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Service Time Analysis For Electric Vehicle Charging Infrastructure

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ABSTRACT

This paper analyzes electric vehicle charging patterns in Jeju City, taking advantage of open software such as MySQL, Hadoop, and R, as well as open data obtained from the real-time charger monitoring system currently in operation. Main observation points lie in average service time, maximum service time, and the number of transactions, while we measure the effect of both temporal and spatial factors to them. According to the analysis result, the average service time is almost constant for all parameters. The charging time of 88.7 % transactions ranges from 10 to 40 minutes, while abnormally long transactions occupy just 3.4 % for fast chargers. The day-by-day difference in the number of charging transactions is 28.6 % at maximum, while Wednesday shows the largest number of transactions. Additionally, geographic information-based analysis tells that the charging demand is concentrated in those regions having many tourist attractions and administrative offices. With this analysis, it is possible to predict when a charger will be idle and allocate it to another service such as V2G or renewable energy integration.

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1. INTRODUCTION

Due to significant environmental benefits mainly coming from greenhouse gas reduction and energy efficiency, many countries are trying to make EVs (Electric Vehicles) penetrate into our daily lives [1]. However, in spite of recent improvement on battery technologies in capacity and charging time, their inconvenience in battery charging still makes them less competitive to their counterparts, namely, gasoline-powered vehicles. To overcome this problem, it is necessary to extensively build and efficiently manage charging facilities over the service area. Here, the modern facility management usually monitors the real-time status of each charger, detects&remedies the problem, and makes a new operation plan [2]. Such management can be built not only upon diverse communication channels easily available these days but also upon intelligent computer algorithms. Digitally controlled chargers allow us to develop a citywide coordination mechanism for smart transportation systems [3].

The big data accumulated in a monitoring system can give us an insight on how the target system works [4]. In the charging infrastructure monitoring system, we can discover which charger is heavily loaded, when EV charging is concentrated, and how much electricity must be stably provisioned for each facility [5]. Moreover, some countries, for example, Republic of Korea, open the data stream captured in their charging system to the public to accelerate the development of a new service, not restricted to the commercial industry. It must be mentioned that the availability of open software, especially belonging to the artificial intelligence domain, makes it possible to conduct sophisticated analysis for a variety of purposes. After all, the development of big data processing techniques such as Hadoop [6], provides an opportunity to efficiently cope with the massive volume of data created in the physical space as well as to timely decide an appropriate control action in the cyber space [7].

There exist many previous or ongoing approaches applying big data analysis in smart transportation systems. In the NEC framework, a set of charging controllers coordinate the energy distribution across hundreds of chargers [8]. For example, a facility-wide coordination can limit the amount of simultaneous charging. Controllers are connected to the remote NEC cloud, which provides huge data storage and sufficient computing power. This high-end server is responsible for remote monitoring, user authentication, and membership management, playing a role of multi-service gateway for billing. In addition, the Hitachi system monitors power consumption, equipment operation, and EV charging for the target charging facilities [9]. The data analysis procedure consists of data interpolation, prediction, and knowledge acquisition to make a high-level timely decision in control applications. Application coordination supports not only an efficient integration of renewable energy to the grid power but also inter-EV cooperation for balanced charging. Particularly, trend prediction makes it possible to shift EV charging load, locates the malfunctioning part, and even invites V2G (Vehicle-to-Grid) applications [10].

Based on the open data and software, this paper first presents how to acquire the monitoring data stream from the well-known website and conducts an analysis to discover the service time for each charger and to obtain charging demand patterns in Jeju city. As one of the most prominent smart grid cities in the world, this place is now consistently carrying out its ambitious enterprise to replace all regular vehicles with EVs by 2030. The EV charging infrastructure, currently working, creates a massive volume of data streams. The main focus of investigation is put on the effect of temporal parameters such as date, hour-of-day, and day-of-week as well as spatial parameters such as administrative region and place type. Here, the data is stored in MySQL database and a series of queries are designed and issued to this dataset. The analysis process also implements Hadoop Pig scripts when necessary. Additionally, the summarized data set is given to the R statistics package for advanced machine learning schemes and elaborate visualization tools [11].

The rest of this paper is organized as follows: After outlining the paper in Section 1, Section 2 explains the background of our research. Section 3 extensively investigates the observation parameters and discusses the result. Finally, Section 4 concludes this paper with a brief introduction of future work.

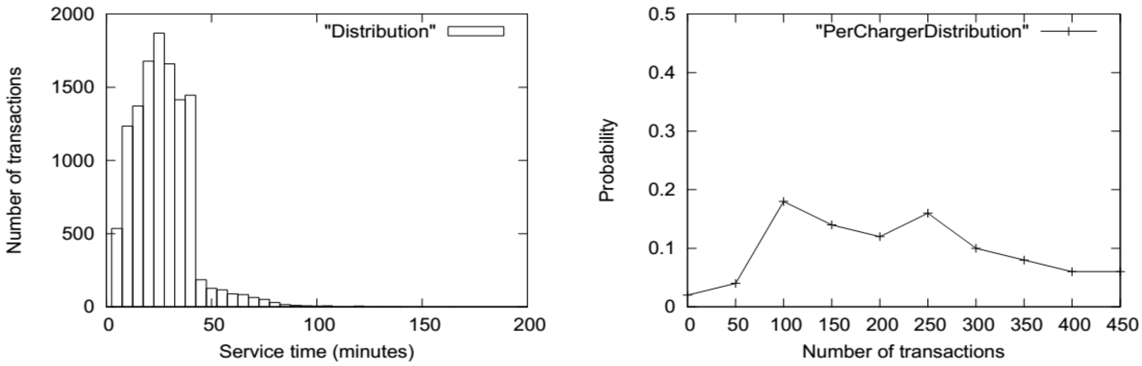
2. BACKGROUND

Jeju city is located at the southernmost tip of Korean territory and has long been famous for a variety of tourist attractions. Since it was designated as a smart grid model city in 2009, many efforts have been made for the sake of testing up-to-date technologies and developing new business models. One of the most outstanding achievements is the penetration of EVs over the island having about 200*km* long coastline. Now, Jeju is pursuing an enterprise called *Carbon-free Island 2030*, which is trying to replace fossil fuels with renewable energies making use of its abundant energy sources like wind, sunlight, and the like. In this city, many smart grid entities are monitored in real-time and the data streams are stored for further analysis and investigation. One problem lies in that even the entities of the same category are managed by different authorities. Anyway, those data streams managed by national or local administrations are likely to be made public to accelerate the development of many different applications having different goals to achieve.

Our research team has built a data acquisition module which periodically retrieves the real-time monitoring status from the open website, namely, *www.data.go.kr*. The data sets come from those chargers managed by KEC (Korea Environment Corporation) [12]. Currently, 49 fast charger records are added in our database table every 5 minutes. We define 2 tables of *OpenLoc* and *OpenCharger*. The first stores static information such as latitude, longitude, charger type, region, and place type of each charger. In addition, *OpenCharger* keeps appending status information, either working or idle, for each charger. It must be mentioned that this monitoring system does not include the amount of energy spent for EV charging. Then, this work conducts a preliminary analysis, including the number of active chargers according to the time flow. Its analysis process integrates geographic maps also opened to the public as a form of ESRI shape files. In addition, the subsequent work investigates the occupancy rate, which means the probability that a charger is servicing an EV at a specific time instant [13]. The investigation finds out that charging operations are counter-intuitively concentrated around the end of office hours.

3. DATA ANALYSIS RESULTS

Service time is very important to trace the behavior of each charging operation, as it can allow us to understand the arrival patterns of EVs at chargers and the length of transactions. Moreover, it is possible to predict when a charger will be idle and allocate it to another service such as V2G or renewable energy integration [14]. In our experiment, the records from 3-21-17 to 4-20-17 are taken. After sorting the records by their timestamps for each charger, our transaction detector captures the change in the working status, that is, from non-working to working or from working to non-working, in the time series. Here, if a charger is working, it is providing energy to an EV. During the interval, the detector finds 12,030 transactions out of 49 fast chargers over the city area. The difference between two timestamps will be the service time. Considering that the data stream comes from fast chargers, the service time longer than 60 minutes is abnormal. Either a new EV may be connected to the charger between the two consecutive retrieve intervals, or the EV is not taken even if it is fully charged.



(a) Service time (b) Per-charger number of transactions

Figure 1. Citywide statistics

To begin with, Figure 1 plots the citywide statistics. Figure 1(a) shows the service time distribution for the whole transaction set. The number of abnormally long (beyond 60 minutes) transactions is just 378, occupying just 3.1 % of total transactions. The maximum of traced service time is 185 minutes. The service time of most EV charging transactions lies in the range from 10 to 40 minutes, as expected. 88.7 % of charging operations belong to this range. Moreover, the service time that lasts just 5 minutes also appears 536 times. Those charging operations have little difference from fueling gasoline-powered vehicles. Next, Figure 1(b) shows the probability distribution for the per-charger number of transactions. According to the figure, 18 % of chargers have served 100 to 149 times during the investigation interval. 2 % of them have charged less than 50 times, while 3 chargers reach around 500 times. This curve indicates the significant difference in service rate between chargers.

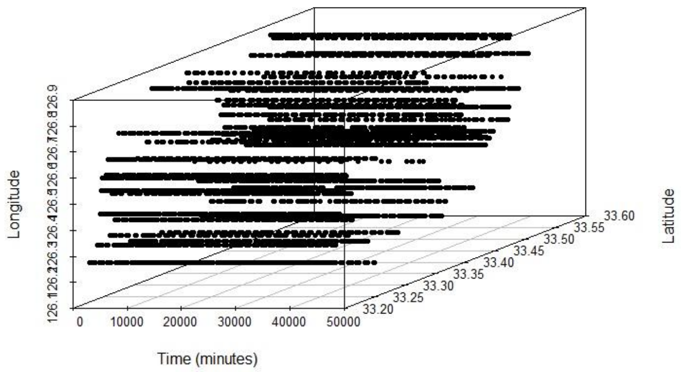
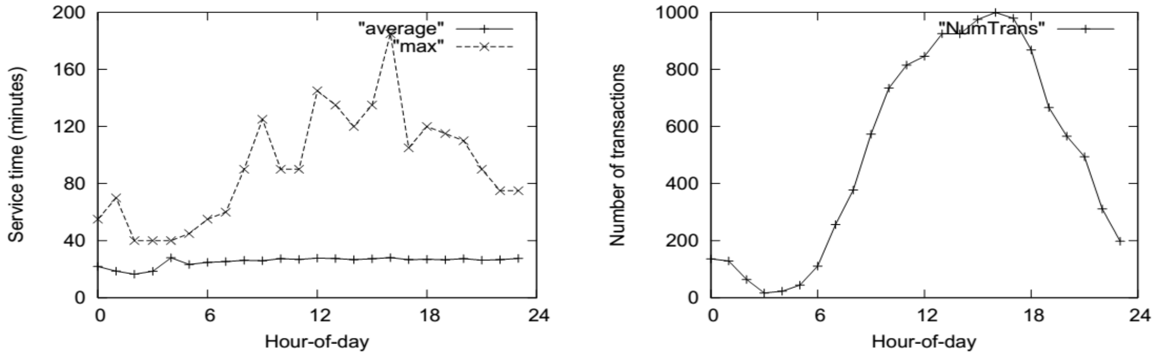


Figure 2. Spatio-temporal arrival time plotting

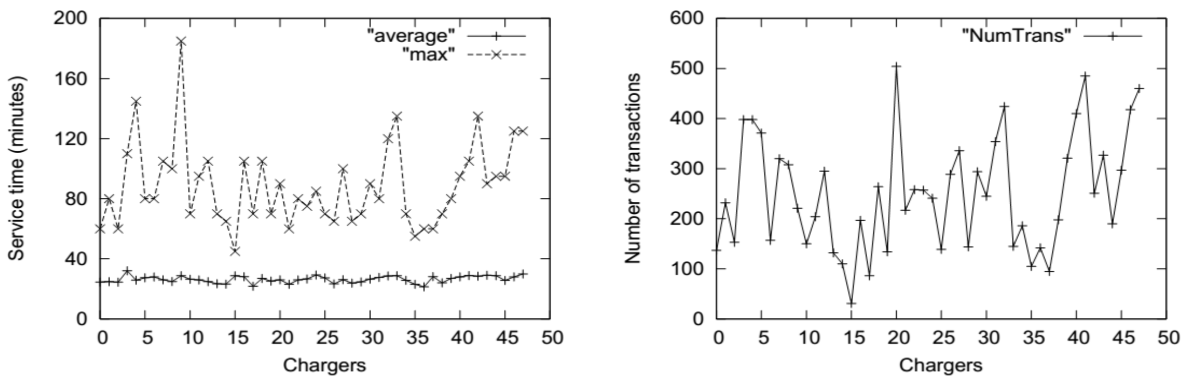
Figure 2 shows arrival times of EVs in each charger and this 3-dimensional graph is generated from the R statistics package, specifically, *scatterplot3d* library. Here, the y-z plane is the geographic map marking the location of each charger according to its WGS84 coordinates, namely (latitude, longitude). The cross-section of this cylinder roughly coincides with the map of Jeju City, as chargers are spread out over the whole city area. The x-axis denotes the time flow. There are 49 straight lines, actually, the series of points, along the x-axis. For a line, each point corresponds to the start time of a charging operation. The figure indicates that points distribute almost uniformly on each line, that is, the charging demand is quite consistent for each charger. The dot density of bottom area, namely, chargers in the south region, looks much higher.



(a) Service time (b) Number of transactions

Figure 3. Arrival time analysis

Figure 3 shows the measurement results for the hour-of-day effect. The average and maximum service time is plotted in Figure 3(a). As mentioned previously, some transactions are prolonged needlessly. However, such cases rarely take place, hence the average service time is quite stable. As shown in the figure, the average service time is relatively short in the early morning, specifically, before 3 AM much before the office hour. Drivers seem to wait just next to the charger and take their EVs as soon as their batteries get sufficient electricity. In the rest of day, the average service time stays at around 27 minutes. This result tells that most charging continues until the battery is fully charged. Additionally, Figure 3(b) shows the number of transactions. Only a few transactions, namely, 413, start during the interval from midnight to 6 AM. The number of EV arrivals increases until 4 PM when 999 arrivals are found, and then decreases. However, we can find more than 500 charging transactions until 8 PM, much after the end of office hours, even though the number of transactions drops quite sharply. Judging from this result, fast chargers seem to be used on as-needed basis, as contrast to AC slow chargers.

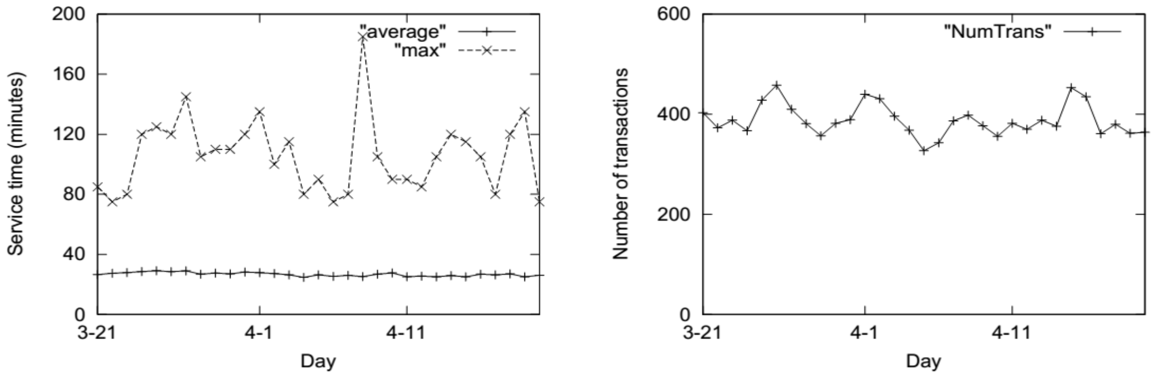


(a) Service time (b) Number of transactions

Figure 4. Charger-by-charger statistics

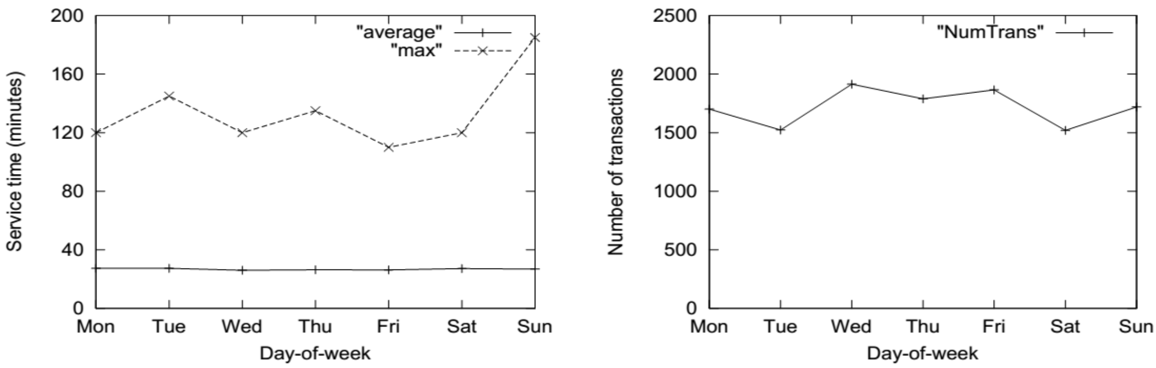
Next, Figure 4 plots the charger-by-charger statistics. In the figure, the x-axis does not denote a charger id but just a simple sequence. As shown in Figure 4(a), the average charging time is almost similar for all chargers, the maximum difference being just 7.0 minutes. This experiment must take into account the inherent measurement error resulted from the length of observation intervals. In addition, Figure 4(b) plots the per-charger number of charging transactions, and its maximum and minimum of them are 504 and 31, respectively, showing a significant gap in service rate between chargers.

Figure 5 traces the daily change in the observation parameters. As shown in Figure 5(a), it is not so confirmative, but the average service time decreases slightly. It can be explained by the fact that drivers are getting more accustomed to using chargers. This phenomenon must be continuously observed for the time being to reach a safe conclusion. Moreover, we can see severe oscillation in the daily number of transactions in Figure 5(b). The maximum and minimum values in the number of transactions during this interval are 458 and 327, respectively, the gap reaching 28.6 %.



(a) Service time (b) Number of transactions

Figure 5. Daily charging dynamics

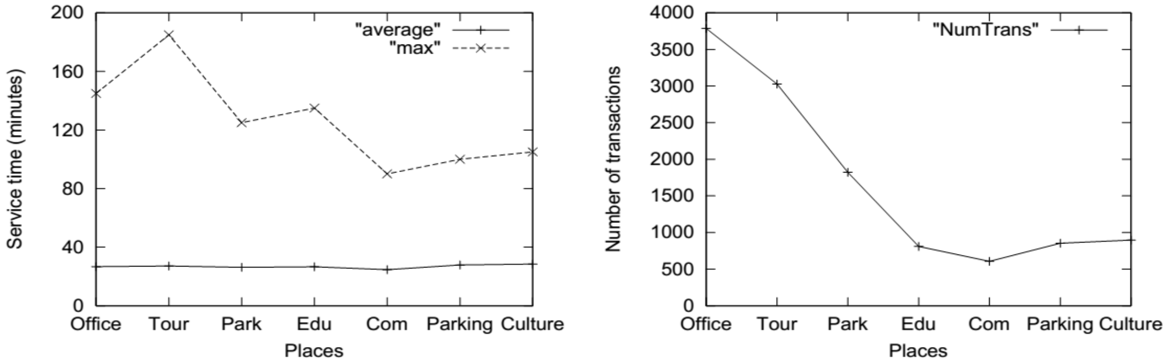


(a) Service time (b) Number of transactions

Figure 6. Day-of-week effects

In the previous experiment, the deviation in day-by-day number of transactions seems to come first from day-of-week. Hence, Figure 6 plots its effect on service time. As usual, the average service time is almost constant for all day-of-week, and we can know from Figure 6(a) that the longest transaction has taken place on Sunday. The number of transactions is smallest (1,519) on Friday and largest (1,914) on Wednesday. It is not easy to explain this curve, as Wednesday is the middle of weekdays and there is no special reason to charge more EVs than other days. Anyway, the difference between maximum and minimum values is 20.0 %, indicating that day-of-week is an important source of the day-by-day difference. Moreover, other causes, such as day-specific tourist activities, climate conditions, and moving patterns must have hidden in the big data.

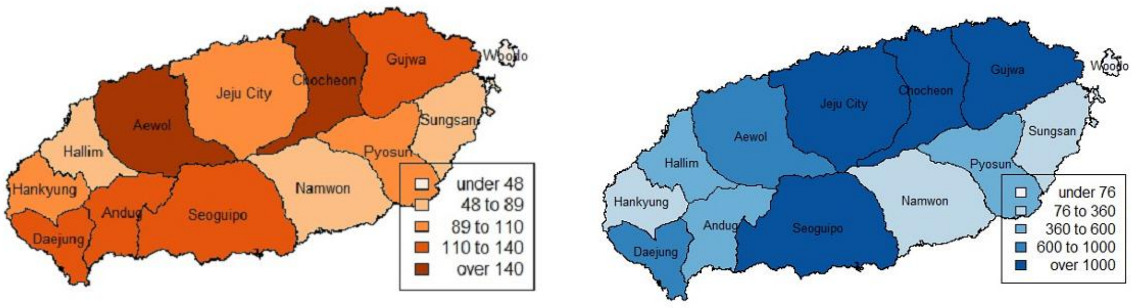
Chargers are usually installed in public or private facilities, from which electricity can be supplied. In Jeju City, 17 chargers are installed in administrative offices, 15 in tourist attractions, 6 in parks or stadiums, 3 in education facilities, 3 in commercial companies or research centers, 3 in public parking places, and 2 in cultural facilities. Such a facility can be a microgrid running its own power management system. Otherwise, a group of them can form a microgrid to efficiently control energy consumption and provisioning [15]. Figure 7 plots the effect of place types. First of all, the average service time is also almost constant for all place types. On the contrary, the maximum service time is longest in tourist attractions. A tourist seems to have taken a tour with his or her EV plugged-in to a charger. The maximum service time is smallest in commercial companies, as users are likely to skillfully charge their EVs. According to Figure 7(b), most charging operations are carried out in offices and tourist spots, indicating that fast chargers are mainly used by public officials and tourists.



(a) Service time (b) Number of transactions

Figure 5. Place type effects

Finally, Figure 8 shows the region-by-region statistics. There are 13 administrative districts in Jeju City and this map is downloaded from Korean National Geographic Information Institute. The choropleth image is generated by the R statistics package, specifically, *GisTools* library. Through the address field contained in the *OpenLoc* table, we can know which district a charger is belonging to. Then, the per-district service time is obtained by joining the *OpenLoc* table and grouping transactions by the district id. Figure 8(a) exhibits the maximum service time, which tends to be longer on non-urban areas. In addition, Figure 8(b) shows the number of charging transactions. Many of them are concentrated in 4 districts having a variety of tourist spots and administrative offices. Here, the southernmost region has over 3,000 transactions, even though it is included in the group of *over 1,000*. This region has lower population density but many tourist attractions.



(a) Service time (b) Number of transactions

Figure 6. Regional statistics

4. CONCLUSION

In this paper, we have conducted the analysis on the charging pattern in Jeju City, taking advantage of a real-time charger monitoring stream. The analysis result tells that the average service time is almost constant for all parameters. The charging time of 88.7 % transactions ranges from 10 to 40 minutes, as can be expected for fast chargers. The day-by-day difference in the number of charging transactions is 28.6 % at maximum, the deviation being affected by day-of-week. Additionally, geographic information-based analysis tells that the charging demand is concentrated in those regions having many tourist attractions and administrative offices. Along with the occupancy rate dynamics obtained in our previous work [13], we can consider another parameters to the demand model, including climate condition, EV penetration, charger density, and the like.

Actually, the goal of our analysis lies in more efficient integration of renewable energy to a microgrid equipped with fast chargers, namely, meeting the microgrid-level demand and supply. It is necessary to fill the microgrid battery according to the future EV charging demand or to make EVs to arrive during the interval of abundant renewable energy generation for each energy source type. Moreover, when the renewable energy is not available, V2G electricity trading will be preferred. Those efforts must be built upon accurate prediction mechanisms and prediction error compensation schemes, while we can enhance the accuracy with bigger data volume.

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