Joint Capacity Modeling for Electric Vehicles in V2I-enabled Wireless Charging Highways

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***Abstract*—Wireless Charging Highways (WCHs) have been introduced by industry and academia to enable charging-while-driving for electric vehicles (EVs) and to combat range anxiety. While detailed planning and performance evaluation of such systems are crucial due to high cost and long life expectancy, most existing works assume a perfect communication environment. In this paper, we introduce a joint capacity model that takes into account both power and communication resources for WCH construction planning, and optimal day-to-day operation. The vehicle-to-infrastructure (V2I) communication and grid power capacities, along with the EV's average service rate are formulated following technology requirements, EV speed-density characteristics, and the EV's energy needs and consumption. In addition, a two-dimension Markov chain-based model is designed to capture the WCH power and connectivity dynamics. The proposed model can be used to calculate the system's Quality of Service (QoS) and profit, provide design insights, and assess the impact of speed regulation, or admission control on the WCH lane. Finally, the performance of the proposed model is evaluated using real US highway data with the results demonstrating its ability to accurately capture the service provision dynamics, and to identify trade-offs between system parameters.**

***Index Terms*—dynamic wireless charging, electric vehicles, wireless charging highway, V2X, capacity planning**

I. INTRODUCTION

Range anxiety is a key factor for the deceleration of the broad adoption of Electric Vehicles (EVs), and the main motivator behind EV charging research [1]. Until now most of the commercially adopted solutions, namely destination charging (e.g., parking lots), and fast-charging stations are often considered inconvenient [2]. Specifically, the fact that (a) EV charging takes more time than traditional fuelling, (b) EV drivers are compelled to make more frequent stops per trip, and (c) they may not find available charging stations upon arrival, significantly increases the time penalty per trip.

In light of the above, dynamic wireless charging (DWC) has emerged as a prominent alternative. The main advantages include the charge-while-driving flexibility that eliminates stops in long-distance trips, along with the opportunity to reduce battery sizes and costs. Thus, if the technology is adopted for use on existing highway systems, the EVs' range can be increased, even be limitless. Naturally, many industry vendors and research teams are working on on-road wireless charging projects. Cases in point include the FABRIC [3] project that was concluded with the development of two e-road charging solutions, the new EU commission INCIT-EV project [4] which is coordinated by Renault and aims to investigate DWC in urban areas, and for long distances, and finally, the Smartroad Gotland project [5] in Sweden aiming to charge electric buses and trucks while driving on a 1.6 km e-road.

However, the broad integration of the wireless charging highway (WCH) technology into existing roads involves several challenges that pertain to infrastructure planning. The cost of integrating on-road charging is substantial as it includes reconstruction and additional resource provisioning for power and communication capacity. The latter is crucial to support control operations, additional data exchange, and charging coordination. In addition, since the newly deployed WCH's life expectancy should span over decades, the installation planning should account for the dynamic road parameters, namely EV speed, incoming traffic conditions, the segment's length, along with local environmental characteristics.

A. Related Work

Numerous research works have examined some of the aforementioned challenges. In [6], the authors solve a mixed-integer optimization problem to find an e-road system's optimal parameters including the number of chargers, power level, battery capacity, and track length. The authors in [7] estimate the EV wireless charging load using the distribution of traffic, and introduce a pricing mechanism to ensure the whole electricity market's social welfare. The work in [8] analyses the steady-state performance of the WCH by modeling the system as an M/M/s/s state-dependent loss queue. The authors take into account the EV power consumption, the power system's capacity, and the transportation system's conditions. Finally, in [9], the authors model the WCH as an M/M/s loss queue accounting for the EV's energy demand with the assumption that the speed is controlled centrally.

B. Contributions and Outline

Though all the aforementioned research efforts model the WCH performance and aid the planning of the power demand components, none of them account for service losses or underperformance due to delayed or non-existing EV-infrastructure communications. Specifically, to the best of our knowledge, the related literature assumes already established [8], or perfect communication without congestion [9]. However, due to the

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dynamicity of the setting, and the safety-critical nature of the application, vehicle-to-infrastructure (V2I) communications should be carefully planned during the design phase. Our paper aims exactly at filling this gap and proposes joint capacity modeling of both communication and power resources for WCHs that also account for the specific road segment conditions. This type of modeling is important for both the infrastructure planning phase and the optimization of the system's day-to-day operation. The main contributions of this work are summarized below:

a) The importance of V2I communications for the WCH operation is described, and the system's communication and power capacities are extracted according to the latest technology requirements, road conditions, and physical limitations.

b) The average service rate of EV charging is derived as a function of the EV's average speed, the speed limit, traffic density, and each EV' energy demand, and consumption.

c) The joint capacity modeling is based on a finite-state continuous Markov chain of two-dimensions that captures the power and V2I capacities, incoming traffic conditions, the wireless communication environment, and the EVs' service rate. Our model can estimate the WCH service's outage probability and the related profit and Quality of Service (QoS).

d) A detailed numerical evaluation is carried out involving a case study of a US highway segment demonstrating the model's ability to predict the WCH performance under different traffic conditions, and parameter settings.

The rest of this work is organized as follows. The V2I-enabled WCH architecture is discussed in Section II. Section III presents the derivation of communication and power capacities along with the stochastic WCH joint capacity model. Finally, Section IV presents a detailed numerical evaluation, while Section V concludes this paper.

II. V2I-enabled WCH Architecture

In this section, we describe the basic architecture of the Wireless Charging Highway, along with the related dynamic wireless charging, and V2I communication technologies.

We consider a lumped inductive power transfer (IPT) highway (Fig. 1) where Double-D (DD) IPT power pads are placed under the road while each EV is equipped with a secondary coil pad placed under its chassis [10]. The highway's primary pads are sequentially and separately energized following the movement of the EV along the WCH lane. When the primary pads are energized the created magnetic field allows the power transfer between the highway-EV air-gap. We assume that multiple EVs can be charged simultaneously, while for optimal charging we will assume that when the EV is between two primary pads, they are both energized (see Fig. 1) as studied in [11]. Specific design considerations and values regarding the orientation of the primary/secondary pads, dimensions, and installation distance will not be taken into account as they are out of the scope of this work, and an active researcher topic.

The dynamic nature of the WCH infrastructure demands hard real-time constrains for all the control and communication processes. First, the WCH should be able to detect and energize the appropriate primary pads as the EV travels on the highway with minimum delay and given that the variable EV speed. Note that for a high speed of 100 km/h and a primary pad of 500 mm, the pad should detect the EV and be energized in less than 18 ms. In addition, to ensure the pad's steady-state operation the EV should be detected 2.5 ms before the optimum charging zone [11]. As far as the IPT system control is concerned the dynamic nature of the WCH requires a combination of controllers where the secondary pad controller on the EV regulates the power, while the primary controller on the WCH sets the primary pad current for the appropriate EV power demand [12]. Moreover, there may be cases where the charging rates are dynamically defined by each EV based on their needs (e.g., travel time, initial state-of-charge (SoC), road conditions) and other contextual information. Apart from that, an excessive amount of data (GPS coordinates, MEMS sensor readings, 3D dead reckoning information, EV pricing/charging preferences, EV camera feed, etc.) should also be exchanged between the EV and the control infrastructure to enable accurate EV authentication, dynamic billing, and ensure coordinated wireless charging (location & timing).

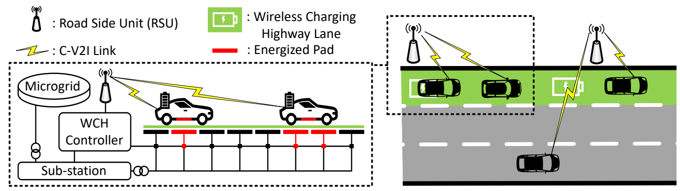

Fig. 1. Wireless Charging Highway Architecture

Regarding the vehicular communication technology, we consider a cellular vehicle-to-infrastructure (C-V2I) architecture. The second phase of such LTE-based cellular standards was completed by 3GPP as Release 15 [13] in June 2018 offering minimum latency bounds of 10 ms which is acceptable considering the needs of our WCH application scenario [14]. Also, latency bounds will be further reduced ($< 3ms$) as the standardization process of next-generation 5G-based NR-V2X system progresses (e.g., 3GPP Release 17 is expected in June 2021) [15]. In this work, we will follow 3GPP Releases 15/16, and will refer collectively to the technology as C-V2X [13], [16]. Each EV is equipped with an On-Board Unit (OBU), and is able to transmit data to Road Side Units (RSUs) through the "PC5" interface that operates in ITS bands (5.9 GHz).

III. System Model

In this section, we present the components of the WCH in detail. For our analysis, we will consider that a large scale WCH lane is divided into autonomous segments of length L and will model V2I-assisted EV charging on a single one.

A. Speed–Density Relationship Model

Intelligent transportation systems often rely on traffic flow theory to extract real-world relationships. In what follows, to account for road conditions in our WCH we will use a speed-density relationship model. According to the general model, the average speed of EVs on the highway is a non-increasing function of the EV density on the road as smaller EV distances require lower speeds. A variety of speed density models have been proposed, both single and multi-regime. In this work, we will use a model based on the energy conservation between physiological potential and the kinetic energy of an EV as discussed in [17]. If c denotes the number of EVs on the WCH lane of length L then we define the EV density as $\rho = \frac{c}{L}$, and the speed-density model $u(\rho)$ as:

$$u\Big(\frac{c}{L}\Big) = \begin{cases} \sqrt{u_f^2 - (u_f - \alpha(\frac{1}{c/L} - \frac{1}{\rho_j}))^2}, & if \ \frac{\alpha \cdot \rho_j}{u_f \cdot \rho_j + a} < \frac{c}{L} < \rho_j \\ u_f, & if \ 0 < \frac{c}{L} < \frac{\alpha \cdot \rho_j}{u_f \cdot \rho_j + a} \end{cases} \tag{1}$$

where $u(\cdot)$ is the average EV speed, u_f denotes the free-flow speed, ρ_j is the jam density, i.e., the EV density when the speed equals to zero, and α is a calibration parameter that expresses the intensity of interaction between EVs [17].

B. V2I Communication System Capacity

The EV capacity of the V2I system depends on channel availability and reliability guarantees. We will assume that multiple RSUs (C-V2X access points) are installed across the WCH sector under study. Also, all RSUs have the same effective communication range r_{ef} (i.e., the minimum required TX/RX communication distance to ensure reliability). Therefore, the number of RSUs across the WCH segment is $\left\lceil \frac{L}{r_{ef}} \right\rceil$.

Regarding the channel availability for each charging EV, the C-V2X NR specification (i.e., Release 15 [13] and onward) defines two possible carrier frequencies (one in the sub 7 GHz space, and one between 24-53 GHz). We will assume that a frequency space B_{tot} is allocated for use in the WCH segment studied as the total system's bandwidth. In addition, the specification allows for a flexible frame structure with various sub-carrier spacings leading to a variety of supported bandwidth lengths for the V2I channels. We will consider a vehicular network of EVs performing V2I connections over mutually orthogonal spectrum bands. Each EV occupies a channel of bandwidth $B_{channel}$, and the maximum number of EV cellular users supported is $V_{bandwidth} = \left\lfloor \frac{B_{tot}}{B_{channel}} \right\rfloor$.

Moreover, to account for reliability and EV speed under the dynamic nature of the V2I communications we define similar to [18] a maximum number of effective users as:

$$V_{effective} = \left\lfloor \frac{2 \cdot r_{ef} \cdot n_{lanes}}{u_{max} \cdot TTC + ev_{length}} \right\rfloor \tag{2}$$

where r_{ef} is the effective range of the RSU, n_{lanes} is the total number of highway lanes, u_{max} is the maximum speed limit of the highway segment, TTC is the time-to-collision between EVs, and ev_{length} is the average EV length. Thus, the total number of channels V available to the EV cellular users (i.e., communication system capacity) is decided as follows:

$$V = \begin{cases} V_{effective}, & if \ V_{effective} < V_{bandwidth} \\ V_{bandwidth}, & otherwise \end{cases} \tag{3}$$

Note that the communication system's capacity corresponds to the highway as a whole (i.e., all available lanes). Also, the RSU's effective range r_{ef}, along with the bandwidth lengths B_{tot}, and $B_{channel}$ can be design parameters of the V2I system chosen during the communication infrastructure planning phase.

C. Wireless Charging Highway Capacity

Evidently, the WCH is able to simultaneously accommodate only an upper-bounded number of EVs, which we will define as power capacity C. This parameter is decided by the WCH control center and depends (a) on the available power supply to the WCH segment and (b) on the segment's traffic capacity.

Assuming that each EV is provided with a charging rate p from the WCH, and that the maximum power capacity is P_{tot} then the capacity due to power constrains is $C_{power} = \left\lfloor \frac{P_{tot}}{p} \right\rfloor$. The maximum power capacity P_{tot} is a design parameter of the whole WCH lane influenced by power grid needs, and can be adjusted by the WCH control unit under different conditions.

To capture the traffic capacity dynamics of the specific highway section under study we will use the speed-density model discussed in Section III-A (i.e., Equation 1). Thus, by fitting the model on realistic traffic data the WCH controller can decide on the traffic capacity with $C_{traffic} = \lfloor \rho_j \cdot L \rfloor$, where ρ_j is the jam density (see Section III-A). Finally, the capacity C of the WCH segment under modelling is given by:

$$C = \begin{cases} C_{power}, & if \ C_{power} < C_{traffic} \\ C_{traffic}, & otherwise \end{cases} \tag{4}$$

D. Average Service Rate

Next, we derive the average EV service rate of the WCH system. We assume that (a) the initial state-of-charge (SoC_{init}) of the EVs entering the WCH follows a normal distribution, (b) all EVs have the same battery capacity, and (c) the objective of all EVs is to fully charge, and therefore a they aim for a full SoC (i.e., $SoC = 1$). Given the above, upon entering the WCH system, the EVs have an energy demand D_{energy} that also follows a normal distribution. In addition, we define the effective charging rate as $P_{effective} = \eta_{ef} \cdot p$ where η_{ef} is the parameter for the WCH's wireless charging efficiency, and p is the constant charging rate for each EV. Also, motion resistance and the related EV speed are the main factors for the EV's energy consumption while on the highway [9]. Therefore, the power consumption can be written as $P_{consume} = \frac{\gamma \cdot u\left(\frac{c}{L}\right)}{\eta_{drive}} + P_{auxiliary}$, where $P_{auxiliary}$ denotes the auxiliary power consumption component, γ is the resistance to motion, $u\left(\frac{c}{L}\right)$ is the EV's speed as a function of lane traffic density, and η_{drive} denotes the efficiency of driveline dynamics. Finally, by also factoring in the cases where the EV's driving time on the WCH (i.e., $\frac{L}{u(c/L)}$) is not enough to meet its service demand, then the charging time of an EV entering the WCH lane under study is:

$$t(u) = \begin{cases} \frac{L}{u(\frac{c}{L})}, & if \ \frac{L}{u(\frac{c}{L})} < \frac{D_{energy}}{P_{effective} - P_{consume}} \\ \frac{D_{energy}}{P_{effective} - P_{consume}}, & otherwise \end{cases} \tag{5}$$

Recall that we model EV speed as a function of lane density. The piece-wise nature of the charging time expression has the following physical interpretation: As EV speeds remain low (high density case) the second piece of the service time function ($\equiv$ charging time) is dominant since the EV remains on the WCH long enough to reach his energy demand target. This service time increases as the EV speed increases (higher speeds force longer WCH stays for the same target SoC) but up to the point where the charging time equals the EV's driving time on the segment of length L. After this point, service time is dominated by the driving time and naturally decreases as the EV speeds converge to the u_{flow} value or the highway's maximum speed limit. The same logic applies to the average service rate that, given the above, is defined as $\mu(u) = 1/\mathbb{E}\Big[t(u)\Big]$.

E. Markov Chain-based Stochastic Model

The aforementioned speed-density modeling and the discussed specifications provide the upper limit for the power and communication capacity of our stochastic model. Specifically, the V2I communication system of the highway segment of length L (all lanes) can accommodate V cellular EV users, while the charging infrastructure and the WCH lane consist of C slots for EVs. An EV, before entering the WCH segment, submits a charging request demanding a spot on the WCH lane and a dedicated communication channel. EVs that do not require charging are provided with a V2I channel and are not allowed to enter the WCH in the middle of the segment of length L (i.e., they are allowed to request charging at the next WCH segment). Arriving EVs that have requested charging, but do not find either a channel or a WCH lane spot are considered blocked and are not allowed to enter the charging lane. Finally, we will assume that the number of available channels is greater than the number of charging slots: $V > C$.

We will assume that EV arrivals to the WCH lane follows a Poisson distribution with an average rate λ. The assumption is supported by real-world measurements as seen in [8], [19] where the inter-arrival time of vehicles entering a specific highway segment follows an exponential distribution. We will further assume that the service times of the EVs are exponentially distributed with service rate μ (Section III-D). Regarding the V2I users, we will also consider that they request channels according to a Poisson process of rate ϵ, while their service times are exponentially distributed with service rate κ (channel availability rate). Note that these V2I user behavior assumptions are directly linked to the EV Poisson arrival process scaled for all highway lanes. Also, the rates ϵ, κ can be easily adjusted for different communication environments including modeling dynamics when the WCH is designed for rural or urban settings with varying channel availability rate characteristics.

Given the above, the WCH dynamics can be modeled by a continuous-time Markov chain with a finite state space of two dimensions [20], [21]. Fig. 2 shows the chain's state space and the related transmission rates. A generic state of the chain is expressed by the (c, v) pair where c is the number of EVs on the WCH lane, and ν is the number of EVs occupying V2I channels in all highway lanes. The horizontal dimension of

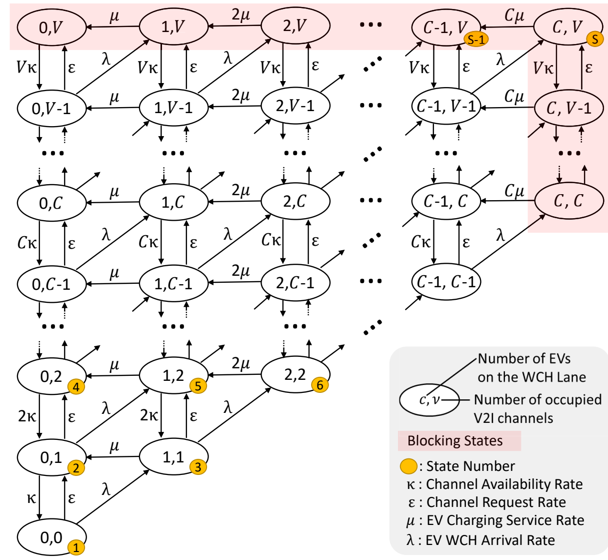

Fig. 2. Continuous-time Markov Chain for WCH Joint Capacity Modeling

the proposed MC is equal to the WCH's capacity C, while the vertical dimension equals the capacity of the V2I system V. The total number of the MC's states S is given by:

$$S = (C+1)^2 - \sum_{i=1}^{C} i + (V-C)\cdot(C+1) = (C+1)\cdot(V - \frac{C}{2} + 1) \quad (6)$$

For the proposed MC, the $S \times S$ transition rate matrix $\mathbf{Q}$ (also known as generator matrix) is constructed as seen in Fig. 3 where the elements satisfy that $q_{i,j} \geq 0, \quad \forall\ i \neq j$ and $q_{i,i} = -\sum_{i \neq j} q_{i,j}, \quad \forall\ i \in (0, S]$. In order to construct the generator matrix, each state (c, v) is associated with an identification number as shown in Fig. 2. A state (c, v) is a blocking one if $c = C$ or $\nu = V$, and we define a set $Z = \{..., |S|\}$ as the set of the blocking states' identification numbers.

Finally, it can be easily shown that since this finite-state MC is irreducible (i.e., all states communicate), it is also positive recurrent, and thus there exists a unique stationary distribution $\vec{\pi} = [\pi_1, \pi_2, ..., \pi_S]$ [20]. The stationary distribution $\vec{\pi}$ is determined by solving the system of linear equations:

$$\vec{\pi} \cdot \mathbf{Q} = \vec{0} \quad and \quad \vec{\pi} \cdot \vec{1} = 1 \quad (7)$$

where $\vec{1}$ is an S sized vector of ones.

The WCH's blocking probability is defined as $\Pi_{blocking} - \sum_{\forall s \in Z} \pi_s$, and jointly captures outage events due to power and communication constrains. Thus, it represents the system's QoS as blocked EV customers are considered dissatisfied due to the lack of service. Also, we define an expected profit model over a time interval τ for the WCH operator:

$$\Xi_{Prof} = \tau \cdot p \cdot \phi_c \cdot \sum_{s=1}^{S} c(s)\pi_s - \tau \cdot p \cdot \phi_g \cdot \sum_{s=1}^{S} c(s)\pi_s - \tau \cdot \psi_{pen} \cdot \sum_{\forall s \in Z} c(s)\pi_s \quad (8)$$

where $c(s)$ is the charging EVs for state s, ϕ_c is the service price, ϕ_g is the grid electricity price, and ψ_{pen} is a compensation penalty fee that the WCH operator pays when the system is in its blocking states and EVs are rejected. The proposed model can be used to maximize the system's revenue while the penalty fee materializes the system's reputation.

$$\mathbf{Q} = \begin{bmatrix} -(\lambda+\epsilon) & e & \lambda & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ \kappa & -(\lambda+\epsilon+\kappa) & 0 & \epsilon & \lambda & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & \mu & -(\mu+\lambda+\epsilon) & 0 & \epsilon & \lambda & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 2\kappa & 0 & -(\lambda+\epsilon+2\kappa) & 0 & 0 & \epsilon & \lambda & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & 2\kappa & \mu & -(\mu+\lambda+\epsilon+2\kappa) & 0 & 0 & \epsilon & \lambda & \cdots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2\mu & -(2\mu+\lambda+\epsilon) & 0 & 0 & \epsilon & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & -(C-2)\mu-V\kappa & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & (C-1)\mu & -(C-1)\mu-V\kappa & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & C\mu & -C\mu \end{bmatrix}$$

Fig. 3. Transition Rate Matrix **Q**

TABLE I
WCH CASE-STUDY PARAMETERS

Parameter	Value	Parameter	Value
r_{ef}	$1.5\ km$	η_{ef}	0.9
B_{tot}	$2000\ MHz$	γ	$0.15\ KWh/km$
$B_{channel}$	$20\ MHz$	η_{drive}	1
TTC	$2\ sec$	$P_{auxiliary}$	$0.5\ KW$
ev_{length}	$4.5\ m$	D_{energy}	$\mathcal{N}(4, 0.8)\ KWh$
P_{tot}	$2000\ KW$	ϕ_c	$0.1\ \$/KWh$
p	$40\ KW$	ϕ_g	$0.08\ \$/KWh$
n_{lanes}	6	ψ_{pen}	$0.5\ \$/h$

IV. Case Study and Numerical Evaluation

In this section, we study how the model parameters impact the design and optimal WCH operation. We model our system on a real-world scenario, namely a US I-10 EAST highway segment of length $L = 8\ km$, and posted speed limit of $u_{max} = 112\ km/h$. The speed-density modeling was based on real data from the California's Caltrans Performance Measurement System (PeMS) [22] (Mile 20 to 30 of I-10 EAST) as shown in Fig. 4. The resulting fitted model ($u_f = u_{max}, \alpha = 0.23, \rho_j = 58\ \frac{EVs}{km}$), was used to extract the average service rate μ as detailed in Section III-D. Table I presents the rest WCH model parameters' values. Arrival rates λ, and e directly represent incoming traffic volumes on the highway segment, and for simplicity we define $e = (n_{lanes} - 1) \cdot \lambda$.

First, we consider the impact of the V2I channel availability rate that captures the general bandwidth usage behavior of the geographical area around the WCH segment. Fig. 5 shows the overall blocking probability of the EVs demanding to charge as the channel service rate increases, and for V2I/power capacity $C = 50, V = 100$ EVs respectively. We also evaluate different traffic rates λ. Evidently, as κ is increased, more EVs are allowed to charge while driving leading to a lower outage rate. Also, for a given (C, V, λ) triplet, the performance increase is negligible after a specific threshold κ. In what follows, we assume that $\kappa = 35$ in all cases.

Next, we focus on how the allocation of power and communication resources impacts the WCH's QoS. Note that the allocation of resources for the V2I system can be expressed either as total available bandwidth, or bandwidth allocated to each channel, while for the charging lane the same holds for the maximum power capacity, and the charging rate. This allocation is translated into available highway spots of V2I channels, and for simplicity here we adjust c and V by changing P_{tot}, and B_{tot}. Fig. 6-(Left) shows the impact of limited power capacity as the incoming traffic conditions (λ) increase

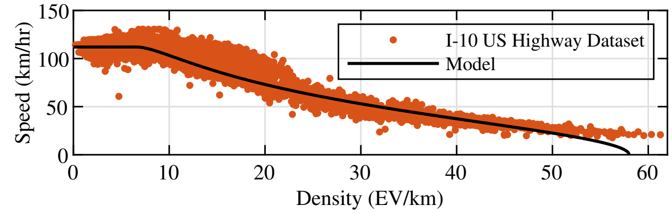

Fig. 4. Speed-Density Model of I-10 US Highway Segment

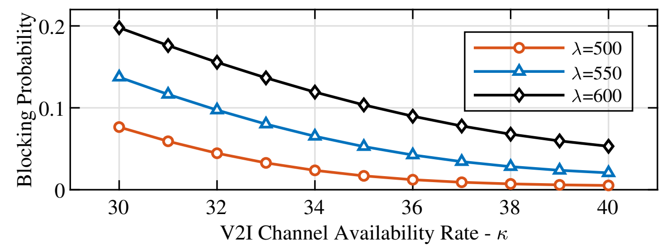

Fig. 5. Blocking Probability vs Channel Availability Rate κ (C=50, V=100)

when the V2I channel number is fixed ($V = 130$ EVs). Fig. 6-(Center) does the same for communication resources when the WCH lane spots are fixed ($C = 80$ EVs). Results show that limited capacity significantly increases the outage probability for both cases (40% of EVs are blocked in some cases) especially under heavy traffic conditions. Fig. 6-(Right) shows how reducing both capacities reduces the system's QoS under moderate traffic ($\lambda = 700$), effectively acting as a sanity check for our model. Note that in all cases, while the WCH operator aims to keep the system's blocking probability under a threshold, increasing the overall capacity frantically does not offer meaningful QoS improvement leading to resource waste.

Finally, we study the WCH's profit as a function of the operator's choices. Given the WCH infrastructure, the operator will be able to optimize the charging service's profit and QoS by performing dynamic speed regulation and admission control on the charging lane. Admission control is achieved by dynamically setting the slot number C, while speed regulation adjusts the speed limit u_{max}, and therefore impacts the charging service rate μ. Fig. 7 shows the system's hourly profit ($\tau = 1$) evaluated against various admission control and speed limit choices for $V = 130$, and as the incoming traffic levels increase with $\lambda = 400, 700$, and 1000. First, we observe that the system under-performs in the low traffic regime due to the lack of EV customers, as well as during heavy traffic as the low QoS increases the system's penalty. In addition, we observe that for moderate and higher traffic, the operator manages to significantly increase its profit with a loose admission policy, and by lowering the speed limit. By doing so, the service time

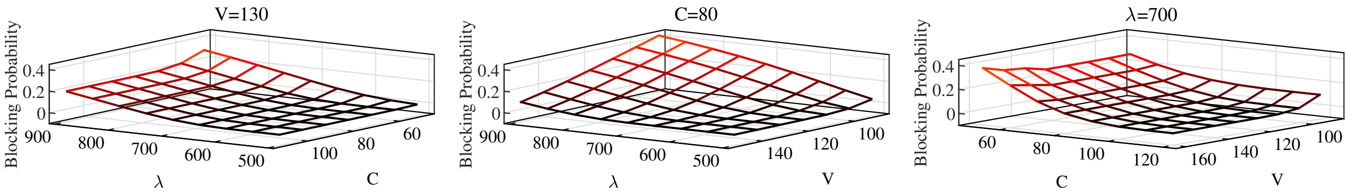

Fig. 6. Blocking probability under various capacities, and incoming traffic conditions

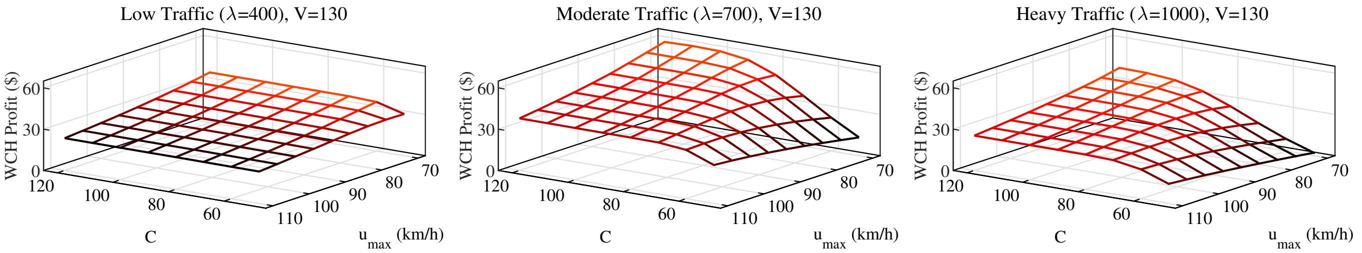

Fig. 7. Hourly Profit under Admission Control (available charging spots C) and Speed Regularization (u_{max}) for Low, Moderate, and Heavy Incoming Traffic

of each EV is reduced as their energy demand is frequently reached resulting in an average service rate increase. On the other hand, when the operator is lacking available capacity, increasing the speed limit will maximize the profit as more customers will be admitted to the system on average.

V. Conclusion

This paper presents a stochastic model for electric vehicle WCH systems that jointly captures the availability of both power and communication resources. Our framework utilizes speed-density modeling to account for road conditions and defines the EV charging service rate as a function of EV energy demands, highway speed limit, and EV road density. A numerical evaluation demonstrates the applicability of our model to real-world cases, and its ability to provide insights on parameter choices during both infrastructure planning, and day-to-day operation. Part of our future work aims for our model's extension to evaluate the use of power storage on the WCH, and analyze the possible performance enhancement.

Acknowledgment

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