5

Management of Electric Vehicles Using Automatic Learning Algorithms: Application in Office Buildings

Andres Alonso Rodriguez[1], Luis Perdomo[1], Ameena Al-sumaiti[2], Francisco Santamaria[3] and Sergio Rivera[1]*

[1]Electric Engineering Department, Universidad Nacional de Colombia, Bogotá, Colombia
[2]Advanced Power and Energy Center, Electrical Engineering and Computer Science Department, Khalifa University, Abu Dhabi, UAE
[3]Department of Electric Engineering, Universidad Distrital Francisco José de Caldas, Bogotá, Colombia

Abstract
Load shifting is one of the main methods of demand response currently influencing electricity consumer demand, mainly to the smart charging Solutions in Electric Vehicles. This process consists of shifting the load from peak to off-peak periods in order to maintain the existing electrical infrastructure. Office buildings have a large influx of vehicles, electrical infrastructure, parking spaces, and many people staying in them for similar and constant periods. In this way, this chapter proposes a charge strategy for charging electric vehicles in office buildings through automatic learning algorithms presenting the benefits of its implementation. In this way, this strategy seeks to optimize the existing electrical infrastructure and vehicle parking space.

Keywords: Automatic learning, charging, office, Algorithms

5.1 Introduction

The penetration of Electric Vehicles (EV) is expected to grow exponentially in the next few years. For this reason, it is necessary to develop a

**Corresponding author*: srriverar@unal.edu.co

Sulabh Sachan, P. Sanjeevikumar, and Sanchari Deb (eds.) Smart Charging Solutions for Hybrid and Electric Vehicles, (143–158) © 2022 Scrivener Publishing LLC

management strategy for charging these vehicles in order to optimize parking spaces and existing electrical installations since buildings are points of high concentration of these vehicles. Load shifting is considered one of the best strategies for load management because it allows the optimization of existing networks, reducing or shifting investment over time. In this way, this work proposes a management strategy for charging electric vehicles in office buildings through automatic learning algorithms presenting the benefits of its implementation.

One of the main drawbacks of a high introduction of electric vehicle technology to the country is the lack of charging stations and adaptation of the electricity network [1], hence, optimizing the existing electricity network and vehicle parking spaces are necessary.

With the growing electricity demand and challenges encountered towards meeting the demand, demand response [2, 3] and load shifting [4-7], and management mechanisms [8, 9], some of the most important features of the electricity network and even more so for future networks. Introducing electric vehicles is increasing in the global market and their flexible energy management features provide excellent characteristics for demand response [10, 11].

It is therefore necessary to have parking areas for vehicle charging services. This poses challenges both to the management of these buildings and to the network operators, as the existing infrastructure may be insufficient and lead to power and energy quality problems [12, 13].

Because of this, it is necessary to develop strategies that manage vehicle charging to take advantage of the existing electrical and parking infrastructure in office buildings. This will allow the introduction of electric vehicles in the local market to increase and use of the existing infrastructure to be more efficient.

Around the world, concerns about climate change and dependence on fossil fuels have led people to seek ways to meet most of their needs by using environmentally friendly technologies. In particular, the transport sector is one pillar of this change, in which the supply of electric vehicles, mainly those based on batteries, is increasing and expected to grow exponentially in the coming years [14].

This great growth is accompanied by the need for space to charge vehicles. Points of high concentration of vehicles, such as office buildings, provide a great opportunity to implement a strategy to optimize the infrastructure [15].

The charging infrastructure for electric vehicles is very limited [16, 17]. Vehicles must remain in the charging station for a considerable amount of time. For this reason, one of the main characteristics of an electric vehicle charging management strategy is to maximize the use of the existing infrastructure so the energy efficiency of the installation can be improved.

One of the energy efficiency approaches is energy management [15-17], which comprises a set of actions aimed at ensuring energy supply through implementing measures to improve the energy performance of loads [18], generation energy distribution [19], and demand response [20, 21]. Demand response lies in achieving changes in electricity consumption by the end user in relation to a usual consumption pattern based on price signals or incentives designed to induce low consumption [22-24].

5.2 Proposed Charging Strategy

A. Overview of the Charging Strategy

This strategy is based on three aspects (see Figure 5.1), which are processes that act dependently: prediction of the power, demand shifting, and selection of the surrounding vehicles.

Although these three aspects are integrated in the management strategy, it is unnecessary for all three processes to always be carried out. This is because the last process (selection of vehicles) depends on the process of demand shifting.

At the end of implementing the strategy, the objective is to charge as many vehicles as possible by taking advantage of the existing electrical and parking infrastructure. The three aspects of the management strategy are described below.

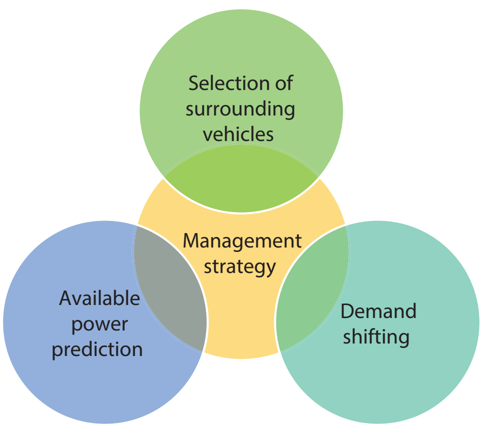

Figure 5.1 Charging strategy for electric vehicles.

One pillar of the management strategy is determining the demand for electrical power of a building for the eight hours following the time of sending an offer and assigning charging to electric vehicles. To achieve this, a supervised automatic learning regression algorithm was implemented by following the process described in Figure 5.2.

The algorithm predicted the power demand of the building without electric vehicle charging for the next eight hours based on the current power. When supervised, this algorithm was previously trained with the historical measured power data.

This information is essential within the management strategy because it makes it possible to decide whether to start the charging of the employees' electric vehicles in the subsequent hours.

B. Demand Shifting

The objective of the algorithm is to move the start of the vehicle charging as close as possible to the end of the parking reservation, so the maximum charging of the vehicle is reached and the maximum limits of power are maintained hourly. Figure 5.3 shows the process.

The calculation of P_{ij} is made with equation (5.1); i corresponds to the parking space and j to the charging time. T_i is the time necessary for the vehicle to reach 100% charge, Z_j corresponds to the maximum number of parking spaces that can be enabled for charging in hour j, M_i is the time in which the vehicle is in the parking space, and X_{ij} is the binary assignment matrix.

$$P_{ij} = \begin{cases} (T_{ij}+j)/M_i \,, (T_{ij}+j)/M_i \le 1 \\ 1 \,, T_{ij}-M_i \ge 0 \\ -(n*m), T_{ij}-M_i < 0 \end{cases} \tag{5.1}$$

$$P_{ij} = (T_{ij}+j)/M_i \tag{5.2}$$

$$max(F) = \textstyle\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij} * P_{ij} \tag{5.3}$$

$$\textstyle\sum_{i=1}^{n} X_{ij} = T_i \;\forall j \tag{5.4}$$

ensure enough energy delivered

$$\textstyle\sum_{i=1}^{n} X_{ij} \le Z_j \;\forall j \tag{5.5}$$

limit available power

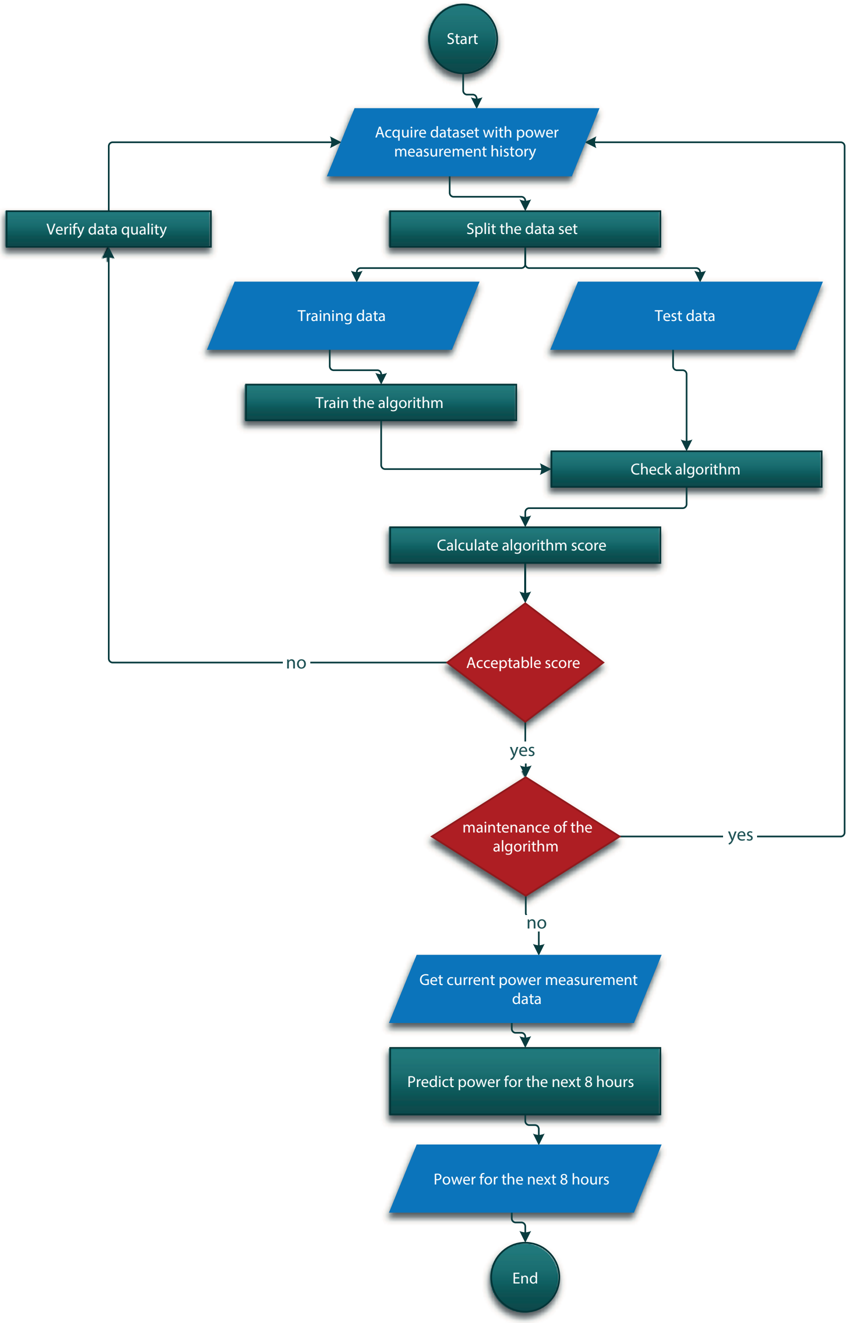

Figure 5.2 Flowchart of demand prediction process.

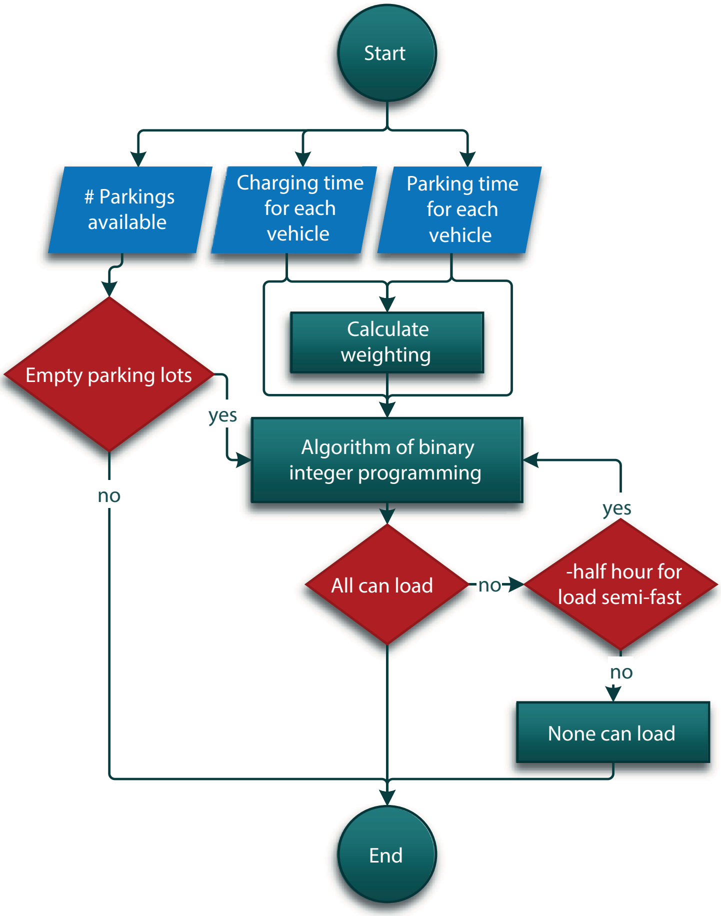

Figure 5.3 Flowchart of demand shifting process.

The problem is treated as an allocation problem. The aim is to maximize function F, which results from the sum of the products of the weight matrix and the binary allocation matrix, as shown in Equations 5.2 and 5.3.

The X_{ij} matrix is constructed iteratively and respects restrictions 5.4 and 5.5, which limit the amount of power available per hour, Z_j, and the minimum energy required per vehicle, T_i.

The P_{ij} weight matrix assigns a weight to each hour of recharge according to the time of departure. The closer the departure time is, the more weight this position has in the matrix in order to move the start of the vehicle charging as close as possible to the departure time from the parking lot.

By applying a modified binary integer programming algorithm, a value of 0 or 1 maximizing the target function F is assigned and the restrictions of energy required per vehicle and maximum hourly available power are considered.

During the iterative process, the algorithm places 1 in the positions of the matrix that maximize the function and meet restriction 5.4, related to the amount of charging time for each parking lot.

The algorithm then validates that the hourly available power restrictions are met, i.e., the number of parking spaces where it is possible to enable charging, as shown in relation 5.5.

If this restriction is not met, the departure times that coincide with the hours in which this restriction is not met are sought and a period is then brought forward; it is always verified that the required charge is reached.

The algorithm finally determines the start times of charging for each vehicle by meeting all the restrictions and starts charging those that can be charged.

C. Selection of Surrounding Vehicles

The objective of the selection process of electric vehicles surrounding the office building is to offer charging to the electric vehicles that transit in the vicinity of the office building only if there is space and electric power available.

The process is composed of several stages, as shown in Figure 5.4. The first stage involves grouping the surrounding vehicles by characteristics, mainly battery charge status and distance from the building.

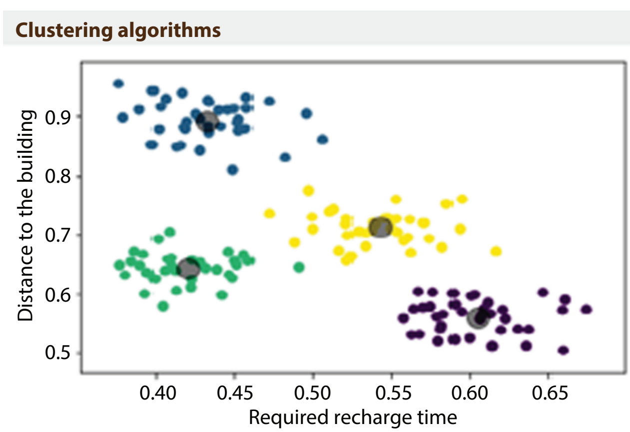

Figure 5.4 Result of clustering algorithm.

For this purpose, an unsupervised machine learning cluster algorithm was implemented. This algorithm groups surrounding vehicles according to their distance from the building and their battery charge status.

The information on charging status and geographic location of each vehicle was previously stored on a cloud in real-time and the algorithm received this information, processed it, and grouped the vehicles according to the information, as shown in Figure 5.5.

In the second stage of the process, the best group was selected based on these two variables and a charging offer was sent to the vehicles. Those vehicles could decide to accept charging automatically or with the user's permission.

The charging of each vehicle was assigned in order of response to the offer until the parking spaces were occupied or the available power limit was reached. If, at this point, there were still vehicles that had accepted the offer, they were sent a message canceling the offer.

5.3 Test Bed and Implementation Results

This section presents the results of the tests done on the management strategy, including some optimization and automatic learning algorithms such as a binary integer programming algorithm, a classification algorithm, and several regression algorithms.

Each of the algorithms proposed within the management strategy was implemented in a program developed on Python.

Initially, the power demand prediction algorithm was trained with the data shown in Figure 5.6, which was obtained by recording the power demand of an office building with a power quality analyzer.

Then, the acquisition of the demanded power measurement was simulated in real time, producing a value with a random value generation algorithm.

In order to validate the management strategy, the power demanded for the next eight hours was generated based on the input data shown in Table 5.1 by using the three algorithms implemented (linear regression, decision tree, and random forests).

Figure 5.7 shows the results of the prediction of power demand in the office building for the next eight hours based on the input data, with a resolution of thirty minutes; a total of sixteen datasets were obtained. This data was the input for the shifting algorithm at the start of the charging of the electric vehicles.

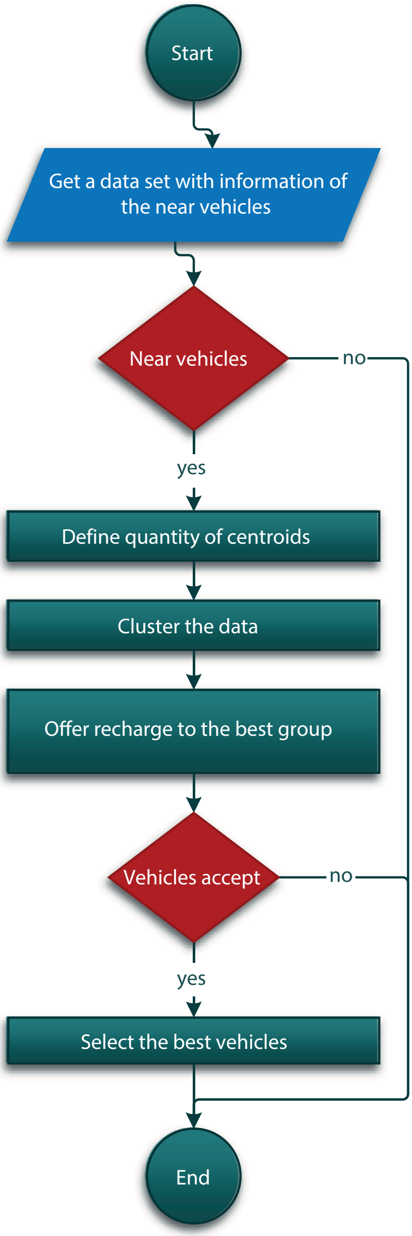

Figure 5.5 Flowchart of surrounding vehicle selection process.

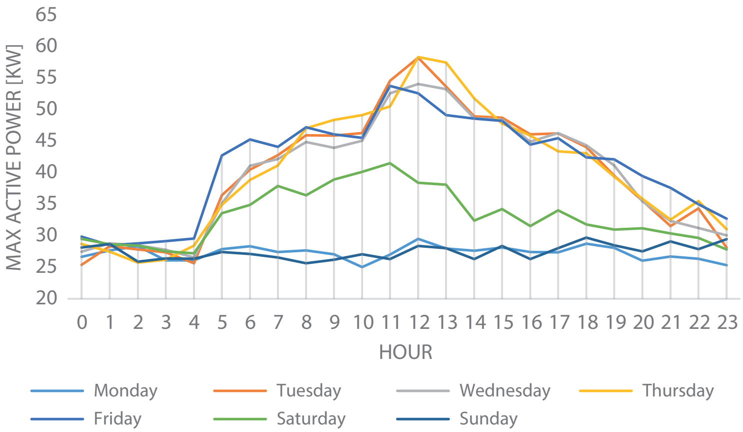

Figure 5.6 Load curve of office building.

Table 5.1 Random input data.

Day	Time	Measured Power (p.u.)
Monday	3	0.176

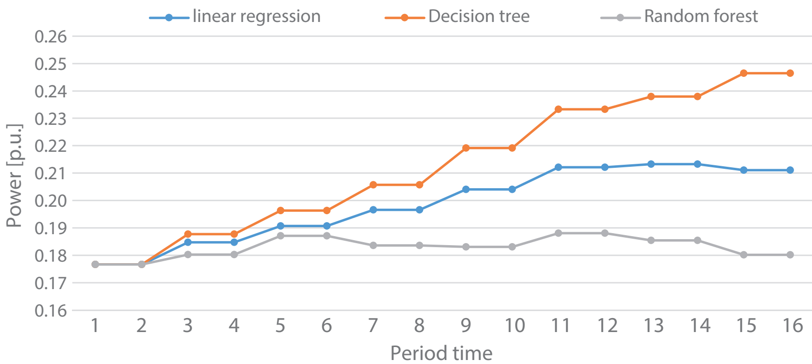

Figure 5.7 Power demand predicted by algorithms implemented.

A cross validation was performed by taking the test data with ten divisions, random data mixing, and active replication. The algorithm score was obtained by using the mean square error method, which measures the precision of the model with 100 being the maximum.

The results of the test done were as follows: regression algorithm, 71.38; decision tree algorithm, 48.65; and random forest algorithm, 85.94.

According to these tests, the random forest algorithm is the most accurate of the three. However, the linear regression algorithm had high performance and can be an excellent option when good computing resources are not available.

The values obtained with the random forest algorithm, shown in Figure 5.7, were taken as input values for the binary integer programming algorithm.

In order to test the management strategy depending on the level of penetration of electric vehicles, four tests of the demand shifting algorithm were done. The number of parking spaces in each test was increased by a quartile, the values of time required for charging and time required or reserved for parking were randomly generated, and, in all cases, the availability of charging in 44 parking spaces of the office building was enabled.

Figure 5.8 shows the result of the binary integer programming algorithm. For 11, 22, and 44 electric vehicles in the office parking lot, it is possible to offer charging to the electric vehicles surrounding the office building because the algorithm could shift the demand enough to leave sufficient available power.

Finally, the operation of the clustering algorithm was validated by generating the input values by means of a random number generation algorithm in a 10-30 range for the required charging time and a 1-100 range for the distance from the building.

Figure 5.9 shows the standardized data set used as input in the clustering algorithm.

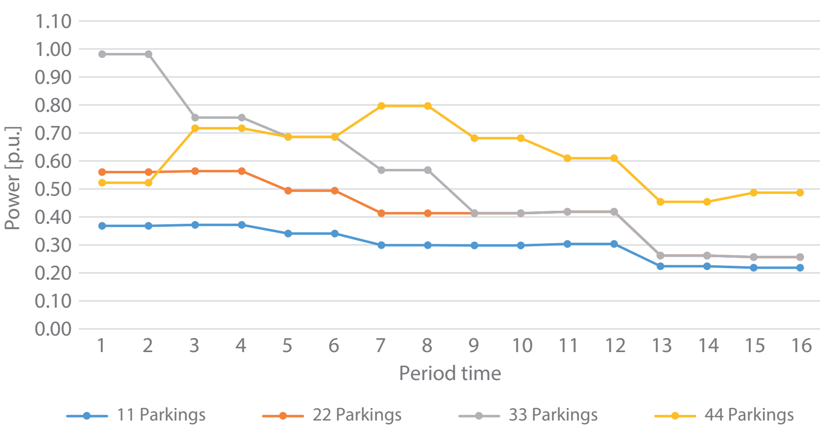

Figure 5.8 Power demand predicted by algorithms implemented.

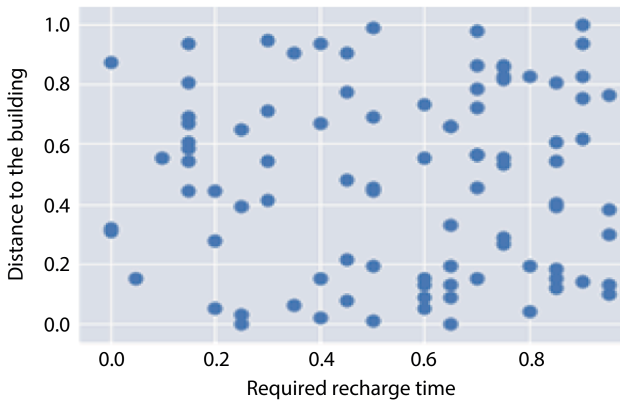

Figure 5.9 Standardized input data set.

By using the graphical methods of silhouette and elbow coefficient, it was estimated that the optimal number of groups is equal to 3. Figure. 5.10 shows the result of the clustering algorithm.

The groups were clearly defined and allow different marketing strategies to be defined for each group. The management strategy aimed to define the group of vehicles that may receive an offer on charging as well as to select the most suitable vehicles among this group to be charged.

The algorithm sent the offer to the groups with centroids with the best ratio of required charging time to distance from the building. The algorithm assigned the charging according to the response time to the offer until it reached the maximum power and maximum number of parking

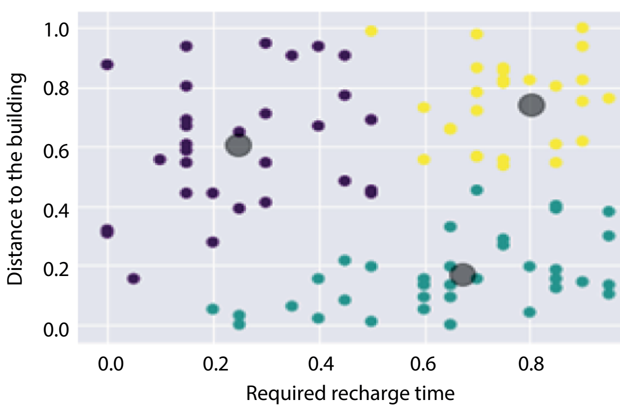

Figure 5.10 Result of data clustering algorithm.

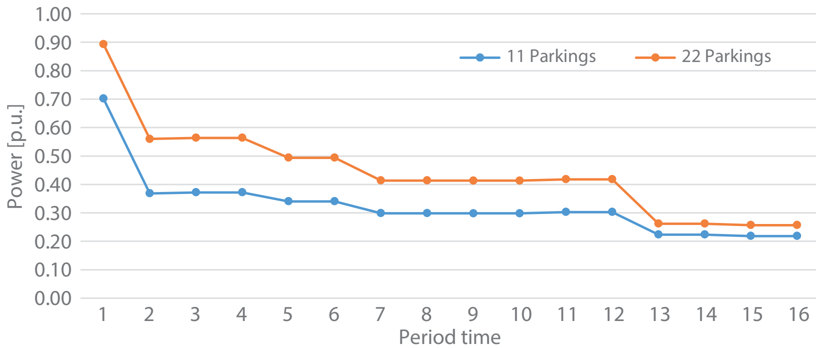

Figure 5.11 Power demand predicted by algorithms implemented.

spaces. In both cases, the power allowed the charging to be assigned to only one vehicle of those that accepted the offer.

Figure 5.11 shows the result for 11 and 22 electric vehicles of power demand in the installation. As for the current time, the power demand was very close to 1 p.u., so both the power and parking spaces would be better used.

5.4 Conclusion

This article proposes a management strategy consisting of three groups of algorithms: demand shifting of power for electric vehicle charging, prediction of the power demanded by office loads, and the clustering of electric vehicles surrounding office buildings and the offer on their charging. These three groups worked together and in being interrelated, they reduced the power available as well as the number of free parking spaces.

Shifting the load is a good management strategy because it allows a more uniform distribution of the load, decreasing the peak and off-peak periods.

In addition, the demand prediction algorithm is restricted by the nominal power of the installation and the algorithm for classification and offer on charging to electric vehicles surrounding the building only works if there are parking spaces and power available.

Finally, the tests done on the algorithms implemented in the management strategy show that the general objective of the research has been met. These tests were carried out for different electric vehicle penetration scenarios and with random input data, so the behavior of the strategy could be evaluated broadly.

References

1. Castellazzi, A.; Gurpinar, E.; Wang, Z.; Suliman Hussein, A.; Garcia Fernandez, P. "Impact of Wide-Bandgap Technology on Renewable Energy and Smart-Grid Power Conversion Applications Including Storage," *Energies* 2019, *12*, 4462.
2. U. Asghar, M.B. Rasheed, A.S. Al-Sumaiti, I. Ali, A. Ur-Rahman, A. Alzaidi, A. Alamri "Smart Energy Optimization Using Heuristic Algorithm in Smart Grid with Integration of Renewable Energy Sources", Energies, vol. 11, (12), 3494, pp. 1–26, December 2018.
3. M. H. Fouladfar., A. Loni, M.B. Tookanlou, M. Marzband, R. Godina, A. Al-Sumaiti, E. Pouresmaeil,"The Impact of Demand Response Programs on Reducing the Emissions and Cost of A Neighborhood Home Microgrid," Applied Sciences, vol. 9, (10), 2097, May 2019.
4. A. S. Al-Sumaiti, M. H. Ahmed, M.M.A. Salama, "Residential load management under stochastic weather condition in a developing Country," Electric Power Components and Systems, vol. 42, (13), pp. 1452–1473, January 2014.
5. A. S. Al-Sumaiti, M. H. Ahmed, M.M.A. Salama, "Smart home activities: A literature review. Electric Power Components and Systems," vol. 42, (3-4), pp. 294–305, February 2014.
6. N. Yu, T. Wei and Q. Zhu, "From passive demand response to proactive demand participation," *2015 IEEE International Conference on Automation Science and Engineering (CASE)*, Gothenburg, 2015, pp. 1300–1306.
7. V. C. J. Sankar, V. Hareesh and M. G. Nair, "Integration of demand response with prioritized load optimization for multiple homes," *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*, Kollam, 2017, pp. 1–6.
8. O. Avatefipour, A.S. Al-Sumaiti, A. M. El-Sherbeeny, E.M. Awwad, M. A. Elmeligy, M. A. Mohamed, H. Malik. "An Intelligent Secured Framework for Cyberattack Detection in Electric Vehicles CAN Bus Using Machine Learning," IEEE Access, August 2019.
9. Gustavo E. Coria , Angel M. Sanchez, A. S. Al-Sumaiti, Guiseppe A. Rattá, Sergio R. Rivera, Andrés A. Romero, "A Framework for Determining a Prediction-of-Use Tariff Aimed to Coordinate of Aggregators Plug-in Electric Vehicles," Energies, vol. 12, (23), 4487, pp. 1–18, November 2019.
10. F. Kong and X. Liu, "Distributed Deadline and Renewable Aware Electric Vehicle Demand Response in the Smart Grid," *2015 IEEE Real-Time Systems Symposium*, San Antonio, TX, 2015, pp. 23–32.
11. H. Li, X. Bai and W. Tan, "Impacts of plug-in hybrid electric vehicles charging on distribution grid and smart charging," *2012 IEEE International Conference on Power System Technology (POWERCON)*, Auckland, 2012, pp. 1–5.
12. S. Deb, K. Kalita and P. Mahanta, "Impact of electric vehicle charging stations on reliability of distribution netw ork," *2017 International Conference*

on Technological Advancements in Power and Energy (TAP Energy), Kollam, 2017, pp. 1–6.
13. A. G. Neagoe-Stefana, A. C. Neagoe, and A. C. Mandis, “Impact of charging electric vehicles in residential grid on the power losses and voltage plan,” in 2014 International Symposium on Fundamentals of Electrical Engineering (ISFEE), 2014, pp. 1–4.
14. G. Mauri and A. Valsecchi, “Fast charging stations for electric vehicle: The impact on the mv distribution grids of the milan metropolitan area,” in 2012 IEEE International Energy Conference and Exhibition (ENERGYCON), 2012, pp. 1055–1059.
15. C. Baron and S. Rivera, “Mono-objective minimization of operation cost for a microgrid with renewable power generation, energy storage and electric vehicles,” Rev. Int. Métodos Numéricos para Cálculo y Diseño en Ing., vol. 35, pp. 20–36, Jun. 2019.
16. J. Arévalo Bonilla, F. Santos, and S. Rivera, “Uncertainty cost functions for solar photovoltaic generation, wind energy generation, and plug-in electric vehicles: mathematical expected value and verification by Monte Carlo simulation,” Int. J. Power Energy Convers., vol. 10, pp. 171–207, Mar. 2019.
17. A. Peña Acosta, D. F. Romero Quete, and S. Rivera, “Generation and Demand Scheduling in a Micro-grid with Battery-based Storage Systems, Hybrid Renewable Systems and Electric Vehicle Aggregators,” WSEAS Trans. Power Syst., vol. 14, pp. 8–23, Apr. 2019.
18. P. Chiradeja, “Benefit of Distributed Generation: A Line Loss Reduction Analysis,” in 2005 IEEE/PES Transmission & Distribution Conference & Exposition: Asia and Pacific, 2005, pp. 1–5.
19. Subdirección de Demanda, “Proyección de la demanda de energía eléctrica y potencia máxima en Colombia Revisión Octubre de 2015,” 2015.
20. D. Zhao, Y. Li, and Y. Liu, “Optimal design and sensitive analysis of distributed generation system with renewable energy sources,” in 2014 China International Conference on Electricity Distribution (CICED), 2014, pp. 456–460.
21. M. Zeng, K. Tian, C. Li, and N. Li, “Method of Capacity Compensation for Independent Distributed Generation in Distribution Network within the Context of Smart Grid,” in 2010 Asia-Pacific Power and Energy Engineering Conference, 2010, pp. 1–5.
22. A. A. Sallam and O. P. Malik, “Demand-Side Management and Energy Efficiency,” in Electric Distribution Systems, Hoboken, NJ, USA: John Wiley & Sons, Inc., 2011, pp. 433–468.
23. Congreso de Colombia, “Ley N° 1715 del 13 de mayo de 2014,” Upme, no. May, p. 26, 2014.
24. Alvarez, D.L.; Al-Sumaiti, A.S.; Rivera, S.R. Estimation of an Optimal PV Panel Cleaning Strategy Based on Both Annual Radiation Profile and Module Degradation. IEEE Access 2020, 4, 1–8.