simulated mean traffic flow of discharged vehicles on a highway at $t = 35$ min and $t = 45$ min respectively. Assuming that the EV charging service is followed by the M/M/s queueing theory, the expected charging demand of the 5 km charging station can be predicted by (39) and (40) as can be seen in Fig. 13. Since it is assumed that discharged EVs only depart for visiting the charging station, there is no permanent departing discharged EV traffic at the 5 km exit in this example (i.e., $\langle \beta_1(t) \rangle = 0$ at the 5 km exit). The expected charging demand during the time interval $(40, 55]$ min was 2.42 times greater than that during the normal hours due to traffic congestion as indicated in Fig. 13. In addition, based on (25) and considering that the time intervals (40, 55] min in this example represents the worst scenario during

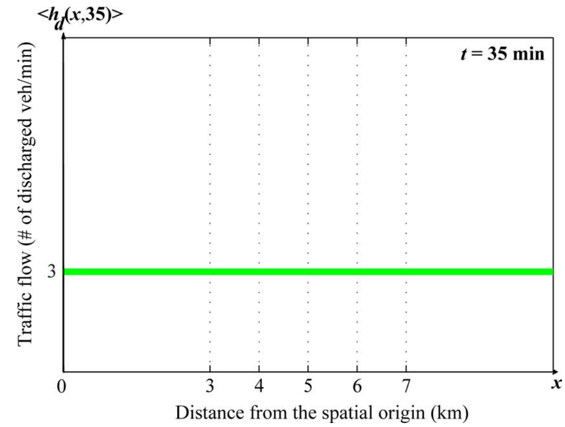

Fig. 11. Simulated mean traffic flow of discharged vehicles at $t = 35$ min.

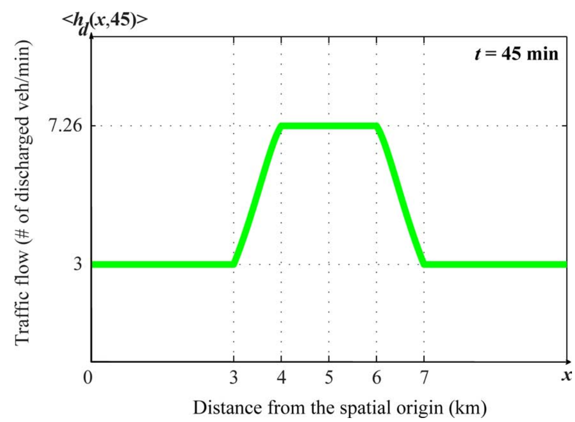

Fig. 12. Simulated mean traffic flow of discharged vehicles at $t = 45$ min.

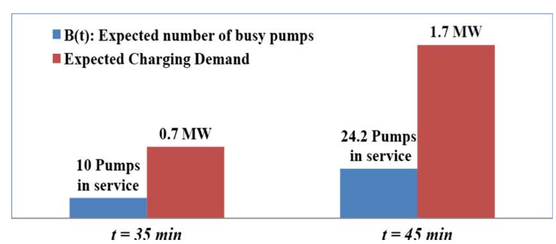

Fig. 13. Expected number of charging pumps in service and expected charging demand at the 5 km fast charging station on a highway.

a day in which traffic jams occur at this location, at least 25 charging pumps should be prepared at this charging station to cope with the demand.

As this numerical example predicts the EV charging demand of a rapid charging station on a highway, the highway EV PALM may allow power system engineers to estimate a charging demand profile for a specific charging station. Based on this demand profile, appropriate distribution systems such as transformers and underground cables can be installed up to the charging station [14]–[16]. In addition, depending on the demand profile, adequate size of energy storage systems can be determined, which will provide flexible energy sources such as renewable energy sources in order to reduce the price of charging an EV as illustrated in Fig. 14. The energy storage system shown in Fig. 14 may be charged with inexpensive electricity from the utility grid during the off-peak hours or with low-priced and "green" electricity from renewable energy sources such as wind and solar energy. This energy storage

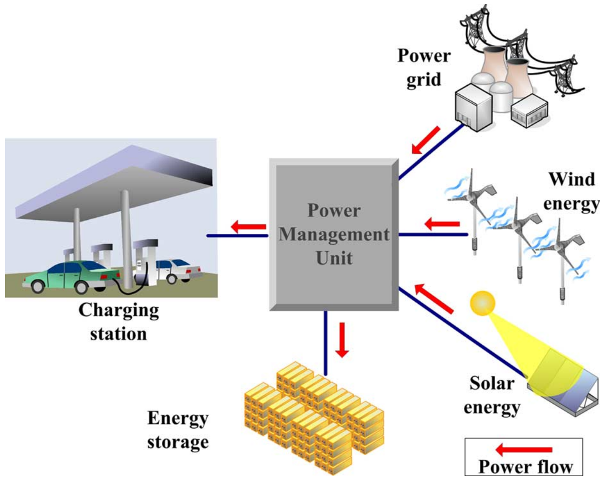

Fig. 14. Flexible charging strategy in a rapid charging station during the off-peak time.

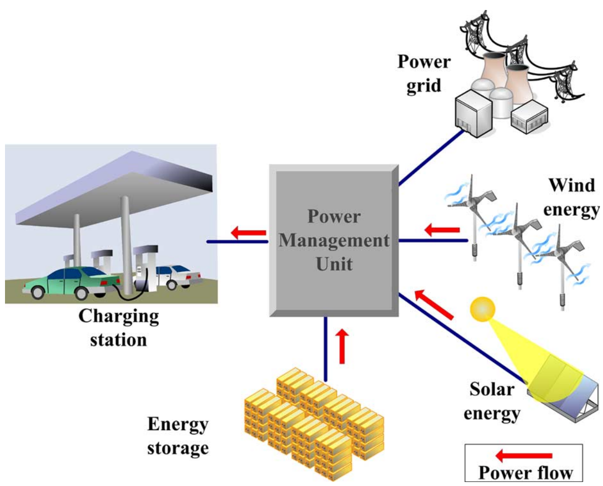

Fig. 15. Flexible charging strategy in a rapid charging station during the peak time.

system may provide electricity for charging batteries of EVs with a reasonable price during the peak hours as depicted in Fig. 15. The charging station may also participate in a demand response program [27]–[31] in this way. Moreover, this charging demand model may allow city planners to determine the geographical location and size of a rapid charging station on a highway depending on the charging demand profile. Furthermore, this EV charging demand model requires relatively known traffic data which are traffic velocities and the number of vehicles entering or leaving the highway at a given exit and for a given time. The former traffic data can be collected through GPSs or CCTVs on a highway without difficulties [32]–[35], and the latter data can be estimated with demographic data.

VI. Conclusions

This paper proposed a mathematical model of EV charging demand for a rapid charging station on a highway. This mathematical model can help to identify EV charging demand which varies by space and time. The charging demand model is based on the fluid traffic model in wireless communication studies [23]–[25] and the M/M/s queueing theory [26]. Specifically, the first step is to identify the arrival rate of discharged EVs at a charging station with the highway EV PALM. This highway EV model is modified from the fluid traffic model [23]–[25] so that an EV user can charge the EV only at a charging station located near a highway exit. Secondly, EV charging demand is calculated with the arrival rate of discharged EVs by the M/M/s queueing theory [26]. As described in Section III, a basic model of the highway EV PALM (i.e., a semi-infinite, unidirectional, single-lane model) is presented for a fundamental building block by which elaborate highway networks can be developed.

EVs change utility distribution planning approach in many ways but a significant change is the following: traditionally, distribution planners only require focusing on local demand or on demand within the domain of the electric utility. With EVs, demand may move from another utility into the area of the utility for which the planner works. Thus, distribution planning is no longer local but may, actually, require coordination among neighboring utilities. The proposed model may help distribution planners to coordinate each other since a numerical example provided here showed that the proposed model is able to capture the spatial and temporal dynamics of charging demand at a highway charging station. Hence, it can be concluded that the proposed spatial and temporal model may help distribution utility planners to identify charging demand for a specific highway charging station and may allow city and rural planners to determine the location and size of a rapid charging station on a highway.

The proposed charging demand model can also facilitate computer implementation of the planning or analysis tool for the distribution system of the highway charging station because it consists of an ODE which can be solved by a difference equation using a digital computer. Moreover, this model requires relatively known traffic data which are traffic velocities and the number of vehicles entering or leaving the highway at a given exit and for a given time. Utility distribution planners may identify these traffic data from GPSs or CCTVs on a highway and from demographic data.

References

[1] L. Dickerman and J. Harrison, "A new car, a new grid," *IEEE Power Energy Mag.*, vol. 8, no. 2, pp. 55–61, Apr. 2010.

[2] M. Duvall, E. Knipping, M. Alexander, L. Tonachel, and C. Clark, "Environmental assessment of plug-in hybrid electric vehicles—Volume 1: Nationwide greenhouse gas emissions," Electric Power Research Institute, Palo Alto, CA, Tech. Rep. 1015325, 2007.

[3] K. Parks, P. Denholm, and T. Markel, Costs and emissions associated with plug-in hybrid electric vehicle charging in the Xcel Energy Colorado Service Territory National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-640–41410, 2007.

[4] C. Samaras and K. Meisterling, "Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy," *Environ. Sci. Tech*, vol. 42, no. 9, pp. 3170–3176, Apr. 2008.

[5] C. H. Stephan and J. Sullivan, "Environmental and energy implications of plug-in hybrid-electric vehicles," *Environ. Sci. Tech*, vol. 42, no. 4, pp. 1185–1190, Feb. 2008.

[6] P. Mohseni and R. G. Stevie, "Electric vehicles: Holy grail or fool's gold," in *Proc. 2009 IEEE PES Gen. Meet.*, pp. 1–5.

[7] M. Kintner-Meyer, K. P. Schneider, and R. G. Pratt, Impacts assessment of plug-in hybrid vehicles on electric utilities and regional US power grids: Part 1: Technical analysis Pacific Northwest National Laboratory, Richland, WA, Tech. Rep. PNNL-SA-61669, 2007.

[8] C. K. Nelson, "Plug-in electric vehicle impact on nashville electric service distribution system planning," in *Proc. 2010 IEEE Power Eng. Soc. Transm. Distrib. Conf. Expo.*, pp. 1–2.

[9] J. Taylor, A. Maitra, M. Alexander, D. Brooks, and M. Duvall, "Evaluations of plug-in electric vehicle distribution system impacts," in *Proc. 2010 IEEE Power Eng. Soc. Gen. Meet.*, pp. 1–6.

[10] Litos Strategic Communication, “The smart grid: An introduction,” 2008, pp. 1–43, prepared for the U.S. Department of Energy.
[11] L. P. Fernandez, T. G. S. Roman, R. Cossent, C. M. Domingo, and P. Frias, “Assessment of the impact of plug-in electric vehicles on distribution networks,” *IEEE Trans. Power Syst*, vol. 26, no. 1, pp. 206–213, Feb. 2011.
[12] S. W. Hadley, “Impact of plug-in hybrid vehicles on the electric grid,” Oak Ridge National Laboratory, Oak Ridge, TN, Tech. Rep. ORNL/TM-2006/554, 2006.
[13] S. W. Hadley, “Evaluating the impact of plug-in hybrid electric vehicles on regional electricity supplies,” in *Proc. 2007 iREP Symp*, pp. 1–12.
[14] C. Farmer, P. Hines, J. Dowds, and S. Blumsack, “Modeling the impact of increasing PHEV loads on the distribution infrastructure,” in *Proc. 2010 Hawaii Int. Conf. Syst. Sci*, pp. 1–10.
[15] S. Meliopoulos, J. Meisel, G. Cokkinides, and T. Overbye, Power system level impacts of plug-in hybrid vehicles: Volume II Power Systems Engineering Research Center, Tech. Rep. PSERC Doc. 09–12, 2009.
[16] C. Roe, F. Evangelos, J. Meisel, A. P. Meliopoulos, and T. Overbye, “Power system level impacts of PHEVs,” in *Proc. 2009 Hawaii Int. Conf. Syst. Sci*, pp. 1–10.
[17] J. Taylor, A. Maitra, M. Alexander, D. Brooks, and M. Duvall, “Evaluation of the impact of plug-in electric vehicle loading on distribution system operations,” in *Proc. 2009 IEEE Power Eng. Soc. Gen. Meet.*, pp. 1–6.
[18] R. Garcia-Valle and J. G. Vlachogiannis, “Letter to the editor: Electric vehicle demand model for load flow studies,” *Elect. Power Compon. Syst.*, vol. 37, no. 5, pp. 577–582, May 2009.
[19] F. M. Bass, “A new product growth model for consumer durables,” *Manage. Sci*, vol. 15, no. 5, pp. 215–227, Jan. 1969.
[20] J. Axsen and K. S. Kurani, “Anticipating plug-in hybrid vehicle energy impacts in California: Constructing consumer-informed recharge profiles,” *Transp. Res.: Part D, Transport Environ.*, vol. 15, no. 4, pp. 212–219, Jun. 2010.
[21] L. Kelly, “Probabilistic modelling of plug-in hybrid electric vehicle impacts on distribution networks in British Columbia,” M. S. thesis, Dept. Mech. Eng., Univ. Victoria, Victoria, BC, Canada, 2009.
[22] J. W. May, “Plugging in: A feasibility study on public plug-in vehicle charging infrastructure investment,” M. S. thesis, Sch. Environ., Duke Univ, Durham, NC, 2009.
[23] K. K. Leung, W. A. Massey, and W. Whitt, “Traffic models for wireless communication networks,” in *Proc. 1994 IEEE INFOCOM ’94*, pp. 1029–1037.
[24] K. K. Leung, W. A. Massey, and W. Whitt, “Traffic models for wireless communication networks,” *IEEE J. Sel. Areas Commun*, vol. 12, no. 8, pp. 1353–1364, Oct. 1994.
[25] W. A. Massey and W. Whitt, “A stochastic model to capture space and time dynamics in wireless communication systems,” *Probab. Eng. Inf. Sci*, vol. 8, no. 4, pp. 541–569, Oct. 1994.
[26] V. G. Kulkarni, *Modeling, Analysis, Design, and Control of Stochastic Systems*, 1st ed. New York: Springer, 1999.
[27] S. Braithwait, “Behavior modification,” *IEEE Power Energy Mag.*, vol. 8, no. 3, pp. 36–45, May-Jun. 2010.
[28] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, “Demand dispatch,” *IEEE Power Energy Mag.*, vol. 8, no. 3, pp. 20–29, May-Jun. 2010.
[29] J. Medina, N. Muller, and I. Roytelman, “Demand response and distribution grid operations: Opportunities and challenges,” *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 193–198, Sep. 2010.
[30] M. Parvania and M. Fotuhi-Firuzabad, “Demand response scheduling by stochastic scuc,” *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 89–98, Jun. 2010.
[31] F. Rahimi and A. Ipakchi, “Demand response as a market resource under the smart grid paradigm,” *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 82–88, Jun. 2010.
[32] J. Gonder, T. Markel, M. Thornton, and A. Simpson, “Using global positioning system travel data to assess real-world energy use of plug-in hybrid electric vehicles,” *Transp. Res. Rec.: J. Transp. Res. Board*, vol. 2017, no. 1, pp. 26–32, Dec. 2007.
[33] J. Gonder, T. Markel, M. Thornton, and A. Simpson, “Using GPS travel data to assess the real world driving energy use of plug-in hybrid electric vehicles (PHEVs),” in *Proc. 2007 Annu. Meet. Transp. Res. Board*, pp. 1–11.
[34] P. Chavan, K. Tufte, C. M. Monsere, M. Stephens, and R. L. Bertini, “Extending the use of archived ITS data as a potential management tool to evaluate traveler information on dynamic message signs,” in *Proc. 2008 Annu. Meet. Transp. Res. Board*, pp. 1–10.
[35] M. Dalgleish and N. Hoose, *Highway Traffic Monitoring and Data Quality*, 1st ed. Norwood, MA: Artech House, 2008.
[36] R. Haberman, *Mathematical Models: Mechanical Vibrations, Population Dynamics, and Traffic Flow*. Philadelphia, PA: SIAM, 1998.
[37] J. Spurk and N. Aksel, *Fluid Mechanics*, 2nd ed. New York: Springer, 2008.

Sungwoo Bae (S’07) received the B.S. degree in electrical and computer engineering from Hanyang University, Seoul, Korea, in 2006, and the M.S.E. degree in electrical and computer engineering from the University of Texas, Austin, in 2009. He is currently working toward the Ph.D. degree in the Department of Electrical and Computer Engineering at the University of Texas at Austin.

Mr. Bae was the recipient of the Grand Prize for his excellent design at the National Electrical Engineering Design Contest in 2005, presented by the Minister of Commerce, Industry and Energy of the Republic of Korea.

Alexis Kwasinski (S’03–M’07) received the B.S. degree in electrical engineering from the Buenos Aires Institute of Technology (ITBA), Buenos Aires, Argentina, a graduate specialization degree in telecommunications from the University of Buenos Aires, in 1997, and the M.S. and Ph.D. degrees in electrical engineering from the University of Illinois, Urbana-Champaign, in 2005 and 2007, respectively.

From 1993 to 1997 he worked for Telefónica of Argentina designing and planning telephony outside plant networks. Then he worked for five years for Lucent Technologies Power Systems as a Technical Support Engineer and Sales Technical Consultant in Latin America. For three years, he was also a part-time instructor in charge of ITBA’s telecommunications laboratory. He is currently an Assistant Professor at the Department of Electrical and Computer Engineering at the University of Texas, Austin. His research interests include power electronics, distributed generation, renewable and alternative energy, smart grids, and analysis of the impact of extreme events on critical power infrastructure which included performing damage assessments after several natural disasters, such as hurricanes Katrina (2005) and Ike (2008), and the 2010 Maule, Chile, Earthquake, and the 2011 Tohoku Region, Japan, Earthquake.

Dr. Kwasinski is also an active participant in Austin’s smart grid initiative: the Pecan Street Project. He was a member of the Executive Committee of the Argentine Electrotechnical Association during the years 1994 and 1995. In 2005, he was awarded the Joseph J. Suozzi INTELEC Fellowship and in 2007 he received the best technical paper award at INTELEC. In 2009 he received an NSF CAREER award. Dr. Kwasinski is an Associate Editor for the IEEE Transactions on Energy Conversion.