International Journal of Electrical and Computer Engineering (IJECE)
Vol. 8, No. 6, December 2018, pp. 5303~5310
ISSN: 2088-8708, DOI: 10.11591/ijece.v8i6.pp5403-5310

Design of a Monitoring-combined Siting Scheme for Electric Vehicle Chargers

Junghoon Lee, Gyung-Leen Park
Department of Computer Science and Statistics, Jeju National University, Republic of Korea

Article Info

Article history:

Received Mar 23, 2018
Revised Jun 14, 2018
Accepted Jul 22, 2018

Keyword:

Cluster-level demand share
EV charging infrastructure
Genetic algorithm
Public charger siting
Real-time monitoring data

ABSTRACT

This paper designs a siting scheme for public electric vehicle chargers based on a genetic algorithm working on charger monitoring streams. The monitoring-combined allocation scheme runs on a long-term basis, iterating the process of collecting data, analyzing demand, and selecting candidates. The analysis of spatio-temporal archives, acquired from the fast chargers currently in operation, focuses on the per-charger hot hour and proximity effect to justify demand balancing in geographic cluster level. It leads to the definition of a fitness function representing the standard deviation of per-charger load and cluster-by-cluster distribution. In a chromosome, each binary integer is associated with a candidate and its static fields include the index to the cluster to which it is belonging. The performance result obtained from a prototype implementation reveals that the proposed scheme can stably distribute the charging load with an addition of a new charger, achieving the reduction of standard deviation from 8.7 % to 4.7 % in the real-world scenario.

Corresponding Author:

Gyung-Leen Park,
Department of Computer Science and Statistics,
Jeju National University,
Jejudaehakno 102, Rep. of Korea.
Email: jhlee@jejunu.ac.kr

1. INTRODUCTION

For the penetration of EVs (Electric Vehicles), it is necessary to build a well-organized charging infrastructure over the target area [1]. Besides slow AC chargers usually installed in drivers' homes for overnight charging, high-voltage DC chargers are working in public places under the control of responsible authorities [2]. Insufficient charging capacity brings unacceptable waiting time to EV drivers, mainly due to long charging time which lasts tens of minutes for a single transaction even with fast DC chargers. Hence, many countries are trying to install DC chargers in appropriate places. At first, they select those places easy to supply power and guarantee electrical safety [3]. Then, the penetration of EVs will create a specific demand pattern, which must be considered for the next step charger installation. As such, charger expansion and demand pattern will interact with each other repeatedly, making it essential to keep analyzing the demand behavior of a target charging infrastructure.

Most modern facilities, not restricted to charging stations, are connected to a management coordinator via ubiquitous and cheap communication channels [4]. In our city, namely, Jeju, Republic of Korea, which is making an extensive effort to prompt the deployment of EVs, many chargers are under construction and report their real-time working status to a central server [5]. Currently, 245 DC chargers are embraced in this management domain and their status records are accumulated every 5 minutes. Our research team acquires the permission to use this archive, stores in our local database tables, and combines geographic information for sophisticated stream analysis with relevant tools such as R and Tensorflow [6]. In this work, we are to exploit the monitoring data stream for the location selection of new public chargers to overcome the weakness of EVs in charging, compared with gasoline-powered vehicles.

It must be mentioned that the site selection has to take into account a variety of factors, mainly due to the fact that chargers are high-voltage devices. As for existing related work for this aspect, Florida Power & Light Company lists the critical factors to consider in deciding charger installation places [7]. The list includes visibility and lighting, proximity to power sources, parking space size, weather and climate, electrical safety, ventilation, and the like. In addition, Transportation and Climate Initiative also chooses selection criteria for charging stations [8]. This report addresses connections to power, networks and communications, interdependency with existing infrastructure, and EV interfaces. Besides, the weight from above-mentioned factors will be different region by region and depend on the forecast on the population growth, customer need change, and new technology appearance.

In addition, as for related work for public charging, [9] tries to maximize the electrification rate, or the travel distance covered by EVs charged at new charging stations. This research is built on the analysis of millions of trips taken by about 11,000 taxis in Beijing. The authors investigate the underlying charging demand over the city area as well as to locate hot spots for the demand. The analysis selects those areas where many taxi drivers are likely to stay for a rest as new charging stations, under the assumption that drivers will possibly move 1 mile to take preferred chargers when necessary. In addition, [10] formulates a mathematical model to find optimal solutions for siting charging stations, achieving about 50 % improvement in the electrification rate. This work defines the objective function based on the travel distance that cannot be covered by any EV charging for the given station placement. The formulation is fed to a mixed integer non-linear programming solver to find an answer.

As far as we know, there is no work directly taking into account the current demand pattern in determining the location of additional chargers. Even if the data is available, it is not easy to find an optimal goal for this problem. This paper attempts to identify a charge placement which can distribute the charging load over the target area. With this goal definition, a genetic algorithm is designed to find a suboptimal solution within an acceptable time bound.

This paper is organized as follows: After overviewing the main issue in Section 1, Section 2 shows the data analysis results to be considered in charger siting. Then, Section 3 conceptually designs a cluster-integrated siting scheme for EV chargers. Finally, Section 4 summarizes and concludes this paper with a brief description on future work.

2. DATA ANALYSIS

To begin with, Figure 1 shows the location of chargers in Jeju City, which is surrounded by about 200 *km* long coastline. The meaning of each symbol will be explained later. Here, the road network is downloaded from the open data site in an ESRI shape file format and plotted on the R workspace. The charger distribution coincides with the population density, displaying high concentration in the center north region. Many chargers are installed at the local government branches as it is easy to get endorsement for EV charger establishment. They are mainly used by local residents. In addition, as Jeju is one of the most famous tour places in East Asia, a lot of tourist attractions provide charging equipment for EV-driving visitors. According to our observation, demand peak of DC charging arises between 4 PM and 6 PM, slightly deviating the grid peak hours.

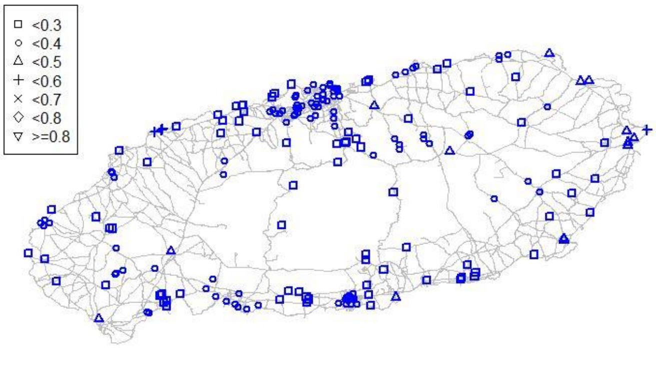

Figure 1. Charger location and expected load

Figure 2 plots the occupancy rate of each charger. Occupancy rate, analogous to the charging demand or load, denotes how many records are indicating that a charger is currently working out of total records. In the figure, each dot corresponds to a single charger. For a charger, the hot hour, in which its occupancy rate touches highest, is obtained first. Then, the hot rate is plotted on a virtual vertical line of the corresponding hour. Chargers having a common hot hour appear on the same line. We can see more dots than others between 16 to 18. By this figure, most chargers are used between 8 to 21. About 20 chargers have the occupancy rate below 0.05 even in their hot hours, while some others exceeding 0.6. One of the goals of the siting scheme may lie in the reduction of the occupancy rate gap.

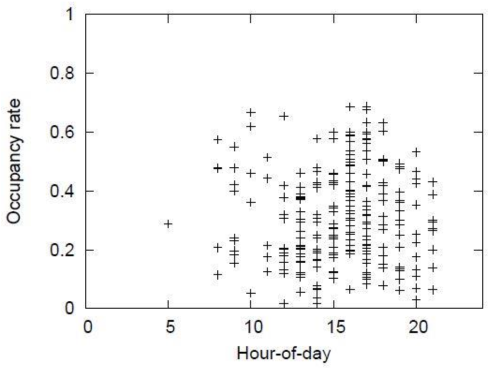

Figure 2. Hot hours and occupancy rate

Next, Figure 3 traces the occupancy rate according to the distance to the closest charger. Here again, a single dot represents a single charger. As the distance is an analog value, dots are scattered over the graph space. The most isolated charger is apart from its closest neighbor by 5.8 *km*. Those chargers installed in the same building or office appear on the vertical line of 0 *km*. As can be seen in the figure, the distance to the closest neighbor has little dependency on the occupancy rate. Even though there are not so many cases, when a charger is newly installed, the occupancy rate around the charger increases together. Drivers seem to want to charge at a vicinity of higher charger density.

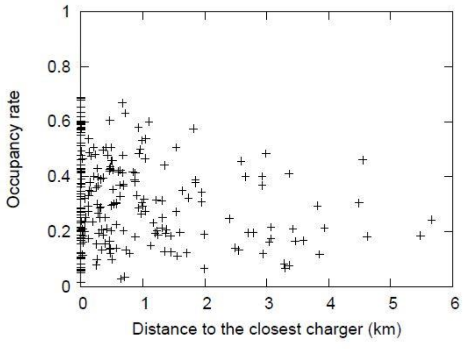

Figure 3. Proximity and occupancy rate

3. SITING SCHEME

3.1. Main idea

Figure 4 outlines the sequence of the siting process. For a current charger distribution, the procedure collects the monitoring data and conducts necessary analysis. Here, additional information such as population growth and EV penetration is integrated into the monitoring series. Then, performance metrics are defined for the selection of new charger locations. The metric includes waiting time reduction, proximity improvement, demand balancing, and the like. Here, the annual budget of the charger operation authority decides the number of chargers to build. Then, a human decision maker recommends all possible candidate locations according to the above-mentioned criteria. Two or more chargers can be listed in a same place.

Here, each selection of a charger can affect the remaining others. The estimation of this effect is a very complex problem, so we take a suboptimal approach [11]. Moreover, the effect of a new allocation is different according to whether it is inside a cluster or not, as chargers belonging to a same geographic cluster tend to evenly share the load.

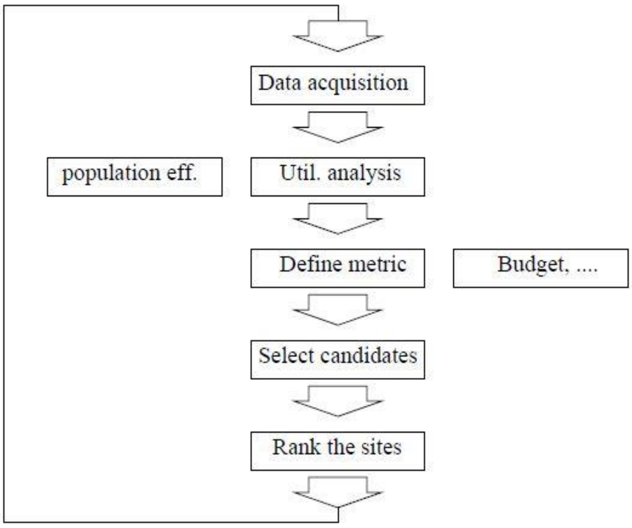

Figure 4. Charger siting process

A pair of chargers apart from each other less than 1.6 *km* belong to a common cluster. A driver will move to the other charger when one charger occupied if the distance between them is less than 1.6 *km*[9]. Out of 245 chargers, the analysis finds 68 clusters as shown in the map of Figure 1. There are 3 big clusters, one having 61 chargers in center north, the other two each having 15 and 10 in center south, respectively. Figure 5 shows the standard deviation in occupancy rates of chargers within each cluster. Those clusters containing just one charger have no deviation. The deviation is at most 0.18 and the charging demand is quite evenly shared within a cluster. There are exceptional cases when some chargers become out-of-service from time to time. After all, the new charger selection can be differentiated into two cases, one adding to a cluster and the other to an independent place.

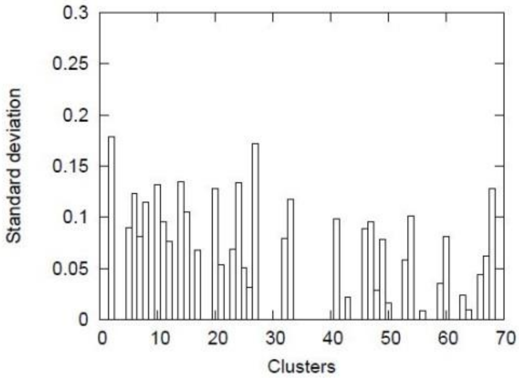

Figure 5. Per-cluster standard deviation in occupancy rate

The load is recalculated so that the charger in a single cluster has the equal occupancy rate by averaging all of cluster members. We can estimate the increase in the demand change stemming from the penetration of Evs just in cluster level, not in charger-level. According to the enterprise schedule, Jeju city will increase the number of EVs by 1.5 times next year, and so will the citywide load. Assuming the cluster-level demand increases by that ratio, the recalculated per-cluster load is displayed also in Figure 1. The clusters forecasted to have larger than 0.5 in the occupancy rate appear all over the target area. It means that EV drivers will wait statistically more than one out of two times.

3.2. Genetic operation

Our scheme represents a site selection as a binary integer vector as shown in Figure 6. Here, m is the number of all candidates and equals to the length of the vector, while n is that of selected locations denoted by 1's. Each location candidate is associated with static information such as latitude, longitude, and cluster id if it is included in a cluster. The cluster id makes it possible to refer to the cluster record consisting of the number of member chargers, average load, and cluster centroid. Figure 6 also shows the crossover operation designed for the genetic algorithm. In this example, m and n are 13 and 6, respectively. The first part contains the vector for those candidates included in a cluster while the latter not. As two parts are assessed differently, crossover operations take place twice, namely, at (C_1, C_2) and (C_3, C_4). After switching substrings, the number of 1's is highly likely different from n. Then, some of them will be changed to make the allocation valid.

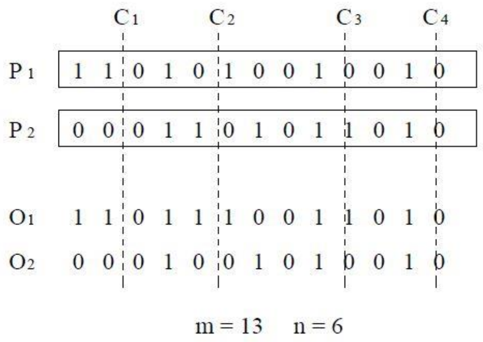

Figure 6. Genetic operation

As for the fitness evaluation of a chromosome, or a single integer vector, the effect of each gene is interpreted as shown in Figure 7. If a candidate is inside an existing cluster, it first draws the load in a cluster. For example, if the number of member chargers is 2 and the average load is 1.2, the addition of a new node in that cluster will cut down the average load to 0.8. Then, not just relieving the load in a cluster, a new charger can absorb the charging demand from adjacent chargers. In this example, the cluster can afford to share the load from its neighbors outside of its cluster by 0.2 x 3. It's called leftover. While it is impossible how much load will migrate to neighboring nodes, it can be expected that the closer to a charger, the more load can move.

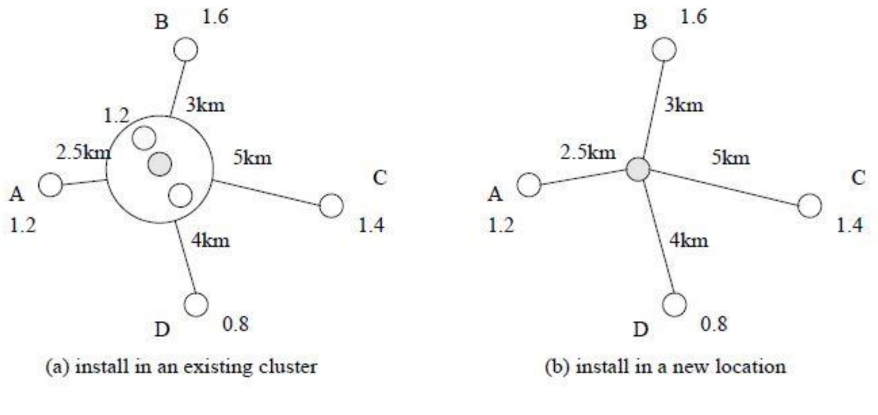

Figure 7. Evaluation process

A linear load migration is designed based on the distance between two chargers or clusters, as shown in Eq. (1).

$$p_a = p_n \times \frac{U-d}{U-L} \quad (1)$$

, where P_n is the overloaded demand of a neighboring charger or cluster, and P_a is the migratable amount. [L, U] is the range a new charger addition will be in effect. Here, a cluster is considered a single charger with its centroid acting as a position value of a charger. d is the distance to a new charger and only chargers residing in [L, U] will be considered. If d is U, P_a is 0, which indicates that the new charger cannot take load from that charger. If it is L, all overloaded amount can be shared. The sum of all P_n cannot exceed the amount of leftover. The fitness value of a new charger addition will be the sum of the load shared in a cluster (if it is inside a cluster) and the load drawn from its neighbors. The genetic operations iterate to improve the fitness value generation by generation with the object function and encoding scheme.

4. PERFORMANCE MEASUREMENT

This section measures the performance of the proposed scheme by a prototype implementation using the C programming language. For simplicity, we assume that we can select any place for a new charger installation. Hence, the distance within a cluster does not matter. For n chargers to add, how to assign them to respective clusters is the main problem. The default parameters are as follows: The number of new chargers is 50 and that of clusters is 78, derived from the current placement in Jeju. The population size is 100, while the genetic loop iterates 1,000 times. In addition, occupancy rate is the probability that a charger is used and denotes the charging demand on a charger [12].

The first experiment measures the basic behavior of the genetic iteration. Figure 8 plots the improvement in the standard deviation in the occupancy rate of each charger according to the progress of genetic iterations. It will show how evenly the charging load is distributed over the target area with the addition of new chargers. Currently, the standard deviation of the occupancy rate for 245 chargers is 8.7%, while the total average is 36.0 %. With an addition of a new charger to a heavy-loaded cluster, the charging load is distributed. At the first stage of the genetic iteration, the standard deviation is 10.56 %, higher than the current value, indicating tht an inappropriate assignment makes worse the difference in the utilization. However, repeated execution of genetic operations improves the performance, reaching 4.7 % after 250 iterations. Beyond this point, no more improvement is observed.

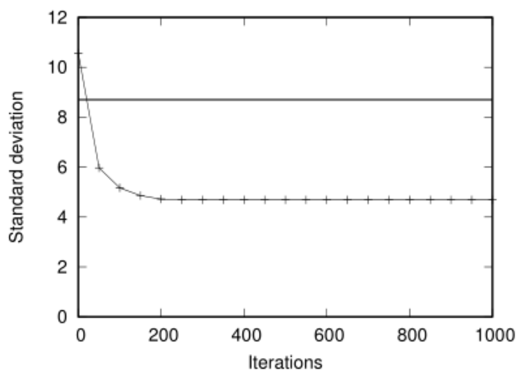

Figure 8. Iterative improvement

Next, Figure 9 shows the effect of the population size in genetic operation. A larger population leads to a better gene diversity. Actually, our implementation prevents duplicated chromosomes from taking place at the same time for the sake of making the population set more diverse. Moreover, the length of a chromosome is 78, namely, the number of clusters. It is quite long and possibly hosts a variety of solutions. However, the figure shows that the population size has little effect on the standard deviation improvement. Even with 50 chromosomes, we can achieve the same improvement as with 500 chromosomes. This comes from the situation that a few clusters dominate the whole occupancy rate.

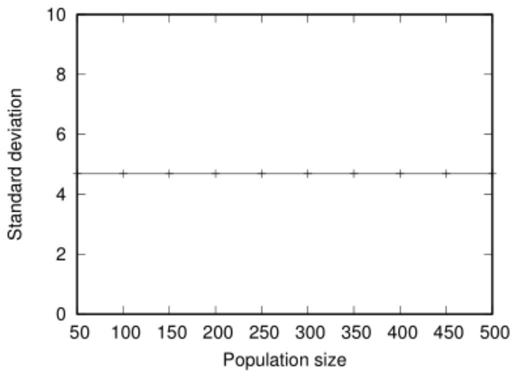

Figure 9. Population size effect

Finally, Figure 10 plots how the proposed scheme can stably improve the load distribution with a new charger installation. The experiment changes the number of new chargers from 10 to 200. In each parameter setting, our scheme finds a reasonable quality suboptimal solution with 1,000 iterations. The standard deviation starts from 7.26 % with 10 chargers and ends up at just 1.6 % with 200 chargers. The performance curve is totally continuous, having no exceptional oscillations or spikes.

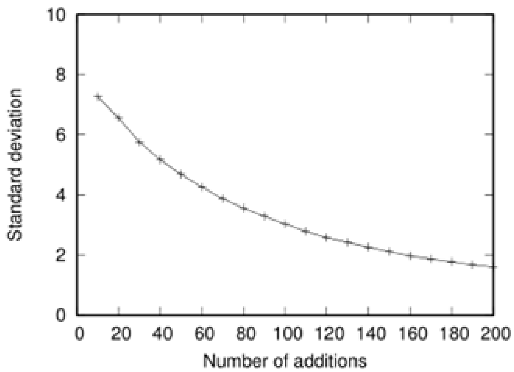

Figure 10 Charger addition

5. CONCLUSION

In this paper, we have presented a conceptual design of a siting scheme for public EV chargers, mainly based on the analysis result of charger monitoring streams. A genetic algorithm is exploited to overcome the difficulty in estimating the effect of a charger placement, while a fitness function is defined for the evaluation of a charger location according to whether a charger is inside of any cluster or not. The accumulation of more monitoring series will refine our evaluation model and reveal the effect of a new charger installation, making the process of charger siting a cyberphysical system approach [13]. Moreover, our research team is developing a variety of business models based on the massive data analysis, including the advertisement and tourist goods trade during the lengthy charging time. Particularly, we are planning to integrate renewable energy into the charger operation, including location determination, battery charger/discharge scheduling, and the like [14].

ACKNOWLEDGEMENTS

This research was supported by the 2018 scientific promotion program funded by Jeju National University.

REFERENCES

[1] C. Develder, N. Sadeghianpourhamami, M. Strobbe, N. Refa, “Quantifying Flexibility in EV Charging as DR Potential: Analysis of Real-World Datasets, in *IEEE International Conference on Smart Grid Communications*, 2016.

[2] E. Kara, J. Macdonald, D. Black, M. Berges, G. Hug, S. Kiliccote, “Estimating the Benefits of Electric Vehicle Smart Charging at Non-Residential Location: A Data-Driven Approach, *Applied Energy*, vol. 155, no. 1, pp. 515-525, 2015.

[3] F. He, Y. Yin, J. Zhou, “Deploying Public Charging Stations for Electric Vehicles on Urban Road Networks, *Transport Research Part C*, pp. 227-240, 2015.

[4] J. Yamazaki, D. Yoshiro, H. Fukuhara, T. Hayashi, “A Comprehensive Data Processing Approach to the Future Smart Grid, in *4th International Conference on Renewable Energy Research and Applications*, 2015, pp. 1033-1036.

[5] J. Lee, G. Park, Y. Han, S. Yoo, “Big Data Analysis for an Electric Vehicle Charging Infrastructure using Open Data and Software, in *ACM eEnergy*, May 2017, pp.252-253.

[6] J. Lee and G. Park, "Integrated Coordination of Electric Vehicle and Renewable Energy Generation in a Microgrid," International Journal of Electrical and Computer Engineering, vol. 7, no. 2, pp.706-712, 2017.

[7] Florida Power & Light, Company Siting Plug-in Electric Vehicle Charging, *www.FPL.com/ electricvehicles*.

[8] Transportation and Climate Initiative, Siting and Design Guidelines for Electric Vehicle Supply Equipment, *https://www.transportationandclimate.org/sites/default/files/EV Siting and Design Guidelines.pdf*.

[9] H. Cai, X. Jia, A. Chiu, X. Hu, M. Xu, “Siting Public Electric Vehicle Charging Stations in Beijing using Big-Data Informed Travel Patterns of Taxi Fleet, *Transport Research Part D*, vol. 33, pp.39-46, 2014.

[10] N. Shahraki, H. Cai, M. Turkay, M. Xu, “Optimal Location of Electric Public Charging Stations using Real World Vehicle Travel Patterns, *Transportation Research Part D*, vol. 41, pp.165-176, 2015.

[11] A. Ovalle, A. Hably ,S. Bacha, G. Ramos, J. Hossain, “Escort Evolutionary Game Dynamics Approach for Integral Load Management of Electric Vehicle Fleets, *IEEE Transactions on Industrial Electronics*, vol. 64, issue 2, pp. 1358-1369, 2017.

[12] J. Lee and G. Park, "Service Time Analysis for Electric Vehicle Charging Infrastructure," *International Journal of Electrical and Computer Engineering*, vol. 8, no. 2, pp.818-824, 2018.

[13] A. Amato, R. Aversa, B. Martino, S. Venticinque, “A Cyber Physical System of Smart Microgrids,” in *International Conference on Network-Based Information Systems*, 2016, pp. 165-172.

[14] B. Banhthasit, C. Jamroen, S. Dechanupaprittha, Optimal Generation Scheduling of Power System for Maximum Renewable Energy Harvesting and Power Losses Minimization,” *International Journal of Electrical and Computer Engineering*, vol. 8, no. 4, pp.1954-1966, 2018.