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On How Smart Cities Can Improve Social Utility of Their Citizens' Commutes

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Abstract: Smart Cities are supposed to be the next generation of not only city infrastructure but also citizenship. Improving citizens' quality of life – referred to as social utility in this paper – should be one of the main targets of a smart city. Electric Vehicles (EVs) offer several new venues in this area. While today citizens are basically on their own when they buy a car while residing in a city, EVs in a smart city is a different topic entirely. Citizens shrink from purchasing EVs today mainly because of high cost and low availability of battery charging. With alternative battery ownership model and Vehicle-To-Home (V2H) systems, citizens can get much more from owning an EV in terms of social utility. This paper shows that high social utility depends on the infrastructure provided by the city. While the battery replacement model presented in this paper greatly increases charging availability, it still heavily depends on battery replacement stations. This paper presents a realistic model for a city-wide EV service infrastructure. The model is based on the real road map of Tokyo. The model evaluates quality of life of citizens, represented by two social utility metrics. Recommendations to battery replacement service providers are made based on simulation results.

Keywords: EV battery ownership model, battery replacement stations, station model, EV service infrastructure, EV social utility, vehicle-to-home, smart cities

1. Introduction

The term *Smart City* does not have a clear definition today. Another way to phrase it is to say that people from different sciences understand the term differently. Yet another way to put it is to say that Smart Cities is intrinsically an inter-disciplinary subject because it incorporates many topics and disciplines some of which may come in contact for the first time. Among several topics, Intelligent Transportation Systems (ITS) is a big part of Smart Cities. Moreover, the specific aspect of ITS – that surrounding the ownership and use of EVs in large cities – can take a leading role in smart cities because it connects the small topic of "citizens' commutes" with a larger topic of "smart grids", where the latter talks about electricity grids which welcome participation of citizens [5].

Electric vehicle (EV) technology has undergone several major changes in recent years. Hybrid cars were the first step towards the fully electric vehicles. Today, hybrid cars can be found on the streets of any major city. In fact, various "green initiatives," with smart cities being one of them, encourage ownership of hybrid cars because of their greatly diminished carbon footprint.

EVs are the next logical developmental step after the hybrids. While the EV technology itself has existed for several years, today EVs are still considered economically unfeasible. For example, at the time of this writing, the lowest price for a 100 km-per-charge mileage is about two to three times the price of a middle-income-class car.

Nevertheless, EVs finally have come out and have become available for purchase. Even with relatively short running distances, the cars can be considered borderline feasible for short commutes within a city. The key aspect is the *charging* part of EV's daily life. EV's owner has to find a third-party infrastructure to charge the EV at work, at home, or at both locations, depending of EV mileage and distance of commute. Using the opportunity it should be noted that terms *owner* and *user* are used in this paper interchangeably depending on context, where modeling mostly talks *EV owners* while simulation treats EV owners as users.

Although charging is still widely used today, *EV battery replacement* has become a popular topic in research community. The problem of battery cost existed since the early EV models. The shared model of battery ownership or, in other words, temporary rental of a battery, solves this problem [6]. The EV can now be purchased separately from its battery, and the battery can become part of EV's continuous service rather than the purchase itself. This seemingly small change can effectively cut the cost of EV in about a half [6].

Another popular topic related to large-scale EV infrastructures is *fast charging* [3]. Although fast charging is placed out of scope of this paper, Section 2 shows how the model presented in this paper can be applied to fast charging without changes. Non-traditional battery ownership can be applied to batteries with fast charging capability based on the same reasons as are applied to battery replacement [6].

This formulation also creates a new player – *Battery Replacement Service Provider* (SP), which can be any business that pro-

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vides at least a city-scale coverage by setting up replacement stations and providing them with replacement batteries. EV owners then can have accounts with this SP which would allow them to come to any replacement station and get a new battery in roughly the same amount of time it used to take gasoline cars to get refueled.

Battery replacement service at the scale of a large city requires direct involvement of the city itself into development of such an infrastructure. The two main players in this "big picture" are the city and the EV owner. The city benefits enormously when its residents start owning EVs in large numbers and is therefore interested in improving the options for potential EV owners. EV owners view their own situation from the viewpoint of personal *social utility* – a theoretical way to express self-interest and continuous desire to improve one's quality of life (*QoL*) on the part of a city resident.

As was explained above, by creating a sound battery replacement infrastructure, the city can improve social utility of EV ownership for its residents. Ability to plug cars into homes, where the power flows in the unconventional direction from the former to the latter, is another way in which social utility of EV ownership can be increased substantially. Note that *EVs powering homes* is a valid topics in *smart grids* where EVs can replace or be used together with solar panels at homes while homes themselves are connected into smart grids of cities [5]. In this case, utility of owning an EV extends not only into *EV-to-home* usage pattern, but even further into the *EV-to-home-to-smartgrid* usage pattern. This paper places the latter pattern out of scope but closely analyzes the former. The term *utility* in this paper is generically defined as a scalar metric which measures the benefits gained by EV owner from owning an EV.

The plug-in function between EVs and homes already exists [7]. For example, Nissan already sells a Leaf model of EV with the Vehicle-to-Home (V2H) function [1]. A pilot house with solar panels and V2H system using a Leaf EV has recently been reported in Japan [10]. The model proposed in this paper uses such a house as the unit entity in simulation.

The fact that houses which have both solar panels and V2H can reach the state of complete independence from the main power grid is obvious. First, EVs can provide power during nighttime. Also, car battery output in recent battery models is sufficient to cover 24-hour requirements of an average house at least two times over [1]. Note that the V2H topic itself is not new and was previously considered in Ref. [7]. However, research literature on the subject is still relatively rare.

A large-scale functioning infrastructure for battery replacement is virtually non-existent today. The famous Better Place project [2] is arguably the biggest such infrastructure. However, even Better Place operates only several stations in USA plus singular pilot stations scattered around the globe. For example, one pilot station was set at a taxi depot in Tokyo in 2011.

One of the objectives of this paper is to show that more cities should invest into such infrastructures because, as this paper shows, such an infrastructure would contribute to a city's well-being while at the same time greatly improve QoL of its citizens, especially those who commute in cars on working days.

Note that Better Place is a private company, not a city. It should be easier for cities to create such infrastructures inside themselves rather than for singular companies to create state-scale infrastructures.

This paper proposes a model which can be used for realistic simulation of city-scale infrastructures. This paper specifically uses the road map of Tokyo but the model can work with any graph.

The original contributions of this paper are as follows:

(1) A realistic model of a battery replacement service (SP: Service Provider) is proposed.

(2) In close relation to the service, this paper proposes a model of a battery replacement station distinct from the one found in Ref. [8]. Specifically, while traditionally the stations are analyzed and modeled as a *stock problem*, this paper uses the model based on *capacity and throughput*.

(3) The unique contribution of this paper is the use of *social utility* metrics which are used to describe how much users benefit from a city-wide infrastructure. Utility metrics are defined separately for commuting and V2H use. As was mentioned before, social utility is a good indicator of the relationship between the city and its residents, where the former should strive to improve social utility while the latter should be able to put the city to test by evaluating practical benefits of the offered social utility.

(4) Simulations are designed to be realistic by using the real road map of Tokyo, distributions of travel time supported by real-life statistics, etc.

A disclaimer is necessary on the part of solar panels. Although this paper talks about solar panels on several occasions, the model itself only cares about the use of V2H systems at night. Such a usage pattern is logical since EVs normally leave homes in the morning and return back at the end of the day.

2. Features of City-Scale EV Infrastructures

This paper talks about infrastructures at the scale of entire cities. Specifically, simulations further in this paper are conducted at the scale of large cities like the Greater Tokyo Metropolitan Area – Tokyo for short. This section attempts to establish a classification which makes it possible to analyze city-scale infrastructures both from the position of individual users as well as the infrastructure itself. Agreeing with the scope of this paper, EV battery replacement is the central purpose of such an infrastructure.

Figure 1 classifies the three charging technologies available in practice today – *battery replacement* (main focus of this paper), common *charging* and *fast charging*. The fast charging technology is a special case of charging where battery can be charged up to 80–90% in 20–30 minutes. Fast charging has recently become popular with several large-scale EV infrastructures [3].

Figure 1 is a simple classification based on *tagging* where each technology is tagged using the prominent features attributed to each technology. All tags represent practical features either for individual users or infrastructures. Naturally, some of the tags have direct relation to the utility analysis performed later in this paper. The rest of this section explains the tags, while Fig. 1 can

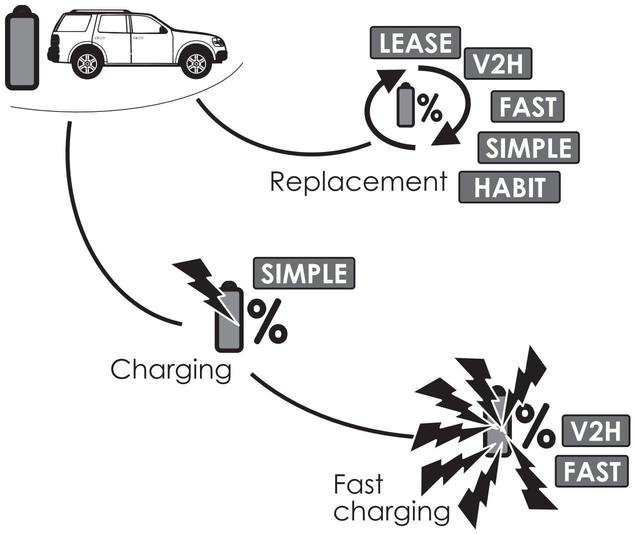

Fig. 1 The three main charging technologies each tagged with relevant features.

be used to match tags to technologies.

The **LEASE** tag is about ability of EV owner to lease a battery rather than purchase one with the car. While most batteries today are sold with the car automatically – meaning that the price of battery is included into the total price of the car – ownership models in which batteries are leased are considered in Ref. [6]. Naturally, leasing should be much cheaper than buying a battery.

The **SIMPLE** tag represents simplicity or accessibility of a charging technology. For example, plugging your EV into a power outlet at home is *simple*. It is equally simple to replace a battery at a station. However, fast charge requires special equipment and most definitely cannot be done at home, which is why this technology is missing this tag.

The **FAST** tag is self-explanatory and refers to the time required for one charge. Only replacement and fast charging are fast, but replacement is faster by comparison.

The **HABIT** tag is a way to represent whether car owners have to change their habits to charge their EVs. The ultimate *habit* is the traditional gas station, where cars (not EVs!) are refueled in under 5 minutes provided there is no waiting line. Only battery replacement lets owners keep their habit because battery can also be replaced in under 5 minutes [2].

Finally, the **V2H** tag shows whether the EV can be used to provide power at home. Only fast charging and battery replacement allow for V2H use because it takes little time and effort for owners to charge/replace the battery in the first place. Battery charge in this case can be considered a consumable good which can be used for commute or at home, or both.

Note that battery replacement in Fig. 1 gathers the most number of tags. This paper will incorporate all these tags into a practical city-scale model of a battery replacement infrastructure. Note that the utility analysis performed in this paper is applicable to both battery replacement and fast charging because both feature *FAST* and *V2H* tags in Fig. 1. The only change in simulation required between the two is a lower station throughput (cars per unit of time) attributed to fast charging, since battery replacement is faster by definition.

LEASE, *SIMPLE* and *HABIT* tags are not considered in analysis but will be revisited in future publications.

3. Related Work

Analysis of city-wide infrastructures requires a model. Several models have been proposed at varying levels of proximity to the scope of this paper.

Research in Ref. [6] is a Microsoft Excel-based model. It is close in nature to the one in this paper because it too models a large-scale infrastructure. However, the main focus of Ref. [6] is cost analysis of battery ownership models, specifically the one in which the battery is *rented* as opposed to *purchased*. In that regard, the model is more helpful to service providers than EV owners. Moreover, the model does not offer details on battery replacement stations and their operation. Use of EV as power supply at home is missing from the model as well. While battery replacement is in the core of both Ref. [6] and the model presented in the paper, modeling objectives are very different. This paper is not burdened with price analysis and instead focuses on utility of owning an EV.

Model in Ref. [7] focuses on EV as part of a V2H system. It is also a practical study based on real measurements of power consumption in homes. The measurement is fed into a Matlab simulation via Simulink on top of which the effect of V2H is simulated. Because of its main focus on infrastructure within a single house, the model has no large-scale components. For example, the concept of a battery replacement station is missing. This paper will do the opposite – the proposed model simplifies home use to a single scalar value – 1/4th of the full battery capacity per night [1], and will instead focus on large-scale components.

Study in Ref. [9] recently released data from a real project. Unfortunately, the project has no battery replacement, only the traditional slow charging. While the study contains many useful statistics on traveltime, time between charges, etc., some of the findings are not applicable to situations with battery replacement. The simple reality is that battery replacement is done very quickly while charging takes several hours. However, this paper models its distributions of travel time based on the statistics presented in Ref. [9].

Research in Ref. [8] is a statistical model of a single battery replacement station. The station operates independently and charges its own batteries, thus being a closed-loop infrastructure. This author considers such a model unrealistic in view of recent experience. Moreover, the study does not consider throughput – defined as number of EVs that can be served per stand per hour of operation – which makes it difficult to apply to models of large-scale infrastructures where many cars have to line up at a replacement station before or after working hours.

On the practical side, Japan recently has witnessed two new entries in the power market – Aeon network of shopping malls and Lawson network of convenient stores. Both announced their entry into the power market as power generators and distributors, where the power comes from solar panels both these players intend to setup on thousands of their locations across Japan. It is very likely that battery replacement operation, when fully commercialized, will happen in a similar manner.

Study in Ref. [12] advocates pooling batteries at the end of their lifespan and their further use as backup in smart power grids. Given the procedure, the technology is referred to as *second life*. This is another reason why large SPs are preferred to single-station operations. The argument is simple: in presence of large pools of batteries, SPs are in a good position to decide when to remove older batteries from the pool and replace them with new ones. It is also easier for SPs to collect old batteries and use them for large projects like emergency backup for solar or wind power plants as is already happening in practice [12].

There are no existing models with the following two features implemented in this paper. **Feature 1** is a city-scale model of battery replacement infrastructure which would incorporate individual owners and models for replacement stations, road graphs, commutes, etc., and **Feature 2** is the analysis based of social utility of EV ownership. A portion of this paper is dedicated to proposing and describing such a model. The model is then used to analyze two kinds of utility in large populations of EV owners in a large city.

4. Proposal: Overall Design

Figure 2 shows the main components of the proposed model. It has three main parts, *user model*, *service model* and *city model*. Each model has smaller components which define either distributions of variables or user strategies. The rest of this section describes each part in detail while numeric descriptions are provided in later sections.

User Model. Users are described using *travel distribution time* and *V2H behavior*. Travel time distribution is modeled after the real statistics from a large scale project at Ref. [9]. Travel time for individual users is randomly sampled from this distribution. V2H behavior model is not found in existing literature but a simple model is created from basic statistics on V2H technology presented in Ref. [7] and battery capacity in Ref. [1].

City Model is relatively simple in that it is simply a road graph. This paper uses a real graph of greater Tokyo. While this paper uses a 2D mesh data (a GIS term) received officially from the Tokyo Association of Roads, future publications will use higher precision graphs generated based on Google Maps as is done in Ref. [4]. Road graph is a pluggable component and can support any technology as long as the basic graph datatype is used.

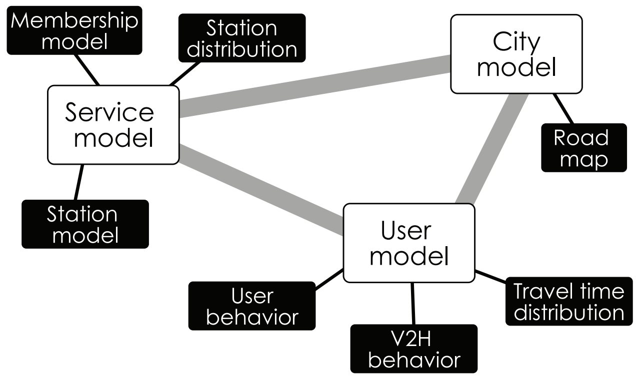

Fig. 2 The main components of the proposed analytical model. The three main parts and elements to each part. This paper presents results from simulations run using this model.

Service Model models a city-scale SP which installs replacement stations in the city and supplies them with batteries. *Station distribution* refers to the distribution of stations inside versus outside of the central part of the city. In this paper the city is split into two parts – the center where most EV owners come to work and suburbs where EV owners live. The model is based on two ratios: one for deciding where to draw the line between the center and the suburbs and the other one for deciding how many stations to install in each part of the city.

Membership model is shown in Fig. 2 for completeness, but this paper uses only a simple model which allows any EV owner to use any replacement station maintained by SP. Future publications will look into alternative membership services which can support various classes of services each targeting owners with a given price range. For example a more expensive *premium service* might have unlimited quota for battery replacements while a less expensive *basic service* would limit weekly or monthly quotas.

5. Proposal: The Analytical Model

This section contains specific and, whenever applicable, numeric details and algorithms related to the analytical model introduced earlier. The overall model introduced earlier is also enhanced by presenting the basic scenario describing daily life of EV and its owner. The model is then used to create realistic and practical simulations at the scale of a city. This paper specifically uses Tokyo as the example model.

5.1 The Basic Scenario

Figure 3 shows the basic scenario used in the proposed model. The main components are: *a home* with V2H power router, *EV* with V2H capability, *solar panel* to provide power supply during the day, *city* where the owner of EV goes to work, and *battery replacement stations* located near home, work, or both. The two main parts of the scenario are *the commute* and *home use*, which will later be represented by respective utilities.

The reason for placing homes outside of the city is as follows. Homes with solar panels and V2H systems need to be houses-on-land, since installation of such equipment in apartment buildings is difficult. Applying this logic to the majority of EV owners, the pattern is developed when majority of people live in the suburbs and use EVs to commute to work. Repeating an earlier statement, solar panels are outside of the scope of this paper, but will be revisited in later publications.

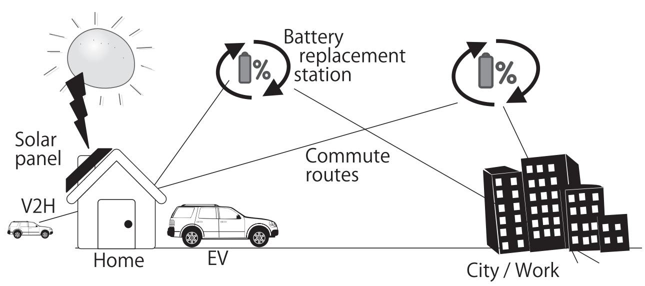

Fig. 3 The overall scenario involving homes equipped with both solar panels and V2H power routers, and battery replacement stations accessible from either home or work locations.

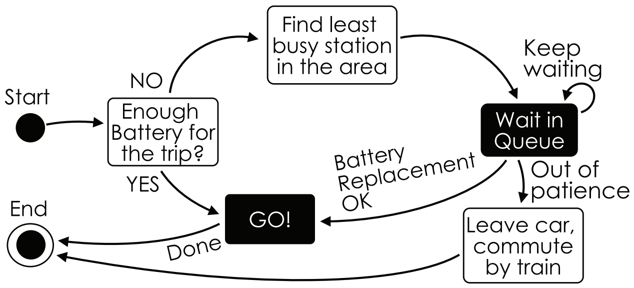

Fig. 4 User strategy for travel *home-to-work* or *work-to-home*. If battery replacement fails, the car is parked at the current location and the trip is done using public transportation. Additional logic for the *work-to-home* trip is explained in text.

This pattern can be simplified as daily cycles with morning and evening rush hours in each day. The majority of EV owners are moving to or from work during these periods. This also simplifies the logic of deciding whether to plug EV into the V2H system at home – the owner makes this decision based on the current charge at the time of arrival at home. More detail on this particular logic is provided later in this section.

5.2 Strategies for Battery Replacement and V2H

Figure 4 shows the decision-making algorithm followed by each EV owner during commutes. Note that some of the trips may be too short and EV may not need battery replacement for each commute or even each day. The term *area* in Fig. 4 is a collective term applied to the total list of battery replacement stations accessible either from home or from work. EV owner then chooses the best one based on station's queue length and the state of EV's battery. To simplify, simulations will select several closest replacement stations and will treat them as *the area*.

The concept of *patience* is used to model owner's behavior while in queue. Owners are configured to tolerate waiting times 2 or 3 hours long. If EV cannot be served by a station during that time, the owner is considered to *run out of patience*, EV is left at current location and the owner commutes using public transportation. Note that two commutes (round-trip) are required to get back to the EV the next day.

There is a minor detail for *work-to-home* commutes which is not mentioned in Fig. 4. When considering whether or not to replace a battery on the way home, its use at home (V2H) is taken into consideration and if there is not enough battery left for home use plus replacement trip the next day, the battery is replaced on the way home. Simply put, EV owner always includes home use when thinking about whether or not there is enough battery charge left on the way from work to home.

Figure 5 shows the logic for using EV for power supply at home. EV is plugged into the V2H system only if there is enough charge to power home overnight plus take a replacement trip the next day. Overnight use at home is fixed in the proposed model at 1/4-th of the total battery capacity [1]. Other values and variability will be considered in future publications. If this condition is not met, EV is parked normally and home is powered by the main power supply. It should be clear that this logic makes V2H use secondary in nature, while EV use for commuting is the primary use. Naturally, if utility of the primary use deteriorates, secondary use deteriorates even further.

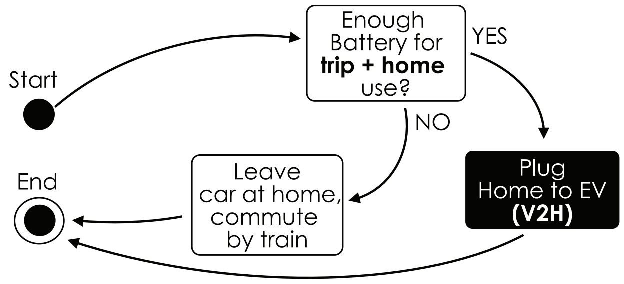

Fig. 5 User strategy for using EV to power home. EV is plugged into the V2H system if the charge is sufficient for home use overnight plus a charging trip next morning.

5.3 Modeling a Battery Replacement Station

The model for battery replacement station proposed in this paper is distinct from the traditional *stock problem* found in Ref. [8]. As was mentioned before, it is very likely that the first big project in Japan will happen via a large service provider entering the market and starting to offer battery replacement services at the scale of individual cities.

Think of it as a new network of convenience stores. Each location will be small, as is commonplace in Japan, and will accommodate only 1–2 EVs at once, however, since it takes only several minutes to replace a battery, even a small facility may have considerable throughput – orders of magnitude larger than the one in the traditional (slow) *charging service*. As was stated above, the same logic can be applied to *fast charging*.

The concepts of *throughput* and *capacity* are key to this model. Let us assume that each lane can replace a battery in 5 minutes. Having 2 lanes, the maximum throughput of the station is 24 EVs per hour. However, with partially centralized distribution of batteries by SP, the actual capacity of the station may be lower than the maximum throughput. In other words, the station can support peak throughput only for a limited period of time after which replacement stops until a fresh delivery of batteries arrives at the station.

The model of this effect is simple. Having maximum throughput of 24 EVs per hour, each station will have a setup parameter for its *hourly capacity* in form of the ratio (less or equal to one) of the throughput. If the hourly capacity is exhausted, EVs have to wait until the next hour starts for the replacement process to resume.

The same model can be applied to *fast charging* with a minimum amount of changes. There is no limit to hourly capacity – the station never runs out of electricity. However, it takes several times longer to fast-charge a battery than to replace it, which is why throughput is much lower.

A larger variety in station models will be considered in future publications.

5.4 Road Map and Distribution Models

City model, specifically the road map is built as the combination of real statistics of travel time of EV owners and the actual road graph of Tokyo. **Figure 6** shows the traditional Beta distribution of travel time confirmed in practice by other studies [9].

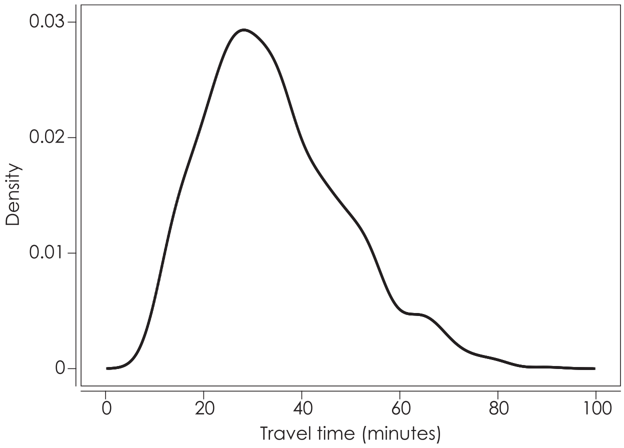

Fig. 6 Density plot for the actual travel time in the area based on Beta distribution with the two shape parameters set to 2 and 10, respectively. The maximum possible travel time is 90 minutes, that given that the longest distance based on the road map is slightly over 100 km.

The longest commute is set arbitrarily at 90 minutes. The largest end-to-end distance on a path is slightly over 100 km based on the real graph below. Given the Beta distribution, most people experience relatively short commutes.

The road map used in the model is based on the actual *2dmesh* (a format used in GIS) data of Tokyo roads officially obtained from the Tokyo Association of Roads. When converted to a graph structure, the graph has 8,005 nodes (intersections) and 63,024 links (mid-size and big roads). Unfortunately, 2dmesh has poor resolution which makes it impossible to plot the graph, but the modeling process itself is not hindered since the correct connectivity is preserved in the graph and end-to-end paths reflect true distances. Future publications will move to higher precision graphs generated based on Google Maps [4].

The following modeling is performed based on the graph. First, statistical distribution of replacement stations as found in Ref. [14] is unrealistic. A more realistic model is the one based on population density [15] which is supported by a much larger body of literature. This paper uses a density-centered process in which more stations are placed in denser part of the road map.

The following process is used.

First, the center of the graph is found – it is simply the node with the smallest average distance to all other nodes in the graph. The graph of Tokyo used in simulation is not perfectly round because density of roads is higher in the central part of Tokyo, more distant areas did not skew the results too much. The center was verified to be and intersection on the inner side of the circular train line (JR Yamanote). A circle is drawn around the center with a given radius (unit: km). The inside of the circle is called *inner city*, or in-city for short. The outside nodes are considered suburbs or out-of-city. EV owners live in suburbs and work in the city. This mode is shown to be prevalent in Ref. [9]. The size of the circle is a simulation parameter.

Note that the above design is not arbitrary and follows the findings in a large body of research roughly referred to as *density of centers* [15], where it is shown that services tend to cluster more densely around densely populated areas. This research has intuitive proof in real life – convenient stores in Tokyo tend to have higher density in the center of the city compared to the suburbs. Also note that the model can support alternative cases. For example, the border can be set to the entire area, thus, providing a layout in which density of stations is the same across the entire area.

Distribution of battery replacement stations also depends on the in-city/out-of-city line but is a separate process. The replacement service in simulations is configured with only one parameter – the ratio of *in-city stations* relative to the total number of stations across the entire infrastructure. This process is related to density – the higher the ratio the more stations are located inside the city. This parameter makes it possible to simulate a wide range of different SPs including those which mostly install stations in-city or possibly prefer to distribute them smoothly across the entire city including the suburbs, etc.

EV owners and replacement stations have the following relation. Each owner keeps the list of three closest stations separately for home and work locations. When battery needs to be replaced, the owner goes to the least busy among the 6 stations, on secondary condition that the battery can afford the trip. The number 6 here is the sum of two 3 s – this is because EV owner can use both local and remote replacement stations with relatively the same distance on the either trip. Such a system roughly models an electronic recommendation service which owners can used to find the most suitable replacement station at a time. In the future, more flexibility will be added in this part of the model.

5.5 Utility Formulations

Utility is an important part of the model because it provides user-side perspective at the infrastructure. Moreover, the insight provided by the proposed model may help owners make a decision on whether to buy an EV or not. Similarly, simulations can help cities decide on whether or not it is worth investing in a city-wide battery replacement infrastructure. The factors such as ability to use EV to power home appliances are among the biggest incentives to would-be EV owners.

The following two utilities are estimated by the model. The EV Utility (*EVU*) if the utility of the primary EV use – commutes between home and work. The V2H Utility (*V2HU*) represents the utility of EV used for power supply at home. The utilities are calculated as simple ratios:

$$EVU = \frac{commutes\ in\ EV}{total\ commutes}, \tag{1}$$

$$V2HU = \frac{hours\ used\ at\ home}{all\ night\ hours}. \tag{2}$$

Note that while the two above utilities are simple ratios, the processes used to produce data for the utilities are fairly complex. As was explained before, users follow non-trivial decision-making algorithms when deciding whether to replace a battery or whether to use EV to power the home. EV owner population size, station throughput, patience while waiting in line in front of a replacement station, etc., all contribute to the raw statistics which are used to calculate the above utilities for individual users.

Future publications will work with utilities of higher complexity, where metrics will be modeled as potential or elasticity of a given EV usage relative to changes in the infrastructure, membership models, etc., while this paper concentrates on the simple metrics presented above.

6. Simulation Setup

Model details including numeric constants for several parts of the model were presented in the previous section. This section describes simulations implemented on top of this model. Note that this section should be considered as a numeric setup for the components in the model described in the earlier sections.

The results shown further in this paper are obtained using the following simulation setup. Note that this setup describes one simulation run.

Each run simulates 100 days. Each day is considered a business day where EV owner commutes to work in the morning and returns home in the evening. For simplicity, all owners leave home/work at the same time, which means that the time itself is not important but can be referred to as *rush hour*. Decision making for whether EV owner needs to replace the battery or not was explained earlier. Each time, EV owner selects only one station and commits to it. Since stations have limited throughput, it is possible that users have to wait in line for a replacement.

Patience for EV owners at battery replacement stations is randomly selected between 2 and 3 hours. Battery capacity is a fixed number – 150 km (24 kW, the case of Nissan Leaf). One use of EV at home via a V2H system requires 1/4th of that capacity. Remaining capacity at the time when EV owner has to leave work or home is used to decide whether the battery needs to be replaced.

The border between in-city and out-of-city is configured as a ratio between 0.2 and 0.8 – fraction of the maximum distance from the center – about 60 km in the actual graph while absolute longest end-to-end path is about 100 km. The other border parameter is applied to the service model where the ratio decides how many stations are located in-city and how many are spread across the out-of-city area. The two parameters are randomly selected independently of each other, simulating various city designs alongside with various station distribution models.

Between 2 k and 20 k EVs owners can co-exist in a simulation run as *EV owner population*. Travel time for each owner is sampled randomly from the distribution presented earlier. The following algorithm is used to decide the location of EV owner's home. Since we know that the longest end-to-end path originating from a node in city center is about 60 km (longest absolute end-to-end path is about 100 km) and longest travel time is 90 minutes, we can randomly select a node from the band of candidate nodes which are located close to the target distance. For each user, two selection operations are performed. First, a node is selected randomly from all in-city nodes, becoming *place of work*. Then, the *home place* is selected as a random node from 10 closest nodes to the target distance from the work place. Note that mapping between distance and travel time is straightforward because maximum travel time is set to 90 m and physical distances are known from the road graph – maximum distance is automatically assumed to take 90 minutes to travel, with all other distances mapping inside that interval.

Number of stations is selected as a ratio of the number of EV owners (see about population size above). The ratio is selected randomly between 0.01 (1%) and 0.5. This population of stations is then distributed in- and out-out-city based on the border parameter above. Stations are assigned to nodes in graph randomly in each part of the city.

All battery replacement stations have the same fixed throughput of 24 EVs per hour – modeling two stands and 5 minutes per car, but the actual capacity is selected randomly for each simulation run as a ratio of that number, modeling the event when a station runs out of stock during the rush hour. Simply put, maximum station throughput is 24 EVs per hour but can be decreased using a simulation parameter.

All random values above are selected as follows. Each random interval is split into 10 intervals of equal size, this creating 10 discrete values. Values are then selected randomly as one of these discrete values in each simulation run. Simulation is executed until at least 10 runs are accumulated for each unit combination of all simulation parameters.

7. Simulation Results

This section presents simulation results in two viewpoints. One viewpoint presents distributions of raw utility values. The other viewpoint studies response of the two utilities to changes in environment. The two viewpoints are necessary to simplify presentation of otherwise multidimensional data. Refraining from 3D plots, each plot presented in this section is a 2D plot but uses a presentation style that contains additional information on top of the base two dimensions. This presentation method makes it possible to increase density of presented information.

Data for **Fig. 7** are selected using the most unfavorable configurations for all variables except for ratio of *stations to users* and *station capacity*, where the two latter parameters are used to group data in plots. The term *unfavorable conditions* here specifically refers to simulation runs under *patience=2*, *city border* $\leq$ *0.3*, and *stations in city* $\geq$ *0.7*, describing a city where most stations are located in-city and EV owners do not like long queues. Filtered simulation results are then grouped by the type of utility in separate columns, ratio of stations to users in each plot and station capacity in each curve. This way sufficient density of presented information is achieved. Essentially, Fig. 7 presents probability of a given level of utility experienced by individual users, where probability is simply calculated as number of users above a given threshold of utility divided by the total number of users. This means that as utility threshold is gradually increasing along the horizontal line of each plot, fewer and fewer users can experience that level of utility. Note that *perfect utility* literally represents that a user can use EV for all commutes and use it to power his/her home all the nights. Also note that axes notations are omitted in Fig. 7 to allow for a bigger plot where distributional artifacts would be more visible.

Note that only the ratio between number of stations and number of users (owners) is used while the absolute values for both counts are not indicated. This means that these results cannot discriminate small from large cities and large from small populations. Absolute analysis is performed later in this section. Also note that Fig. 7 presents averages on points in all curves.

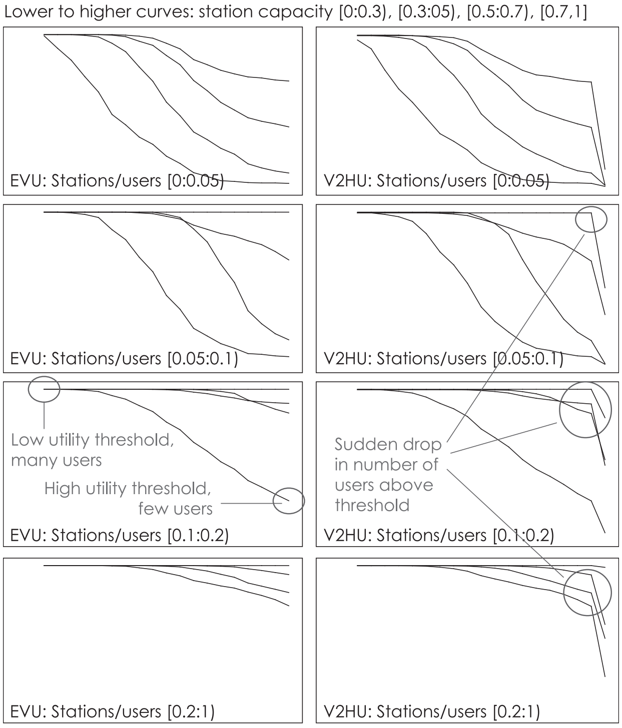

Fig. 7 Utility distributions $P[x \geq a], a \in (0 : 1]$ (horizontal axis, right to left) for both utility metrics (*EVU left, V2HU right*) with gradually increasing stations/users ratio (*top-down*). Each plot shows four curves for four intervals of values for *station capacity*, where each higher curve signifies improved conditions and therefore better utility. Axes are the same for all plots but hidden to avoid crowding the figure.

The reading from Fig. 7 is as follows. With the stations/users ratio at 0.2 to 1 – cases when there are many stations spread across the city – both utilities are near perfect. Exceptions are curves for relatively lower station capacity in V2HU plots, where nearly 50% of users find themselves below 90% utility threshold. It is interesting that some of these users are still able to use EV for commutes because the same curves in the EVU plot do not experience drops of this magnitude.

The same two plots also reveal that performance is sensitive to station capacity because in both plots the curve for the maximum capacity indicates perfect utility for nearly all users. The drops in V2HU are experienced only for simulations where station capacity is diminished. This sensitivity is explained as follows. Even with relatively many stations, density of EV owner populations which decide to replace their batteries at work (in-city) is very high and results in longer queues and in some cases failure to replace the battery. On the other hand, density of stations out-of-city is low and battery may not have enough charge for allow a round trip for replacement. Note that this basic dependency on density of station distribution in cities is also found in Ref. [9].

With each next row of plots (bottom to top), distributions deteriorate further. However, in all cases EVU performance is always smooth with no sudden drops. However, the drops exist for all V2HU curves, this time without a curve of *perfect utility*. In fact, all V2HU curves which retain high number of users until a relatively high utility threshold seem to experience a sudden drop past 90% threshold indicating that perfect V2HU is difficult to achieve.

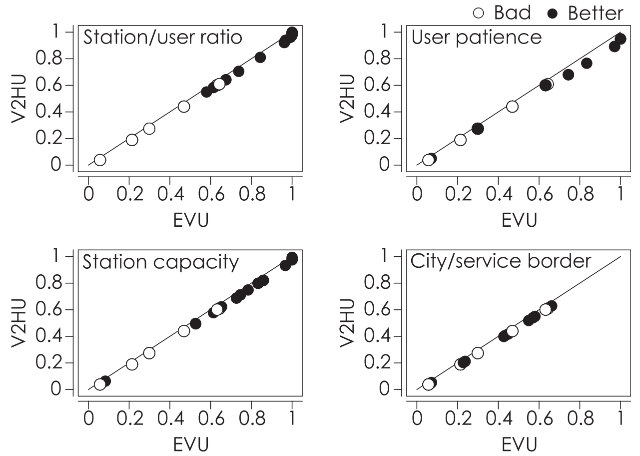

Fig. 8 Effect of improving one parameter while keeping the rest unchanged on the utilities. White (bad) dots indicate initial conditions and Black (better) dots indicate the utility after the change.

In general, Fig. 7 indicates that both the stations/users ratio and station capacity have considerable effect on the utilities.

Figure 8 starts the same as Fig. 7 by using worst-case configurations as initial conditions – marked with white (Bad) dots in the plots. For each white dot, the specific parameter in each plot was allowed to change towards a higher value after which the new value of utility is plotted as a black (Better) dot. Although this is not a traditional presentation method, the plots visualize response of both utilities to changes in specific environmental parameters. Note that response in both utilities is measured simultaneously where EVU is plotted on horizontal and V2HU on vertical axes. To avoid crowding the plot, all utility values are rounded to 0.05 and 10 most frequently occurring pairs of dots are displayed in each plot.

Note that no actual increases/decreases happen in simulation. In reality, increase is simulated by selecting two simulation runs where one run comes from the worst-case configuration and the other with a configuration in which only the target parameter was given a higher setting. This method of selection is time consuming but enough simulation runs are executed to find matches for all parameters at all change magnitudes.

Figure 8 should be interpreted in context of how far black dots move away from the white dots. Black bullets higher on the diagonal line than white ones indicates improved utility – referred to as *positive utility response*, and vice versa.

The following reading of Fig. 8 can be offered. Increasing ratio of stations to users reliably results in positive utility response, which is an expected result. Similarly, both utilities response positively to increases in *station capacity* and *user patience*. In all these cases, the response is consistently positive. User patience has rare exceptions where higher patience results in inferior outcomes. This happens because more patient users can block other users while waiting longer in line.

However, increasing *city/service borders* – meaning that city centers are bigger and in-city stations are more scattered – do not necessarily result in better performance. For simplicity, these parameters are merged into one by increasing both at the same time. Higher values in both metrics can cause outcomes at both better than baseline and worse than baseline extremes.

The following interpretation of the results can be offered. When owners have higher patience while waiting in line, some replacement stations are more prone to prolonged congestions, which effectively splits the users into two groups – those that came to a congested station and failed to replace a battery and those who came early or found an uncongested station, hence the opposite extremes in the figure. Note that increased utility is a more common outcome than the other extreme.

Likewise, in large cities and less density of in-city stations, distances between stations are larger. It is now likely that you can find a replacement station closer to your home but it is also likely that it will be congested on the way to work or when returning home. Because distribution is now smoother, this plot does not show the two extremes as was found for the patience plot. Instead, black and white dots are completely mixed.

Although this artifact is very subtle in Fig. 8, similarly to Fig. 7, V2HU values are slightly lower than EVU values at the higher end of the range.

The lessons from Fig. 8 are as follows. Among all the parameters, the best utility response is found for *station/user* ratio and *station capacity*. This is a very clear and intuitive message for SPs in that increasing number of stations and building bigger and faster stations should result in better user utility. This, however, does not mean that other parameters cannot help improve utility. For example, increased patience can help some users achieve their goal. Given that utility response for the other two parameters is mixed, SP should develop a complex strategy when trying to improve utility through them.

8. Conclusion

This paper views a city with its many EV owners as a game-theoretical model governed by the concept of social utility. This paper is the first attempt to model EV infrastructures at the scale of large cities while existing studies restrict the focus to local scale or individual features of EVs. Models of large scale infrastructures are different in that they can consider non-traditional uses for EVs. This paper considers the well-known example where EV can be used as a source of power supply at home. This usecase can be extended to scenarios where cars can be plugged into homes which themselves are plugged into a city-wide smart grid. This paper focuses on the user prospective in city-wide infrastructures by focusing on the use of EVs for commutes and power supply at home.

Simulations in this paper incorporated EVs, V2H technology, battery replacement stations and battery replacement service provider where the provider is put in charge of supervising replacement stations at the scale of the entire city. Potentially, solar panels should also be part of the model, but to retain focus on EV-based infrastructure they were placed out of scope in this publication. The use of EVs at home as part of a V2H system is not a new topic. However, to the knowledge of this author, this publication is the first to consider V2H together with battery replacement.

Another unique contribution of this paper is the realistic modeling of large-scale infrastructures. Simulations in this paper were based on a real road graph of Tokyo. Also, features like "live in suburbs, work in city" are very close to reality in most big cities. Simulations were run over a wide range of parameters which mimicked real conditions in many cities other than Tokyo. This means that the model can be used for other cities as long as the road graph is replaced and parameters are configured after realistic conditions in another city. Note that in order for a large-scale EV infrastructure to work, cities have to invest a considerable effort to make battery replacement infrastructure readily available to its citizens. For example, the current availability of battery replacement is close to zero in Tokyo, which makes owning an EV a luxurious endeavor as opposed to the socially reasonable formulation presented in this paper.

A very important part of realism in the proposed model is in how battery replacement stations are modeled. While traditionally the problem posed is that of stock provisioning, the proposed model views the problem as that of throughput and capacity. In fact, the paper repeatedly makes the point that battery replacement with its 5-minute-per-battery replacement cycle, closely resembles how gas stations operate today. This is another plus for battery replacement infrastructures – people are used to 5-minute gas refills and will be happy not to break this habit when switching to EVs.

In general, the proposed model is very close to what is soon to become reality for EV owners. The new battery ownership model where owners only temporarily rent batteries without purchasing them is expected to become industry default in near future. The main reason for this evolution is not the high cost of the battery but the emerging secondary uses for end-of-life batteries, which can be pooled and used for energy storage.

Such an infrastructure can only be handled by big players in the market. It is to be expected that the same players will operate both a battery replacement service and second-life operation of batteries, all part of the future smart power grids. Such projects are difficult to imagine without direct involvement of the cities themselves.

This paper analyzed two types of utilities – one for utility of owning an EV to use it for commutes, and the other for the side utility from using the battery for power supply at home. Simulation results show that distribution of the former utility is smooth across the population of EV owners. On the other hand, utility of using EV for power supply exhibited a clustered distribution with about half of the users not being able to achieve the threshold of 90% in the latter utility. This means that EV was still useful for commutes but could not be used for power supply on some nights.

Analysis of utility response to changes in environmental parameters revealed that positive response was found for increases in number of stations and capacity of each station, as should be expected. Response for populations of EV owners who were ready to wait 3 hours in line instead of 2 hours was split into two clusters at both positive and negative extremes. Response to increasing the reach of stations into areas farther from city center revealed no consistent positive response.

There is a large volume of potential future work based on this paper. Avoiding too much detail, the specific next study will look into the threshold of battery replacement station availability above which EV ownership becomes reasonable for mid-income citizens. This study will consider several practical scenarios in which battery replacement station chains are built as extensions of existing infrastructure. Japan recently experienced several similar developments where Lawson convenient stores or Aeon malls announced their entry into power generation market. It is likely that city-scale battery replacement infrastructure will happen in a similar manner.

Future work will also look into various membership models, where EV owners will lease the battery but will also have a choice of membership classes each having a limit on number of monthly replacements and different price. Future analysis will retain the focus on user-side social utility in such services.

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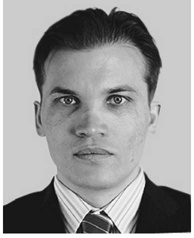

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