Decentralized Control of Electric Vehicles in a Network of Fast Charging Stations

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***Abstract*—To facilitate the adoption of electric vehicles (EVs) and their plug-in hybrid (PHEVs) counterparts and to avoid straining the capacity of the power grid there is a strong need for developing a network of fast charging facilities and coordinate their service. Incorporation of EVs in the vehicle fleet would decrease green house gas emissions and overall dependency on fossil fuels.**

A key issue in charging EVs is that the corresponding time is fairly large, which can lead to very long delays. Hence, for the network of charging stations to provide good quality of service to customers, we first propose an admission control mechanism based on pricing for a *single* charging station. Subsequently, we develop a decentralized routing scheme of EV drivers, employing a game theoretic model. The latter entices drivers through price incentives to require charging from less busy stations, thus leading to a more efficient utilization of power across the network, while it enhances profit for the charging facilities operator. Of note, the proposed scheme does not require advanced monitoring tools for power usage and pricing calculations. The drivers receive and send back the necessary information through the a communications infrastructure and the routing is initiated only when the network has exceeded a critical threshold. The numerical results illustrate the discussed benefits of the proposed scheme.

I. Introduction

It is anticipated that the electric vehicle (EV) population will represent a sizable portion of the US national fleet (at least 10% of the US National fleet by 2020 and 50% of new car sales by 2050) [1]. However, in order for this penetration of EVs to occur seamlessly, development of a network of DC fast charging facilities is required. The main reason is that at present, about 40% of the EV owners' daily trips exceed their all-electric-range [2]. However, adding the required number of charging stations to accommodate the projected EV population is extremely costly and constrained by the limits of the power grid (e.g. generation capacity, transmission and distribution network constraints). Straining the grid beyond capacity could lead to cascading failures and outages [3]. Thus, the broad objective of this study is to introduce a decentralized routing mechanism that optimizes the quality of service provided to EV drivers, subject to grid capacity constraints.

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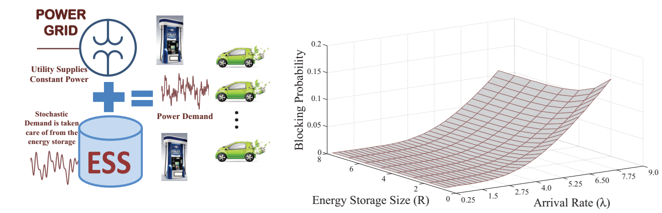
Although car manufacturers have started selling EVs, there is a limited number of studies on EV charging [4][5], especially for a network of charging stations. In the proposed framework, it is assumed that each station in the network takes the grid constraints into account and thus does not impact the reliability of the power grid.

The utility (level of satisfaction) of the EV users will greatly be determined by the availability of the service (when they enter a charging facility), the trade-off between getting the service as soon as possible (temporarily and spatially), and minimizing the charging cost. On the other hand, the utility of the charging network owner is to serve more customers to acquire more profit with scarce grid resources. In a network of charging stations, the utilization of each charging station is understandable related to spatial and temporal distribution of EVs. In real life the distribution of vehicles is far from being uniform. In fact, people tend to drive between points of interest, such as their home, school, workplace, etc., and their patterns vary in time e.g. weekdays/holidays. Such a statistical behavior creates uneven customer demand among the charging facilities. Hence, the utility company has to properly allocate the EVs to charging stations based on the power network constraints. Accordingly, in this work we focus on the role of pricing in partially controlling customer preferences to coordinate EV chargings. We map this behavior into game theoretic framework. The main contributions of this work are:

- An Electric Vehicle Admission Control mechanism that uses *congestion pricing* to alleviate customer load and meet QoS targets.
- A utility function for a single EV that captures the experienced QoS (blocking probability) and the spatial (distance from charging station) and temporal (time to travel to charging station) considerations of drivers.
- A framework in which the load balancing of EVs is done through a system of pricing incentives. Also, advanced monitoring tools are not needed since the system offers incentives only after a certain threshold is passed.

II. Previous Work

Most studies on the control of EV charging assume stationary vehicles located at customer premises or large parking lots. For example, [6] employs a central authority (dispatcher) that controls and mandates charging rates, start times, etc. On the other hand, [7] presents decentralized decision making models by EV owners. Since decisions are taken individually, game theoretic models are used. However, the mobility of EVs is



(a) Single Charging Station Architecture (b) Performance Evaluation of a Single Charging Station

Fig. 1: Proposed Architecture and Performance Evaluation

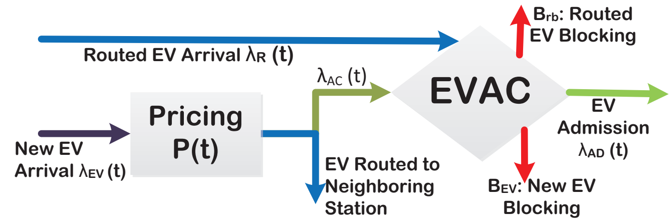


Fig. 2: Electric Vehicle Admission Control for Single Charging Station

not taken into account, which is a major goal of this study. A study that shares a number of similar features to this work is [4] and [8]. [4] introduces a framework for EVs selecting charging stations using oligopolistic game theoretic ideas and [8] proposes an admission control mechanism for charging stations. In this study, we build on our previous work [9], [10], [11] that proposed a fast charging station architecture employing local energy storage and also introduced a stochastic model for customers arrival and service (both from the grid and the local energy storage device) to assess its performance. We introduce a decentralized routing mechanism that aims to increase the number of EVs a network of charging stations can accommodate over a baseline scenario that assumes EV routing to the nearest station.

Next, we summarize the dynamics of the single charging station model introduced in [9], [10] and depicted in Figure 1a. Each charging station draws constant power from the power grid, which is expressed by the number of EVs that can be charged simultaneously, up to capacity of S vehicles. Similarly a local energy storage is employed which can accommodate up to R electric vehicles in a full charge state. Energy storage will be used to meet stochastic power demand upon exceeding the available grid power level. Since we always draw constant power from the grid due to a long term contractual agreement between the grid and the station, this model also aims to isolate the former from demand spikes and hence enhances its reliability.

Given the above assumptions, we represent the single charging station model as a two dimensional Markov chain with the following parameters: the arrival of EVs is is a Poisson process with rate λ, charging times both from the grid and/or the storage unit are exponentially distributed with rate μ, while the charging time of the storage unit is also exponentially distributed with rate ν. As mentioned above, EV charging occurs first from the grid and if that reaches capacity only then is the storage unit engaged. Finally, if a customer comes to a charging station when all power/energy resources are used, she could not receive service and consequently will be "blocked". The long-term "blocking probability" is the QoS performance metric. Numerical methods are used to calculate steady state probabilities [9]. In Figure 1b, the single charging station model for $S = 8$, $\nu = 3$, $\mu = 2$ and for different energy storage size and arrival rates is evaluated.

This work also builds on [12], that evaluated the above described charging model in a network context using real world traces from the Seattle bus system. The obtained results indicated that the spatial distribution of EVs follows a Beta distribution, which is also used in the present study. The consequence of that finding is that at given times (e.g. weekdays rush hour), some regions (e.g. downtown) are busier than other ones. Accordingly, stations near a high density area are busier than other stations and unless an EV routing mechanism is in place, they would fail to meet preset QoS requirements.

III. Electric Vehicle Admission Control (EVAC) for a Single Charging Station

We discuss an Electric Vehicle Admission Control mechanism that can be employed at a single charging station level to provide QoS guarantees. The EVAC will: (1) balance the customer load among different charging facilities, (2) attain given QoS targets and (3) increase total revenue for station operators by more efficient use of energy resources. Such an admission control mechanism can be implemented through a pricing mechanism. For instance, during high EV demand for charging, the station operator can offer relative lower prices in a neighboring charging station to balance the customer demand.

A. System Parameters

Next, we explain the dynamics of the single charging station admission control presented in Figure 2. We assume that each vehicle chooses to go to the nearest station to get service. The arrival rate for each EV is represented by $\lambda_{EV}(t)$. Each new EV enters the pricing block, and $\lambda_{AC}(t)$ is the proportion of the arrival rate that accepts the offered price. Similarly, $\lambda_R(t)$ is the arrival rate for routed vehicles from neighboring stations and $\lambda_{AD}(t)$ is the arrival rate of admitted EVs. We define two types of EV blocking probability: (i) B_{EV}: blocking of EVs who come to the nearest station (ii) B_{RB}: blocking of a routed EV.

B. QoS Metric & Pricing Block

As explained in [10], we define the blocking probability as the key QoS metric. The performance metric is denoted by (P_{BT}) as the weighted sum of the two blocking types: $P_{BT} = \gamma_1 B_{EV} + \gamma_2 B_{RB}$ where $\gamma_1 + \gamma_2 = 1$. Since blocking an EV that is routed from a neighboring station leads more dissatisfaction, it is assumed that $\gamma_2 > \gamma_1$.

Pricing policies in loss systems can be classified into three categories [13]. The first category includes static policies that use flat prices at all times. Even though they are easy to implement, such pricing schemes fail to alleviate congestions. On the other hand, dynamic policies monitor the load of the system continuously and adjust the prices accordingly to prevent congestions. However implementation of such pricing mechanisms for charging station operations is rather impractical, since it requires expensive real time monitoring and measurement tools.

The pricing block, $P(t)$ in EVAC uses myopic policy that falls in between the first two categories. Pricing $P(t)$ works as follows. Unless the arrival rate $\lambda_{EV}(t)$ exceeds a threshold λ^*_{EV}, the station offers normal prices p_{normal} that are acceptable by each EV. During a congestion period, $\lambda_{EV}(t) > \lambda^*_{EV}$, the station operator increases prices to *congestion price* $p_c > p_{normal}$, so that EVs will prefer to go to neighboring stations.

The station pays a penalty p_b for each blocked EV (see [10]), because (1) it leads to dissatisfied customers and degrades the reputation of the station, (2) it enables to control the QoS to foster EV adoption [1] and (3) it allows station operators to size their capacity so as to maximize profit. It is assumed that the paid penalty is more than the price charged for service.

Next we define the optimal arrival rate λ^*_{EV} as follows: it is the maximum arrival threshold that satisfies blocking probability targets δ and can be calculated by:

$$\lambda^*_{EV} = \arg\max_{\lambda_{EV}}(P_{BT}(\lambda_{EV}) \leq \delta) \tag{1}$$

where the QoS target δ is specified in the Service Level Agreement (SLA). Also note that the pricing block $P(t)$ determines the percentage of EVs that will accept the offered price at time-t, thus $\lambda_{EV}(t)P(t) = \lambda_{AC}$ and this yields $P(t) = \frac{\lambda_{AC}}{\lambda_{EV}} \leq \frac{\lambda^*_{EV}}{\lambda_{EV}}$. This shows that the percentage of customers who accept the offered price will be inversely proportional to the load of the station. Thus, to capture the response of EVs to price changes, demand functions are used. From microeconomics, it is known that the inverse of the demand function explicitly gives the price function $p(t) = D^{-1}(\frac{\lambda^*_{EV}}{\lambda_{EV}})$ where $\frac{\lambda^*_{EV}}{\lambda_{EV}}$ is the load on the system. In this paper, we use the demand function proposed in [14]. Then, $p(t)$ the price at time t becomes:

$$p(t) = \begin{cases} p_{normal} & \text{if } \lambda_{EV}(t) \leq \lambda^*_{EV} \\ p_c = p_{normal}\left\{1 + \theta\sqrt{-\log(\frac{\lambda^*_{EV}}{\lambda_{EV}(t)})}\right\} & \text{if } \lambda_{EV}(t) > \lambda^*_{EV} \end{cases} \tag{2}$$

where p_c is congestion pricing and θ is a positive constant set by the station operator.

IV. Decentralized Control for a Network of Charging Stations

The rationale for introducing decentralized control strategies is to examine how to accommodate a large number of EVs under QoS guarantees without requiring significant upgrades on the power grid's capacity. To that end, we employ a game theoretic framework and propose a decentralized control mechanism to balance the EV load at different charging stations. The customer's objective is to receive service that has a QoS guarantee and to minimize total cost, which is proportional to the price paid for charging and the distance to the charging station. The operator of the charging stations objective is to maximize profit and provide QoS guarantees to the EV drivers. Recall that the QoS metric used is the long-term probability is "blocked" when it arrives at a station. The end goal is to incentivize selfish EVs to cooperate and route customer demand to neighboring stations with lower utilization, if necessary.

To make this framework operational, it is assumed that each charging station can communicate with a central unit that can forward price signals to EVs and influence their choices, while EVs communicate their positions. The EVs respond to these price signals following a best response strategy outlined below. It is assumed that the necessary communications infrastructure is in place (e.g. 3G/4G or a wireless mesh network) to support the proposed mechanism.

A. Game Formulation

EVs have access to location information and pricing offers by the central communication unit, whose role as outlined above is to communicate with each charging station and forward their price signals; e.g. offer relatively lower prices to attract customers to drive to a more distant station to balance the arrival rate at each station. Thus, the operator of the charging stations network acts as a *leader* who can commit to a strategy before *followers* (EVs) pick their strategies. In this respect, a Stackelberg game will help us to model this system. Let us define the game in its strategic form $\Gamma = \{\{\mathcal{N} \cup \mathcal{K}\}, \{\vec{p}_k\}, \{X_{k\in\mathcal{K}}\}, \{U_{n\in\mathcal{N}}\}, \{U_{k\in\mathcal{K}}\}\}$, where $\mathcal{N}=\{1, \cdots, N\}$ is the set of charging stations and $\mathcal{K}=\{1, \cdots, K\}$ the set of EVs that require charging at a given time. The strategies of each set of players are as follows. $\{\vec{p}_k\}$ denotes a $1 \times N$ price vector offered by the network operator. The EVs strategy, X_k, is to choose a charging station from $\mathcal{N}$. U_n and U_k are the functions that represent the payoffs (utility) for the players. Next, we describe the components of the game in detail.

B. EV Customers

Based on the assumption of rationality, and in the absence of any incentives, each EV will just choose to go to its nearest charging station. Through the use of two-way communications, the network operator aims to route EVs to less busy stations (if necessary) by offering relatively lower prices, but still avoid penalties for poor QoS (blocked EVs). The EVs can either *Accept* to go to a less busy charging station or *Reject* and go to the nearest one. The EV strategy is given below.

$$EV_{Strategy} = \begin{cases} Accept, & \text{if } c_{k_{near}} - c_{k_{desrd}} \geq c_{k_{inctv}}\ ,\ P^{desired}_{BT} \leq \delta \\ Reject, & \text{otherwise} \end{cases} \tag{3}$$

Suppose that EV-k, $k \in \mathcal{K}$ needs charging from station-n, $n \in \mathcal{N}$. The cost of selecting the nearest station is equal to $c_{k_{near}}=p_n + c(d^2_{nk})$, where p_n is the price paid to the station, and $c(d^2_{nk})$ is the cost related to driving to station-n for EV-k. Note that p_n equals p_{normal} when there is no congestion at the nearest station-n, and to the congestion price p_c otherwise. Similarly, when the network operator wants to route a vehicle to a station

TABLE I: Systems Parameters

Parameter	Definition
p_{normal}	Normal price accepted by every driver. The same price at each station.
$p_{congestion}$	Congestion price depends on the station load.
p_B	Penalty paid for blocking a customer.
δ	QoS target may be different at each station.
λ^*	Maximum allowable arrival rate to support QoS calculated by equation 1.
$c_{k_{inctv}}$	Minimum amount of desired savings to accept routing.
$c_{k_{near}}$	Cost to drive to nearest station.
d_k	Distance vector for each customer k.
θ	Vector of price tuning parameter for each station set by station operator.
S, R, μ	Single station parameters. Denotes grid power, energy storage size, and EV charging rate respectively.

other than the nearest one, it costs $c_{k_{desrd}}$. In order to project customer behavior into our formulation, we assume that EV-k will only choose to go to the desired station if it gains at least $c_{k_{inctv}}$ (considering current electricity prices there should be a reasonable level of savings e.g. 10% savings).

The utility function of a single EV is a function of QoS metric $\vec{P}_{BT}$, the offered price for each station $\vec{p}_k$, and the distance to each station $\vec{d}_k$. Note that each component of the utility corresponds to a $1 \times N$ row vector, where the position of each element is associated with the corresponding station parameter (blocking probability, price, and distance). Also the pricing scheme proposed in section is employed at each station. Then, the utility function for EV-k becomes:

$$U_k(\vec{P}_{BT}, \vec{d}_k, \vec{p}_k) = h(\vec{P}_{BT})\vec{e}_n \left\{\vec{p}_k + c_k(\vec{d}_k) + f_k(\vec{d}_k)\right\} \qquad (4)$$

where $h(\vec{P}_{BT}) = e^{\xi(\vec{P}_{BT}-\delta)}$. The $h(\cdot)$ function denotes the disutility of experiencing high blocking probability [15], ξ is a constant and δ is the QoS target. These components capture the dissatisfaction introduced by a high blocking probability. Note that $\xi = \begin{cases} 0 & \lambda \leq \lambda^* \\ \xi \in \mathbb{R}^+ & \text{otherwise} \end{cases}$. The EV chooses one station $n \in \mathcal{N}$ and $\vec{e}_n$ represents a column vector comprising of all zeros except for the n^{th} position which is 1. Similarly, $\vec{p}_k$ is the price vector offered by the network operator. The next term in the utility function reflects the cost of driving to a charging station which is a function of distance to each station from the current location of EV-k. Finally, $f_k(\vec{d}_k)$ is related with the dissatisfaction of EV-k when it selects to go to a more distant station. Even though the total cost is lowered, some level of dissatisfaction occurs due to spending extra time to drive the extra miles (e.g. time cost etc.). Thus, the optimization problem of the EVs is a mapping $\mathbb{R} \rightarrow \{\text{reject}, \text{accept}\}$ that gives rise to a vector $\vec{e}_n$, where ($Accept$) sets the n^{th} position to 1 while all other remain 0 ($Reject$). Note that the objective is to minimize driver's cost. This can be expressed as follows:

$$\begin{aligned} \arg\min_{n} \quad & h(\vec{P}_{BT})\vec{e}_n \left\{\vec{p}_k + c_k(\vec{d}_k) + f_k(\vec{d}_k)\right\} \\ \text{s.t.} \quad & n \in \mathcal{N} \end{aligned} \qquad (5)$$

where EV-k picks station-n and pays p_n unit of money. The second parameter represents the cost of driving: $c_k(\vec{e}_n\vec{d}_k) = p_{dr}d_{kn}^2$ (price of driving one unit of distance times distance to station-n). The last component reflects the dissatisfaction of drivers to go extra miles. A linear dissatisfaction model is used $f_k(\vec{e}_n\vec{d}) = p_{dis}(d_{kn} - d_{nearest})$ where p_{dis} is the cost of driving one unit of distance, and (d_{kn}-$d_{nearest}$) is the total amount of extra miles traveled. This component approximates the behavior of drivers in real life, since it is unlikely that one would drive a significant extra distance for limited savings. Moreover, the above optimization problem is subject to the EV having stored adequate energy to drive to station-n, which we assume that this is the case (about $0.5 - 1kWh$ of stored energy).

Algorithm 1 Decentralized control with pricing

Require: $\theta \geq 0$, $|\mathcal{N}|, |\mathcal{K}| \in \mathbb{Z}^+$
  for customer-k $\leftarrow$ 1 to K **do**
    network owner offers $\vec{p}_k(\theta) \in \mathbb{R}^{\mathbb{N}}$ to Eq.(5)
    calculate utility $\vec{U}_k \in \mathbb{R}^{\mathbb{N}}$
    pick station n=indexOf(min($\vec{U}_k$))
    enter station, set $\vec{e}(n)$=1
    if gets service **then**
      set $\vec{q}$=$\vec{e}(n)$, $\vec{q_B}$=$\vec{0}$
    else
      set $\vec{q}$=$\vec{0}$, $\vec{q_B}$=$\vec{e}(n)$
    end if
    calculate Eq.(6)
  end for

C. Charging Network Operator

In the Stackelberg game, the network operator acts as the *leader* who is willing to coordinate non-cooperative EV charging so that, he can maximize his profit while minimizing customer blocking. The strategy of the *leader* is to set the pricing parameter vector-$\vec{\theta}$ at each station. Then the offered $1 \times N$ price vector becomes a function of vector-θ, $\vec{p}_k = h(\vec{\theta})$. Also we assume that regulations and policies do not allow the operator to take advantage of the EV's location information to demand a high price of those whose battery levels are low. The utility function of the operator becomes:

$$\begin{aligned} \arg\max_{\vec{\theta}} \quad & \vec{p}_k(\theta)\vec{q} - p_B\vec{q}_B \\ \text{s.t.} \quad & \vec{p}_k, \vec{q},\ \vec{q}_B \in \mathbb{R}^{\mathbb{N}},\ p_B \in \mathbb{R}^+ \end{aligned} \qquad (6)$$

where, $\vec{q}$ is calculated from equation 5 and equals to $\vec{e}_n$. Similarly, $\vec{q_B} = \begin{cases} \vec{0}, & \text{If gets service} \\ \vec{e}_n, & \text{If blocked} \end{cases}$,and the price vector $\vec{p}_k$ is the same as in Equation 5. Finally, p_B is a scalar and represents priced paid when blocking occurs. All of the system parameters are presented in Table I.

V. Numerical Results

In this section, we illustrate the proposed EV routing scheme. The simulation scenario is set as follows: there are five charging stations in a 30×30 unit square area. The coordinates of the locations of the five stations are: $(5, 25)$, $(10, 10)$, $(25, 25)$, $(15, 15)$, and $(25, 5)$. To capture the spatial variability of EVs we used the following mixture distribution, whose parameters are calibrated based on results from [12].

$$f(X) = \left\{15 \times Be(4.42, 0.763) \quad , 0 \leq \text{X} \leq 15 \right. \qquad (7)$$

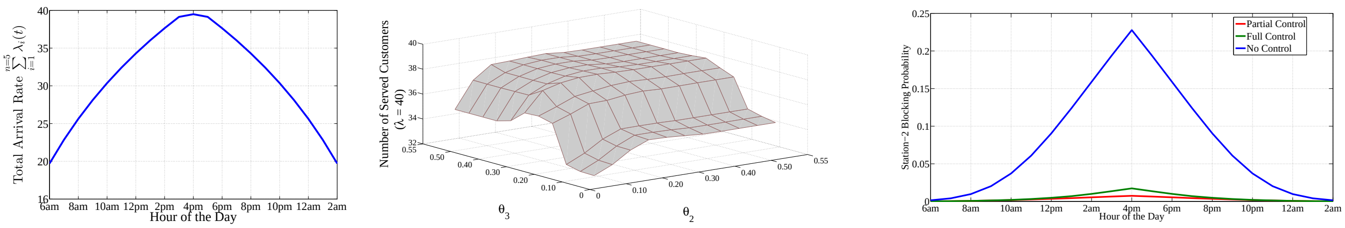


Fig. 3: System Performance Evaluation-1: Total Customer Demand for Five Stations (L), Pricing Strategy of Station Owner (M), and Station-2 (most congested) Performance Evaluation (R)

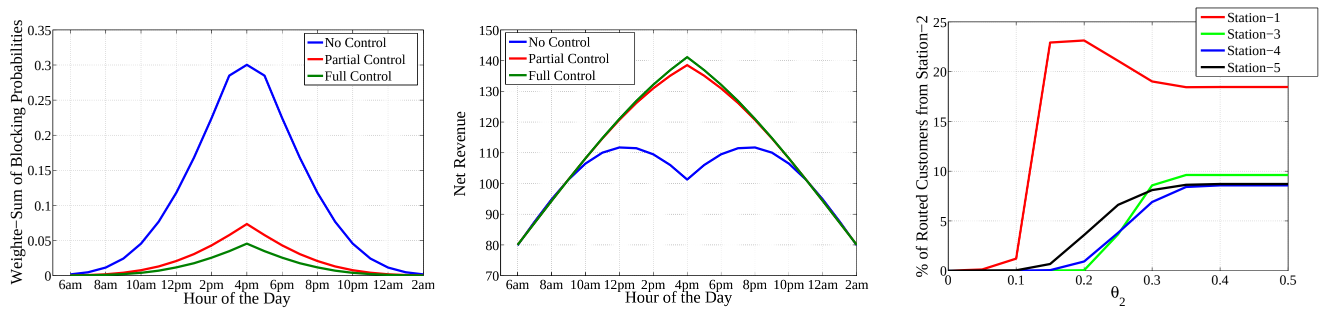


Fig. 4: System Performance Evaluation-2: Weighted-Sum Blocking Probability Performance (L), Total Revenue for the Charging Network (Normalized) (M), and Traffic Shaping for Station-2 (R)

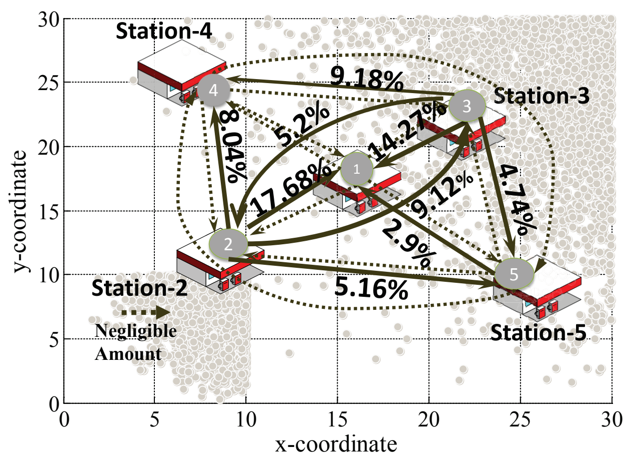


Fig. 5: Traffic Shaping Among the Charging Facilities (at hour=4pm)

$$f(Y) = \Big\{ 15 \times Be(2.42, 0.799) \quad , 0 \leq \text{Y} \leq 15 \qquad (8)$$

where *Be* denotes the Beta distribution function. The spatial distribution is illustrated in Figure 5, which shows that half of the EV population resides in the lower left of the area under consideration, while the remaining half in the rest of the area. Given this spatial distribution of EVs and in the absence of a control mechanism, customer demand for each station would be 1%, 50%, 42%, 2%, and 5% for stations $1-5$, respectively. Given this baseline scenario, the parameters of each single charging station are set as follows. Stations under heavy traffic have bigger capacity S_2=S_3=8 and R_2=R_3=8. Since station-1 is the nearest to congested regions, it has S_1=6 and R_1=6, while stations 4 and 5 that do not operate under heavy load, have S_4=S_5=3 and R_3=R_4=3. Moreover, the charge rate to satisfy one EV charging request is $\mu_1 = \ldots = \mu_5$=2, while the charging rate from local energy storage unit is $\nu_1 = \ldots = \nu_5$=3.

Next, we elaborate on the settings of the discrete event simulation. The overall charging requests (or arrival rate) is depicted in Figure 3(L). Customer demand to each station is proportional to the traffic load calculated above; for example, for station-2 it is about $\lambda_2(t{=}6am){=}20 \times 0.5 = 10$. The charging station operator aims to provide service to the EVs with QoS guarantee $\delta = 0.05$ and dissatisfaction parameter $\xi = 0.1$. Based on these charging station specifications, the *leader* (system operator) solves equation 1 and starts the game when the arrival rate exceeds this threshold, which corresponds to the following thresholds for each individual station: $\vec{\lambda}_i^* = [10.3,\ 13.4,\ 13.4,\ 4.2,\ 4.2]$. Since it may be challenging (and possibly wasteful) to update arrival rates in real time, we set 15 minute intervals at which arrival rates are recalculated.

The pricing parameters are set as follows: in the absence of congestion, EVs pay the operator $p_{normal} = 4$, whereas if customers are blocked the operator rewards them with $p_{block} = 5$. As mentioned before, this cost is a penalty to the operator for poor service which can impact customer loyalty and its long term reputation. Also, to calculate blocking probabilities we set γ_1=0.45 and γ_2=0.55. For the k-th EV, $c_{k_{inctv}}$ is a uniformly distributed random number in the interval $[0.5, 0.75]$ and p_{dis} is a uniformly distributed random number (per unit of distance) in the interval $[0.02, 0.05]$. We assume that driving duration is linearly correlated with distance (based on an average speed of 40 mph). Currently popular EV models (e.g. Nissan Leaf) exhibit $0.22 kWh/mile$ energy consumption; thus, we set $p_{drive} = 0.03$ per unit of distance.

Next, we present the strategy of the *leader*. Since stations 1,4, and 5 operate under light load, we set θ_1=θ_4=θ_5=0.5 and vary the strategy parameters for the congested stations, namely θ_2 and θ_3, between $0-0.55$ for a generic rate of $\lambda = 40$. Note that (θ_2, θ_3)=$(0, 0)$ implies no congestion control at stations-2 and 3. As shown in Figure 3(M), with appropriate pricing parameters, the network of charging stations can accommodate up to 20% more EVs. Further, net revenue becomes constant after θ_2 and θ_3 exceeds 0.4. The reason is that the proposed congestion price already offers enough incentives for customer routing for the given set of system parameters. However, if the *leader* wants to route customers in order to accommodate a higher arrival rate, she needs to pick a higher θ parameter.

The proposed decentralized control mechanism is simulated with the given set of parameters for three different scenarios. In the first scenario, $\vec{\theta}$ is set to 0, which implies no congestion control at any station. This case serves as a baseline scenario to evaluate the performance of the proposed control mechanism. Partial control is considered for the second scenario with the following strategy parameters $\vec{\theta}$=$[0.05, 0.5, 0.5, 0.05, 0.05]$. Note that stations-2 and 3 can fully route customers when there is congestion, whereas the rest of the stations may not provide strong enough incentives to their customers to drive to stations further away. The final scenario provides strong incentives with all θ_n parameters set to 0.5. In Figure 4(L), the weighted-sum of blocking probabilities for all five stations and for the three scenarios is depicted. The weight of each station is proportional to the customer load each station serves. Note that with the proposed control mechanism more EVs can be served with the same amount of grid resources. To illustrate the effect, the busiest station (#2) is selected. Without customer routing, this station can not satisfy the QoS guarantee (δ=0.05), but with the proposed mechanism it can provide high quality service. Note that in the partial control setting, station-2 lowers its blocking probability (depicted in Figure 3(R)) since congestion control at the neighboring stations is weaker. Nevertheless, strong incentives to route customers to more distant stations exhibits the best performance both in accommodating more EVs and as shown in Figure 4(M) also leads to increased revenue for the operator.

Moreover, in order to show how the proposed pricing scheme balances the load, we quantify the percentage of successfully routed customers. Figure 5 shows traffic shaping between charging stations. For instance, during the busiest hour 17.68% of station-2 customers accept to go to station-1. Note that since the proposed utility functions consider the physical distance of the stations, only a relatively small percentage of EV prefer to drive to distant stations. In Figure 4(R), the percentage of routed EVs from station-2 versus the pricing parameter θ_2 is presented.

VI. Conclusion

In this paper, we introduced an admission control mechanism based on pricing signals to reduce congestion at a single charging station level. Next we presented a decentralized control for charging EVs over a network of charging facilities. It is assumed that the network operator has the first move advantage to incentivize selfish EVs to move to nearby stations, if necessary, to load balance traffic at each station. The preferences (spatial and temporal) of EVs are captured through utility functions and the system is modeled with Stackelberg game. It was established that not only this strategy can achieve better results in terms of blocking EVs from receiving service, but it also leads to a more efficient power/energy resource. In future work, we plan to evaluate the performance of communications delay and jitter between the operator and the EVs, and the case where EV do not respond with their best strategy.

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