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CATEGORY-BASED DAILY PATTERN ANALYSIS IN AN ELECTRIC VEHICLE CHARGING NETWORK

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ABSTRACT

This paper analyzes the daily occupancy rate pattern in an electric vehicle charging network running over Jeju Island, aiming at discovering per-category common features. For the monitoring data archive collected from 244 DC chargers with a 5 minute period for 52 days, the daily utilization is calculated for each operating company, area type, and administrative region to understand inherent time series behavior for the whole day and hot hours. Next, charger-by-charger patterns are grouped by the hierarchical clustering scheme combined with the discrete time warping strategy on a statistical package workspace. The analysis finds 4 categories, one of which embraces all outliers. A strong dependency is identified from area types and operating companies to the utilization category. The category-based analysis can help the development of a new supplementary service capable of compensating for the long waiting time in battery charging.

Keywords: electric vehicle, charging infrastructure, series clustering, discrete time warping, group dependency.

1. INTRODUCTION

In spite of the limited driving range, EVs (Electric Vehicles) are penetrating into our daily lives, mainly due to their eco-friendliness in greenhouse gas reduction as well as capability in renewable energy integration [1]. They require the charging infrastructure of the same level as the existing gas station network built for gasoline-powered vehicles. As a new energy framework, it brings unprecedented business models, such as regional fast charging networks, local business initiatives, commercial EV charging, E-fleets and enterprises, and municipalities and sustainable e-mobility [2]. Particularly, commercial EV charging may introduce a large chain such as hotel groups and fast food chains. The appearance of promising business models will prompt back the construction of more charging stations over the wide area and make it more convenient for EVs to charge their batteries.

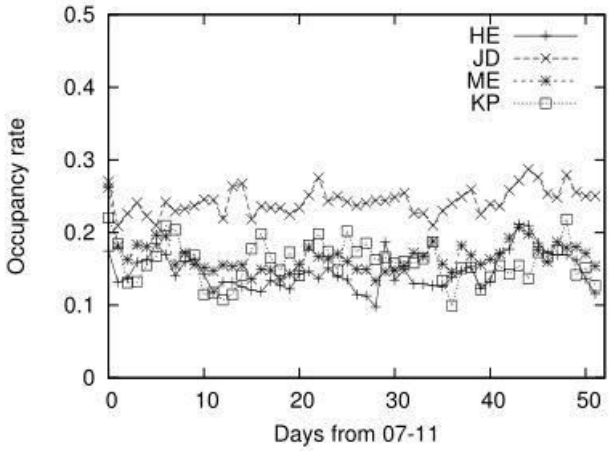
Generally, EV charging facilities are monitored by a central authority, taking advantage of commonly available digital communication channels to maintain reliable service level [3]. The real-time monitoring capability allows fast detection and timely remedy in the target facility. Besides, the data archive created in the monitoring system allows us to conduct the analysis on the demand behavior, power consumption patterns, and the like [4]. The EV charging big data, combined with intelligent analysis tools, can help public EV charger deployment in many ways [5]. For example, we cannot only scan entire city to find the best places for EV charging but also analyze and validate individual potential sites. In addition, it is possible to identify hot spotscapable of improving the estimation quality in grid load and electricity cost, combined with appropriate data streams.

In the meantime, Jeju city, Republic of Korea is extending its EV charging infrastructure under its ambitious enterprise called Carbon Free Island 2030, which replaces all gasoline-powered vehicles with EVs by 2030. In this place, after several changes in management authorities and record specification, the monitoring system is now stably generating and accumulating real-time status reports for about 250 DC chargers over the island surrounded by a 200 km-long coastline [6]. Our research team has acquired this dataset and conducted a series of analysis, focusing on the occupancy rate according to several parameters such as operating companies, regions, hour-of-day, and working place types [7]. Now, it is possible to look into the temporal behavior of the charging demand for each charger. Hence, this paper traces the occupancy rate for 52 days and groups those streams by means of the DTW (Discrete TimeWarping) method. Then, how each parameter affects the category a charger belongs to is to be investigated.

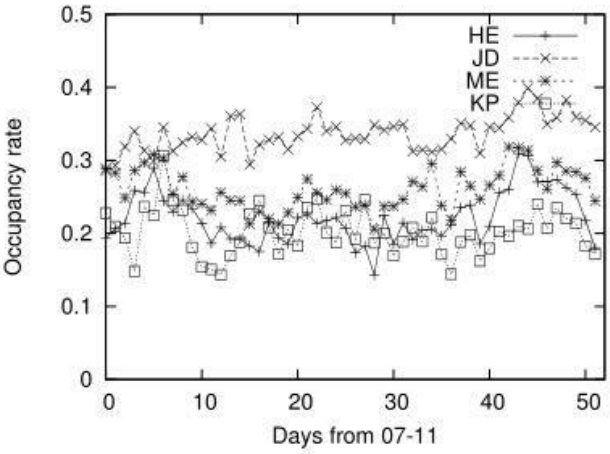
This paper is organized as follows: After overviewing the main topic in Section 1, Section 2 describes the basic features of the dataset. Then, Section 3 demonstrates the analysis results on the data flow and the clustering result, while Section 4 summarizes and concludes this paper with a brief description on future work.

2. DATASET DESCRIPTION

There are 250 DC chargers in the monitoring system which provides EV drivers with the current availability of each charger. Among these, 244 are active, that is, they have reported at least 20 out of 52 days. Chargers are owned and managed by 4 companies or authorities, including KEPCO (KP), Ministry of Environment (ME), Korea EV Charging Service (HE), and Jeju Provincial Government (JD). Each charger registers its id (company, station, charger), location, charger type, and address. We add region and place type according to the registered information on the charger address. The region field represents the administrative district a charger is located at. In addition, the place type can be governmental office branches, tourist spots, hotels, residential parking places, company buildings and convenient facilities. The classification considers who will charge and when a charger will be used. The data archive includes the periodic reports from each charger from July

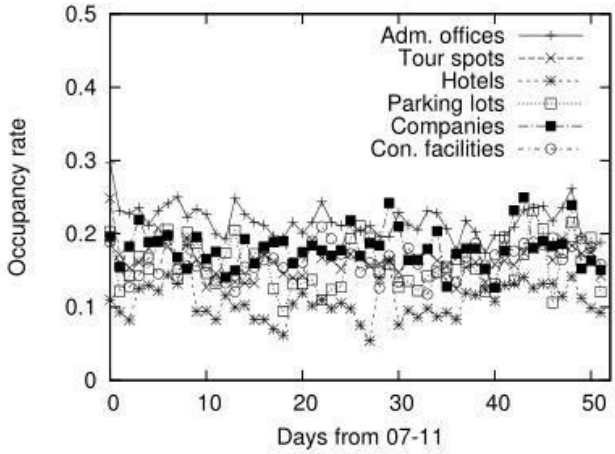


(a) Full day

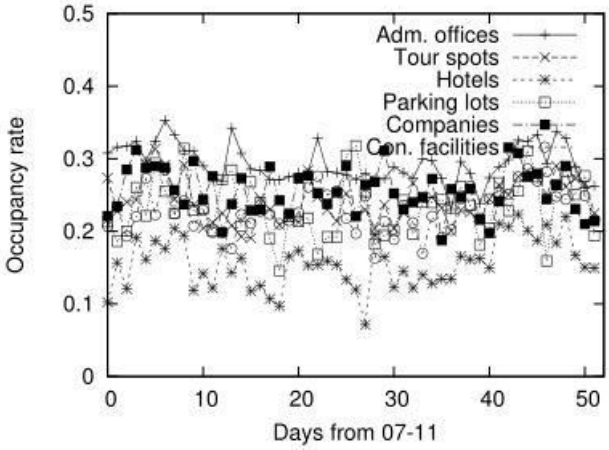


(b) Hot hours

Figure-1. Per-company statistics.



(a) Full day



(b) Hot hours

Figure-2. Per-area type statistics.

11 to Aug 31, 2017. Each report consists of charger id, timestamp, and the flag which indicates whether a charger is currently supplying electricity to an EV. For more details, refer to [7].

The main focus is put on the occupancy rate, which is calculated by dividing the number of those records with the status fields set to working by that of the total records [6]. As only the status field is given to us in each periodic report, we cannot know the exact start time of a charging transaction. Instead, this rate implies charging demand or charger utilization. Here, some specific criteria can be given on operating companies, time intervals, regions, place types, and the like. In addition, subsequent investigations separately measure occupancy rates for the whole day and for working hours. The working hours, including the evening commute, span from 9 AM to 9 PM, during which charging activities are concentrated. The whole records are stored in the MySQL database and SQL commands are issued to them.

3. DATA ACQUISITION

3.1 Demand pattern

This subsection investigates the temporal demand pattern during the observation interval lasting for 52 days. The main categories are operating companies (or authorities), area types, and administrative districts. The pattern analysis tries to find the factors affecting the demand in EV charging and then estimate the future demand according to a change in those factors such as further installation of charging facilities.

First, Figure-1 plots the daily occupancy rate according to the operating company. JD, KP, HE, and ME runs 60, 85, 51, and 48 DC chargers, respectively. EVs can get energy from JD chargers for free. On the contrary, it costs about 6 USD to fully charge a depleted battery with HE and KP chargers. With ME chargers, 3 USD is needed. JD chargers have a higher occupancy rate than the others. As a mobile application tells the location and type of each charger, EV drivers tend to select free chargers. Moreover, local residents are well aware of the locations of free chargers. As shown in Figure 1, the full day occupancy rate hardly exceeds 0.3, but the hot hour occupancy rate reaches 0.4 for JD chargers. In some chargers, it gets

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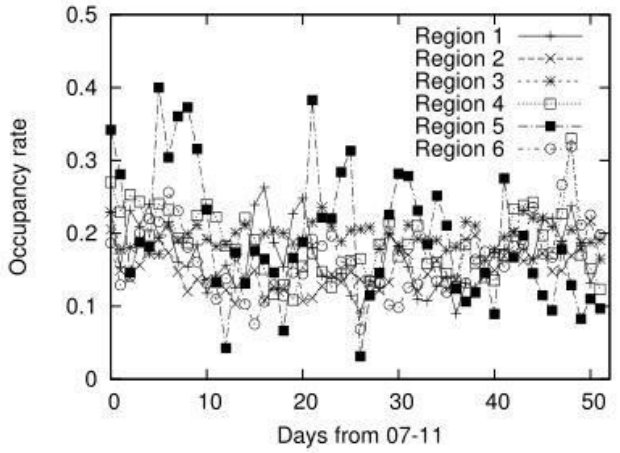
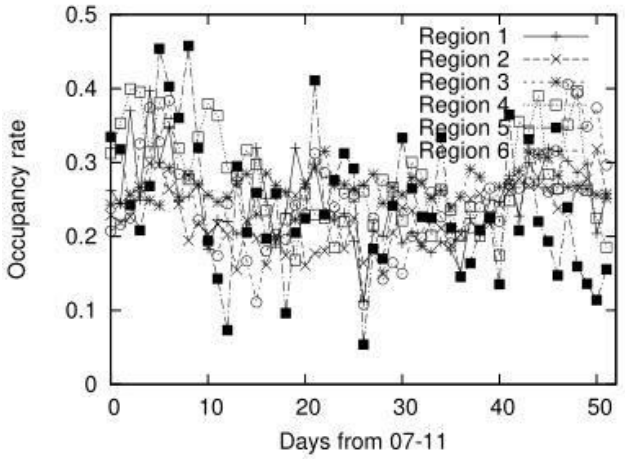
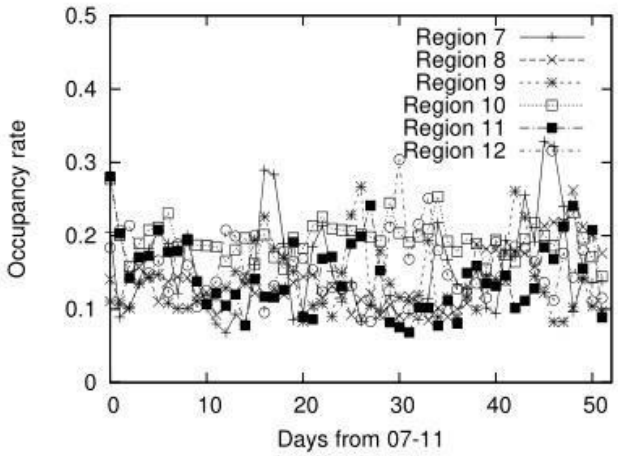


(a) Full day

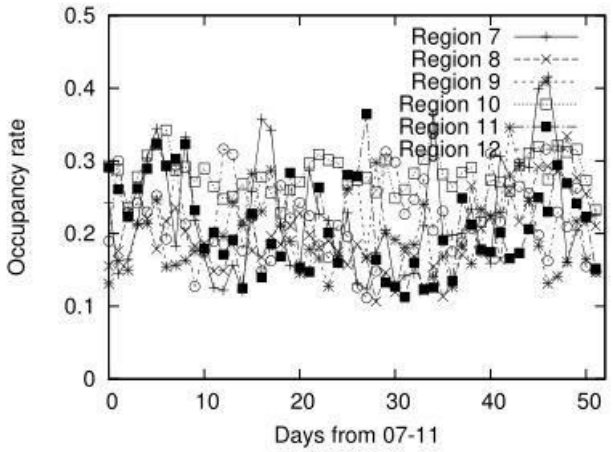


(b) Hot hours

Figure-3. Occupancy rate on north regions.



(a) Full day



(b) Hot hours

Figure-4. Occupancy rate on south regions.

higher than 0.6. With the penetration of EVs, those chargers will soon suffer from infinite queue length. Even though non-free chargers show some demand gaps between each other, free chargers are used more frequently by up to 0.11 for the full day, and 0.14 for hot hours. The difference is stable for the full day rates.

Next, Figure-2 plots the occupancy rate for each area type. At the early stage of EV charging facility expansion, many chargers are installed in governmental office branches, as the installation expense is not yet affordable for individuals or private operators. In addition, Jeju is one of the mostfamous tour places in East Asia; it has a lot of tourist attractions, which install chargers to host more EV-driving tourists.Hotels also provide EV chargers and they are used by tourists during the night time. The number of hotels providing DC chargers is not so large.Parking lots are used by local residents also at night. Some companies and research centers install DC chargers and they are used during the office hours. Finally, convenience facilities include shopping malls, sport complexes, theaters, and the like. They are occupied by local residents quite irregularly.

The number of DC chargers for each type is 74, 50, 6, 12, 34, and 74, respectively. In the hotels, the occupancy rate is very low, as tourists charge through AC chargers overnight or other public DC chargers just before the end of their trips. Considering that administrative offices show a higher occupancy rate, EVs are mainly charged by local residents. However, tour spots will be the next during the holiday season.

In addition, Figure-3 and Figure-4 show the occupancy rate on each administrative district. There are 12 districts in Jeju Island and two are most populated. Jeju city, marked by region 3 in the north, possesses 97 chargers, 4 out of which are most frequently used ones. In this region, the average occupancy rate is not so high, as supply is sufficient for demand currently. On the contrary, Region 5 in the north, running 11 chargers, has a long drive course embracing many scenic places. The occupancy rate in this region is quite fluctuating, as most demand comes from the tourists. Except for this region, the gap is not significant. In the south area, Region 7 is just next to Region 5 and has 7 chargers. Even though the demand is not higher than Region 5, its demand behavior is similar to Region 5. Region 10 is the second most

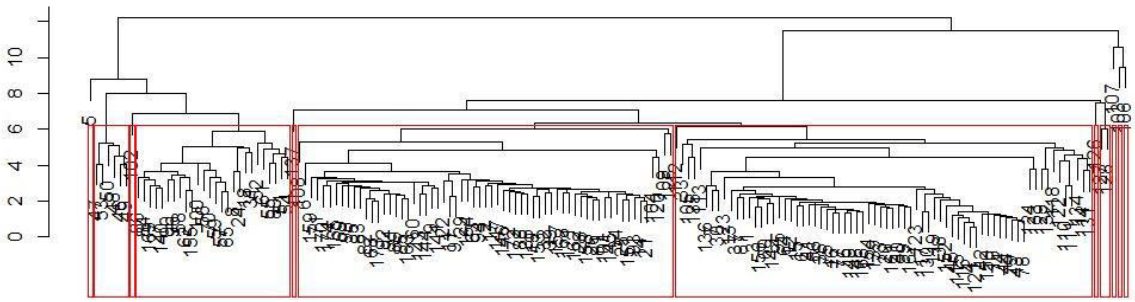


Figure-5. Clustering result.

populatedarea in the island and currently possesses 44 chargers. This region has the largest number of tourist attractions and hotels, but they are densely located. Hence, the demand pattern looks stable.

3.2 Clustering analysis

This subsection tries to find common features in the demand pattern for each charger during the observation interval and how the pattern is related to those parameters described in the previous subsection. The experiment begins with the identification of those chargers which have stably reported during the whole observation interval. 142 out of 244 chargers have reported everyday irrespective of whether a charger has served an EV during a day. Actually, some chargers have taken no EVs in a day. Then, 142 time series, each of which contains the daily occupancy rate for 52 days, are extracted from the database. The experiment applies the well-known hierarchical clustering method [8] built upon the DTW (Discrete Time Warping) similarity measures, the result being shown in Figure-5. The experiment sets the number of clusters to 16, while we can see 3 major clusters and small outliers. Even if we increase the number of clusters, only small outlier chunks are created. Each major cluster has 69, 61, and 20, while 4 groups and named Cat 1, Cat 2, and Cat 3, respectively. Outliers are grouped and named Cat 4. 3 major groups have respective common features.

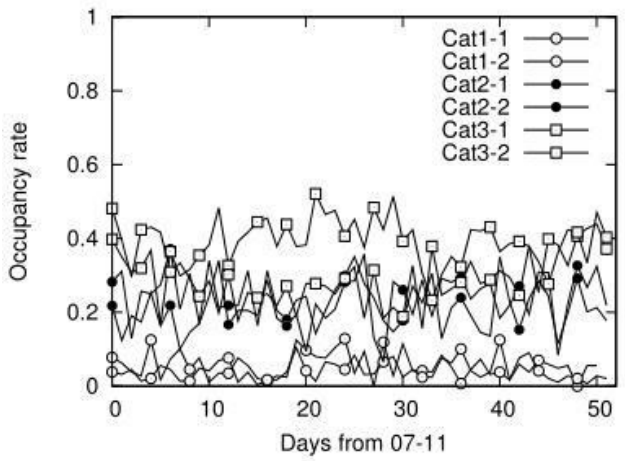


Figure-6. Sample demand patterns.

2 series are randomly chosen from each category and plotted in Figure-6. Actually, the experiment also selected a series from Cat 4, but its plotting makes the graph quite confusing due to its unexpected behavior. In the Figure, Cat 1 series show relatively low occupancy rates, while Cat 3 has the highest. Cat 2 goes through the middle range and its oscillation is not so large as Cat 1. The figure indicates that the series are clustered not by shapes but by the strength of values.

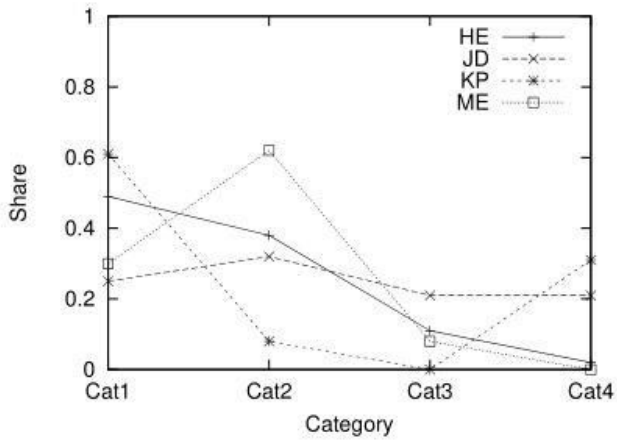


Figure-7. Per-company daily pattern groups.

First, Figure-7 shows the relationship between the category and the operating company. Here, as the number of chargers is different for each operating company, it is converted to the share in the total. JD chargers evenly distribute across the 4 groups, even to Cat 4. Free charging makes the demand spread over the category boundary. More HE chargers are belonging to Cat 1 and Cat 2 than other groups, showing higher utilization. As only a few of them are included in Cat 4, it is possible to make a trace model for the energy demand. On the contrary, KP and ME chargers have a vivid tendency in the demand clustering. For both, up to 60 % of chargers belong to Cat 1 and Cat 2, respectively. Both operating companies can develop an EV charging-supporter service to EV drivers according to the utilization.

Figure-8 presents the place type effect on the demand pattern. Even though the number of chargers in hotels is just 6, the majority of chargers belong to Cat 1, having high utilization and large fluctuation. It is expected

that hotels will install DC chargers as more tourists rent EVs. As contrast, tour spots are not sufficiently biased to any group. Besides, on parking lots, mainly used for overnight parking in the residential area, Cat 2 takes about 0.6 of the share. Administrative offices show evenly distributed demand for all categories, as both locals and tourists are well guided by the helper application. Hence, their demand pattern cannot be restricted to a specific category. Here, Cat 4 also takes 27 % of total chargers.

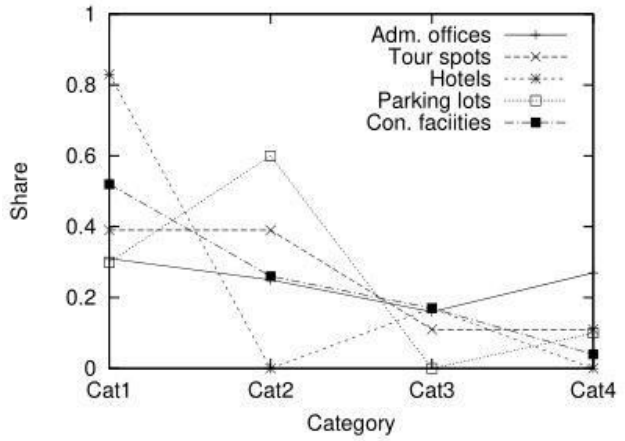


Figure-8. Per-area type daily pattern groups.

Finally, Figure-9 shows regional effects on the category. 3 regions having fewer than 6 are omitted. Except for SS, Region 7 in the north, which have lower population and tourist attractions located relatively far away from each other, there is no dependency between region and category. In some regions, Cat 1 has more chargers, and in some others, Cat 2 has more. In Jeju city, more chargers belong to Cat 4 than the other regions, as there are different demand patterns coming from EV driver diversity. Anyway, regional effect is not so significant in demand categorization.

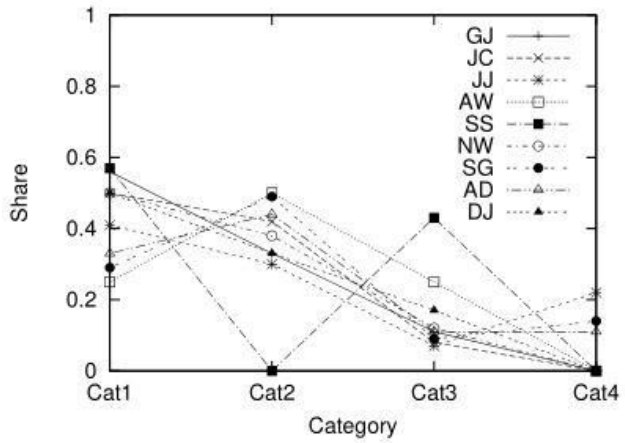


Figure-9. Per-region daily pattern groups.

4. CONCLUDING REMARKS

In this paper, we have conducted a category-based analysis on the EV charger monitoring system running in Jeju Island, Rep. of Korea. The dataset comes from 244 active DC chargers reporting during the observation interval of 52 days. Daily pattern analysis on each operating company has found the effect of free charging and availability of a charger location service. The area type effect leads to driver groups mainly consisting of local residents and tourists. The hierarchical clustering scheme is applied to each daily utilization series for 142 chargers which have completely reported during the whole observation interval. This investigation has found 4 categories, one of which embraces all outliers. A strong dependency is identified from area types and operating companies to the utilization category.

The utilization pattern will give us a guideline for the development of supplementary services which can compensate for the long waiting time in EV charging. These services can be on-line advertisement, food trucks, diverse surveys, and the like. Moreover, the tourist places sparsely populated can benefit from mobile batteries equipped on EVs [9].

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