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A Clarion Call for Credit Based Wireless EV Charging

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Abstract

We argue for the design of credit-based EV charging while predicting the balance of electric power supply versus power demand for electric vehicles (EVs). We wish to a herald pivotal step toward modeling electric power availability versus power consumption for the consumers as well as utility providers for EV and the corresponding dynamic wireless charging facilities will benefit from our model for analysis and prediction of electric power

1 Introduction

With the rise of electronics and smart devices, there is increased demand for more processing power and faster results. While most technologies have paced well with the demand for more power in processing, there have been more lagging electric power advances. By allowing EV users to charge wirelessly with credit based, dynamic wireless charging, drivers have an easier EV power access.

Most mobile phone users carry around portable batteries that augment their power needs. A similar plan for EV creates a problem for locating mobile power sources and portable batteries would reduce premium real estate on the EV. With wireless charging on the rise for its ability to reduce material cost and for its convenience, it is only natural to find a way to provide power as a service. Businesses can provide consumers not only the ability to charge their phone, EV, and possibly other accessories requiring power. In addition, there is additional opportunity to promote additional products or service to their consumers [5][6][7]. The consumer would drive through the establishment that provides power, log into the app on their phone or an online portal. On the consumer side, they would have to have a powered devices and EV with wireless charging capabilities. On the business side, there would have to be power delivery devices. While there have been many advancements in wireless technologies, there is still limitations on how far or close an EV must be to be charged wirelessly. There is no possibility to transfer a charge through a long distance like data transmitted over long distances. It is important that businesses have the physical capacity to charges gathered by the EV. With further development, EV would provide feedback to the business such as “when are peak hours”, “what devices do their consumers have onboard EV”, “how long do consumers transit”, etc. Not only does investing into a service such as this increase the traffic for the business but can also provide valuable information that the business can use to develop their brand, new services, or improve upon their efficiency.

In the current technologic landscape, there has been a massive growth in research for more wireless systems and networks. While more businesses and firms transform to further improve current technologies such as mobile phones, there is a greater need for longer battery life. Not only does a credit based wireless device charging service streamline power access, but it also provides businesses the opportunity to profit by having more traffic and be able to gather data on their customers that they can then use to improve their business. Section 2 will present the fundamentals for power availability versus power demand culminating with the results of our implemented simulation. Section 3 will sum up our position for credit-based EV charging.

2 Fundamentals

Electric power supply and corresponding consumption demand in the smart grid are volatile and change dynamically. The lack of large-scale storage power storage creates challenges to adjusting the supply-demand balance of electricity. Power needs to be produced during the overlapping period that it is consumed, and this dynamic characteristic motivates the need for forecasting the consumption ahead of time. Dynamic wireless charging is a promising technology in nascent stages that offers EV power availability during driving. Dynamic wireless charging (DWC)) is part of proposed work that facilitates the purchase and consumption of power for EV [9]. Goggle CEO's (Eric Schmidt) who recently promoted DWC for EVs has already been prototyped in the Netherland and Israel. We envision DWC US experimentations in the next five years driven by the ongoing results of the smart grid deployment. Electrifying roads would remove range restrictions of EVs and potentially add to the fuel savings. It is estimated that 25 percent of all miles traveled are on one percent of the US roads, so electrifying high-volume roadways could displace up to 25 percent of the fuel used by an appropriately equipped vehicle. EV power demand profile heavily depends on the driving behavior, traffic patterns, ambient temperature, and road conditions. Therefore, a dynamic demand model will include these attributes. The impact of EV power demand on the smart grid is well explored and not in our scope. Figure 1 shows a high-level outline of place of EVs in relationship to the smart grid.

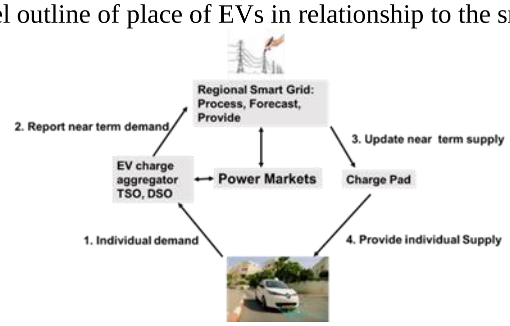

Figure 1. EV in the Smart Grid

Monitoring vehicular power usage patterns and availability of dynamic power charging sources (stations as well as wireless) are a data analytic arena partially explored using machine learning. Predictive patterns of power demand versus power supply will identify degrees of power demand versus degrees of power availability. Basic game theoretic analysis will yield adequacy of on the road demand versus supply for given locations and segments of the road for given windows of time. Recently, there are suggestions of a commercial middleman between a system operator and plug-in EV, called aggregator shown in Figure 1 who participate in the short-term power market, namely day-ahead and real time, submitting forward regulation offers. EVs must pool to represent an energy aggregator agent. In the beginning of each market session, the aggregator will buy electric energy to charge batteries. The transmission system operator (TSO) defines the needs for the next hours or days. The aggregator makes its decision to participate or not in the market, having the possibility of profit through the adjustment of the charging rates. As these processes entail high costs, usually the TSO is a monopoly. The TSO oversees transmission of the electrical power from the power plants to the regional or local distribution operators. The roles of the TSO in the entire electricity market include managing the security of the power system in real time and coordination between generation and load. TSOs are required to maintain a continuous, second-by-second, balance between electricity supply from power stations and demand from consumers and also ensure the provision of reserves that will allow for sudden contingencies. This is achieved through an optimal economic dispatch, according to the load [10]. A variety of bidding algorithmic strategies are available for aggregator negotiation that we will explore for optimal power demand versus supply balance. Modeling EV power demands depends on many attributes such as hour of day, days of week, weekends, months, seasons, holidays, traffic congestion rates, and the weather conditions. We envision a competitive market where every participant strives for better analysis and prediction models to gain a competitive edge. EV power consumption forecasting is a significant part of the solution for energy market participation.

Artificial neural networks are a widely used prediction method [8]. A generic economic supply and demand balance in markets in shown in Figure 2. Consumers are the buyers whereas power providers are the sellers. The shapes of the supply curve are determined by the offer prices of the market participants, also called merit orders. The last supply side offer indicates the marginal asset or power plant. If supply and demand curves do not yield an equilibrium (i.e., do not intersect at any point), a Market Clearing Price (MCP) is settled by shifting the demand curve until an equilibrium point is established. MCP is the key factor that affects all market participants since it is the reference price for all transactions. The formation of MCP depends on a robust demand side prediction. Demand and supply of power will be separately modeled prior to analysis and prediction.

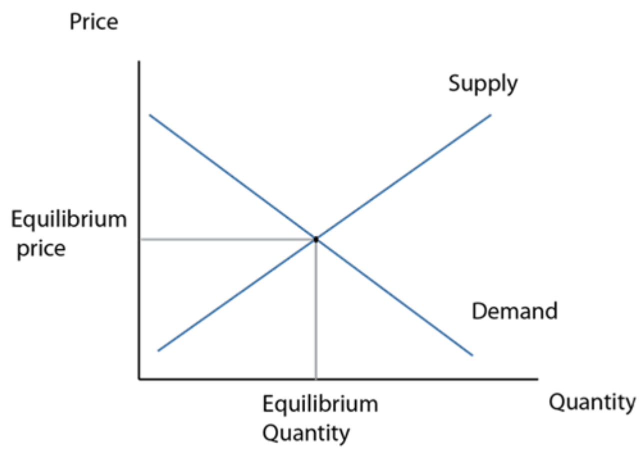

Figure 2. Depiction of a generic power supply and demand, with crossing curves

The supply and demand for electricity are two sides of the market for electric power, and this market includes a demand by EV users and by others as well. Electricity is a flow variable, and the market for electricity allows buyers to purchase electricity which flows through a network or "grid" that delivers it. The regional supply of electric power typically has economies of scale that motivate a single supplier (monopolist). The regional demand for electric power includes demand by households, firms, and government entities. During a week, electricity demand can vary dramatically from day to day, and demand also varies over the course of a day, month, or season. Classic economic models of energy markets identify the effects of demand fluctuation on market outcomes – price and quantity – see [11] and [12]. Figure 3 illustrates the basic outcome in a market with a monopolist supplier and many buyers – represented by the demand curve. The profit-maximizing monopolist chooses to provide a quantity at which marginal demand equals marginal cost, generating the equilibrium price and quantity outcomes. In the short run, the monopolist's marginal cost curve is relatively rigid, whereas the demand curve may vary widely – and with it the marginal revenue curve, thereby causing market price and quantity to vary. The government can elect to regulate the monopolist, reducing its profit and effecting market outcomes, though sometimes with unintended negative consequences – see [13] and [14]. Fluctuations in the demand for electricity are predictable, to a degree, as are their effects on market outcomes. Variations in market outcomes can be modelled via regression models such as the following adopted in a simplified form from [14].

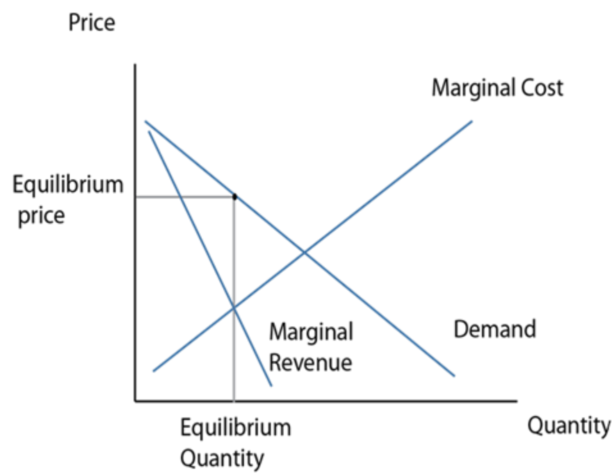

Figure 3. Depiction of market outcome with monopoly supply

$$\ln(p_t) = c_0 + c_1 \times Friday + c_2 \times Saturday + c_3 \times Sunday + c_4 \times ln(p_{F,t-1}) + u_t$$

In this model, p_t is the "off peak" price per unit of power on day, Friday, Saturday, and Sunday are dummy variables representing days of the week, $p_{F_{t-1}}$ is the "peak" price on the previous day, and u_t is a regression error. This model includes some regressors – days of week – that may capture variation in demand from day to day, as well as a dynamic effect of a previous day's price on today's price. The nascent market for electric (and hybrid) vehicles includes a supply by numerous automobile manufacturers and a demand by many consumers. With the list of suppliers and varieties growing over the past decade, demand has also grown. Changes in demand reflect changes in the price of oil and gasoline – as these significantly affect the cost of using a gasoline-powered vehicle.

By nature, electronic vehicles are mobile, and the need to recharge them creates a potential demand for fast-charging stations which may become an important part of the energy grid for EVs, see [15]. As part of the demand for electricity, the power demands of electric vehicle users are in some ways like that of other electricity users. By charging EVs at a home or business, then travelling, then returning to base to recharge, EV users create a demand pattern that may resemble that of other parts of home and business electricity demand. Yet the timing of this sort of EV demand may be special in some ways, as significantly higher demand may precede days or times of high demand for transportation. Also, as the market for EVs grows, the emergence of fast charging stations may – analogous to gas stations – significantly alter future transportation opportunities and EV electricity demand. In turn, the market for electricity may usefully evolve to accommodate EV electricity demand, with a more dynamic and information-intensive set of transactions [4]. Predicting electricity demand by EV users, and relating demand changes to market outcomes (price and quantity), can be achieved using dynamic regression models -- see Section D.3.A. A useful specification of such models reflects those factors likely to affect the demand and the industrial organization of the electricity market, such as a monopoly, regulated monopoly, or regional consortium of electricity providers. Regression models can be linear in the regressors, like the one in Section D.3.A, or can be nonlinear. A modern sequel to nonlinear regression is artificial neural network modelling. Depending on a given market's identifiable characteristics, neural networks may provide advantages as a prediction tool.

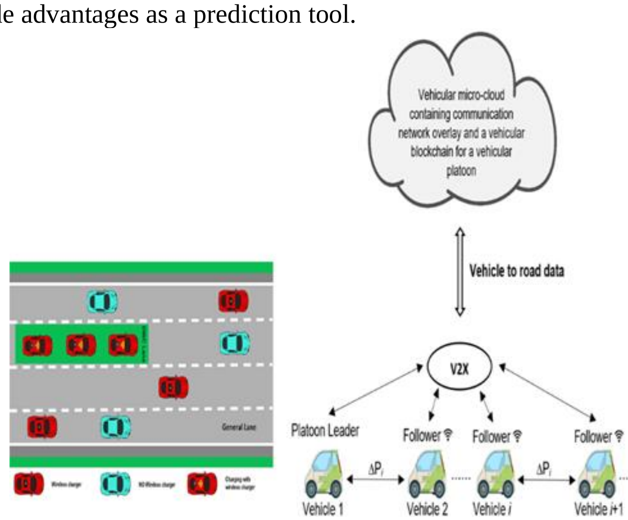

Figure 4. The framework that contains a dynamic wireless charging component

EV must be allowed to wirelessly establish credentials with charging pads and initiate credit based wireless dynamic charging as depicted in Figure 4. Encryption-based charging transactions like transactions maintained in the blockchain will provide secure and immutable transactions. To make DWC a routine activity, we must develop smart contract protocols that track charging patterns for specific EV and their specific EV aggregators, charge rates and amounts of power used. To expedite charging, the smart contracts will rate the payments made by EV to establish a trust-based credit for them. Just as in the traditional credit-based economy, credit-based charging payment will facilitate DWC while driving. Machine learning predictive algorithms are suggested for supply and demand models and will be applied to determine projected revenue and accrued consumer fiscal obligations from charging pad use. There have been recent attempts to use a distributed trust model to create end-to-end trust between Internet of Things (IoT) devices without relying on any common root of trust [16]. They use an obligation chain as a form of credit-based payment tracking system. Obligation chain payments are foundational for tracking as for modeling distributed trust and cooperation among EVs, aggregators, the regional smart grid, and on the road charging pads. Figure 5 shows a common power demand curve. The power demand curve makes it obvious that demand for power varies over time. This can be contrasted against availability of power for the same period. A typical 120-volt outlet can produce around 1.3 kilowatts per hour, but it can take 12 or more hours for a vehicle to be fully charged. A 240-volt circuit can deliver a substantially faster charge and can be wired in a typical home or business. Direct current (DC) fast charging uses 440-volt charging that can "refuel" an electric vehicle battery in less than an hour.

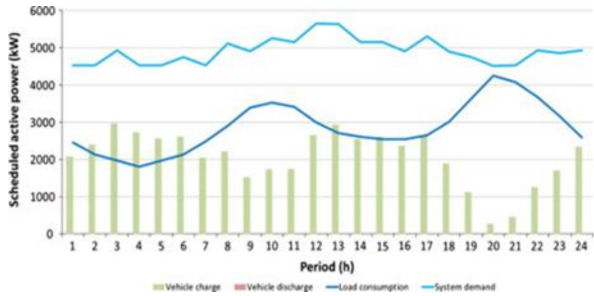

Figure 5: Power Demand Curve

Figure 6: A dynamic charging lane on roadway

Figure 6 shows that charge will be available to EV as they drive over specific road segments. The amount supplied depends on the utility company providing that power based their projection of demand on that segment at that time. In their most recent electric vehicles forecast, the Edison Electric Institute breaks down the 9.6 million estimated charging ports required by 2030. Charging stations will vary in cost and complexity, depending on the loads they are expected to serve (home vs. public), and the type of charge (Level 1, 2 or DCFC). Beyond that, three layers of service equipment are required to support an EV charging infrastructure.

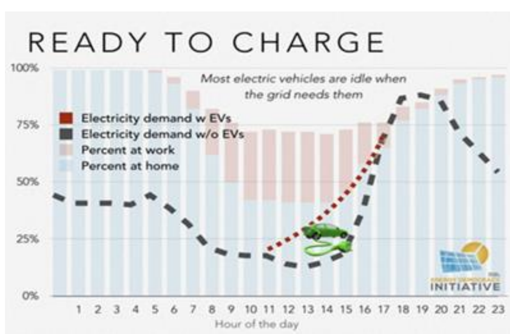

Figure 7: Supply of Electricity from the Grid

Figure 7 shows that charging electric vehicles in the afternoon can make the grid efficient. Timed charging of electric vehicles ensures that, through gradually growing demand from electric cars, afternoon spikes in energy demand can be smoothed out (shown right). In addition, by charging overnight to consume surplus wind energy, electric cars can suck up excess energy supply, as seen in the following chart from the Midwest Independent Device Operator.

The demand for charging at a point in time is the total amount of energy that an EV Service Equipment (EVSE) draws from the electricity grid in a geographical region. EVSE includes charging stations, ports, cabling, and connectors. draws Usually, this is seen as a charging demand curve versus time, which is often referred to as a load profile. For several residential EVSEs in The EV Project, Figure 8 shows the charging demand curve during a 3-week cycle. This curve is based on 15-minute measurements of rolling average power obtained from the EVSE.

The charging demand curve is a periodic curve, with trends close to the charging supply curve, both daily and weekly. The frequent peaks and troughs correspond to the nighttime and daytime, respectively, of the charging demand curve [2]. Typically, demand at night is strong, although demand for the EVSE according to the International Symposium of Electric Vehicles for Battery, Hybrid and Fuel Cell Symposium during the day is close to zero. This suggests a clear preference among participants of the EV Project for residential night-time charges. The weekly trend is focused on the weekends. On weekend days, the lowest demand exists. On any weekday, demand increases until it hits a peak on Wednesday or Thursday night. As the weekend arrives, demand declines again [1]. Since the charging demand curve follows the same periodic trends as the charging supply curve, time-of-day plots can also be used to visualize the demand for charging on weekdays and weekends.

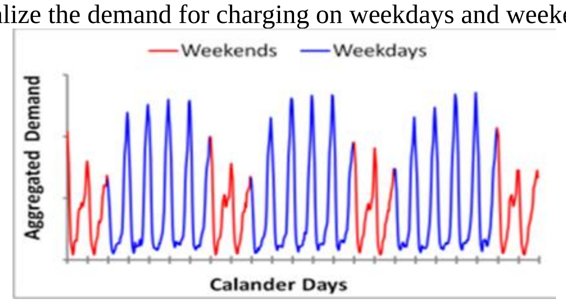

Figure 8: Charging demand curve for many residential EVSE in The EV Project.

Figure 9 depicts the state of these EV samples at various points in time, including when they are moving, just arriving at home or office, parking at home, and parking at the destination. EVs that are not used for commuting are used for shopping, recreation, and other personal pursuits. First, a Rayleigh distribution with a minimum value of □ □ 0.5 times and a mode value of □ □2.0 times was used to compute the number of trips, which was then rounded to the nearest whole number. Figure 10 depicts the results. The first journey typically begins at home, and the last journey concludes at home [2]. When there were more than four trips, there were several trends in the goals of each trip, as shown in Figure 10. When both goals were possible, we assumed that half of the EVs would return home and the other half would travel to other locations. In addition, the following procedures were used to calculate the first departure time, driving times for all trips, and sojourn times at all destinations to obtain the behavior of all EVs [3].

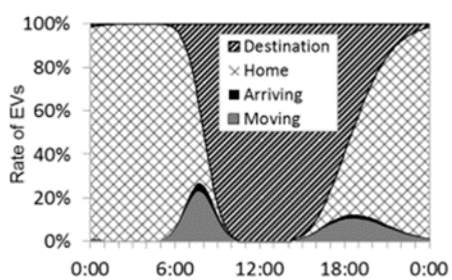

Figure 9: States of Commute-Use EVs

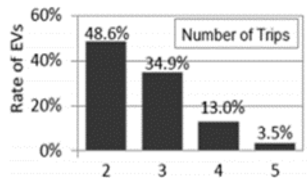

Figure 10: Number of Trips for Non-Commute-Use EVs

We have implemented a simulation and Figures 10 and 11 illustrates the results of our comparison between demand and supply on hourly basis.

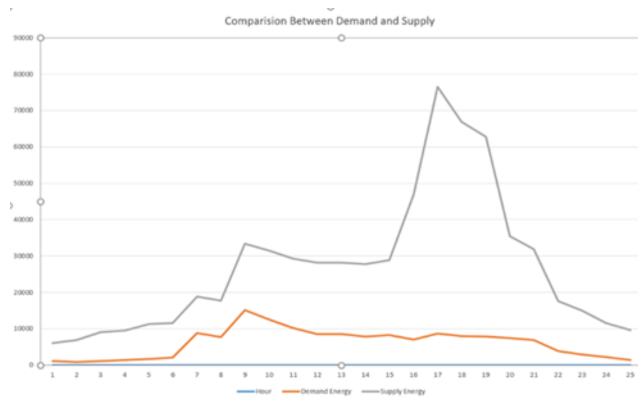

Figure 11: Comparison between Demand and Supply with our simulation

3 Conclusions

The ongoing ascent in electric vehicle (EV) provides a cleaner option in contrast to conventional vehicles. To achieve social acceptance and feasibility for EVs, advances in energy distribution is required. Currently, EVs are commonly charged in the early evening when power interest of families is high and energy generation capability is low. EV clients need to be urged to act in a more economical manner by effectively or latently shifting charging request or to participate in responsible charging or vehicle-to-framework plans including those for the energy aggregators.

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