International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075, Volume-8 Issue-12, October 2019

Electric Vehicles Aggregator Participation in Energy Markets Considering Uncertainty Travel Patterns

C. Villanueva, J. Luyo, Alexi Delgado, Ch. Carbajal

Abstract**:** ***This research studies a general modeling to evaluate different scenarios of travel patterns and their impact on the daily cost negotiated in the Real Time and Day-Ahead market, using the GAMS methodology in a MILP model, evaluating also a characterization of the PQP market (price quantity probability). The purpose of this characterization is to determine the behavior of the electric energy market, considering also the deterioration of batteries and the negotiations of it in real time in situations of shortage and overload, optimizing in this way the effects of the analysis of the cost of the application of the battery on the different travel patterns, consequently triggering the emergence of the development of the local electric transport aggregator industry.***

Keywords**:** ***Day Ahead market, electric vehicle aggregator, energy price, Real Time market, state of charge, travel patterns.***

I. INTRODUCTION

An analysis of the literature [1]–[7] shows that converting the typical transport fleet to electric is an important energy policy among governments since electric vehicles (EVs) are a convenient alternative for improving environmental concerns and reducing carbon emissions. Nevertheless, the introduction of plug-in hybrid electric vehicles (PHEVs) would present some challenges in the distribution network (DR), which should be resolved before an EV is adopted; for this, the adoption of an intelligent charge/discharge management system (SCDMS) is a measure that will help to improve the system performance.

Different studies [1]–[4] have described that SCDMS could be evaluated in both centralized and decentralized approaches, where Electric Vehicle Aggregators (EVAs) should take a relevant role in activating a decentralized SCDMS, so their bidding system should be optimized for each country's electricity market. For this purpose, the investigations [8]–[12] consider the bidding strategies of real-time and day-to-day market EVAs and the operation of SCDMS, to solve these problems the research model can be considered as an LP model so that it can be solved using GAMS and the CPLEX solver [13].

Revised Manuscript Received on October 05, 2019.
***** Correspondence Author
C. Villanueva, J. Luyo, Faculty of Mechanical Engineering, Universidad Nacional de Ingeniería, Lima, Peru. Email: cwvillanuevam@uni.pe
Alexi Delgado*, Department of Engineering, Mining Engineering Section, Pontificia Universidad Católica del Perú, Lima, Peru. Email: kdelgadov@pucp.edu.pe
Ch. Carbajal, Administration Program, Universidad de Ciencias y Humanidades, Lima, Peru. Email: ccarbajal@uch.edu.pe

Studies shown in [8]–[12] were based on different sources of travel information, batteries and market price data. Therefore, in order to compare and unify the research, an analysis of multiple vehicle fleet patterns was carried out, considering the analysis of travel patterns as distributed probability of departure and arrival time [14], which will be considered with trip time and average speed scenarios.

The purpose of this research is to contrast the different stochastic and robust EVA scenarios in terms of fleet patterns of electric vehicles and optimization of tenders, in order to choose those that best suit the pricing systems of both national markets and traffic patterns of locations [15].

In the section II of the present study, a review of the methodology will be presented, focused on the limitation of modelling and on the different objective functions that are taken into account in the research to model the bidding and operating approaches of EVAs. In section III, a wide description of the case study will be presented. Therefore, section IV will show the results obtained in the case study on the different scenarios of vehicle fleet patterns; and finally, section V will provide conclusions on which one has the best national development benefits.

II. METHODOLOGY

A. Optimization Model

EVAs modeling is principally based on cost optimization, continuous restrictions related to energy charge and discharge, battery charge status, and price quantity probability diagram analysis [10][11].

B. Objective Function: Costs

The objective function in the modelling of EVAs is strongly related to the performance of the electricity market, mainly in price and uncertainty analysis. Therefore, to model the day-ahead market (DA) it is necessary to consider a probability of shortage or overproduction in the availability of energy proposed to the DA market and, finally, a cost related to the compensation to EVs owner compensation for time-life battery reduction. Thus, the following equations are established.

$$\min C = DAEM - RTEM^{\downarrow} \qquad (1)$$

$$+RTEM^{\uparrow} + BATCOST \qquad (2)$$

$$DAEM = \Delta t \sum_{t}^{T} \lambda_t \times (P_t^{EM}) \qquad (3)$$

$$RTEM^{\uparrow} = \Delta t \sum_t^T \sum_s^S \pi_{t,s} \times \lambda_{t,s}^{\uparrow} \times \left(P_{t,s}^{-}\right) \quad (4)$$

$$RTEM^{\downarrow} = \Delta t \sum_t^T \sum_s^S \pi_{t,s} \times \lambda_{t,s}^{\downarrow} \times \left(P_{t,s}^{+}\right) \quad (5)$$

$$BATCOST = BC^{ES} \times \sum_t^T \sum_v^V \sum_s^S \frac{m_v}{100} \times \frac{soc_{t,v,s}^{deg}}{BC_v^{ES}} \times C_v^{ES} \quad (6)$$

Where:

- C represent the total cost related with market participation of EVAs.
- t is a set of time intervals Δt and T correspond to the period.
- s and v with S and V correspond to sets of scenarios of shortage and vehicles with their respective universe of sets.
- λ_t, $\lambda_{t,s}^{\downarrow}$ and $\lambda_{t,s}^{\uparrow}$ represent the DA and RT market prices corresponding to t time and s shortage scenario.
- P_t^{EM}, $P_{t,s}^{+}$ and $P_{t,s}^{-}$ represent DA, RT overage and shortage power market traded respectively.
- $\pi_{t,s}$ represent the shortage and overage probability.
- Additional terms of battery degradation:
- m_v represent a linear approximation of the battery life.
- C_v^{ES} represent the Price of energy storage (ES) (typically in \$/kWh).
- BC^{ES} represent the capacity of ES.
- $soc_{t,v,s}^{deg}$ represent the degradation equivalent to state of charge for each vehicle in t time and s shortage scenario.

C. Constraints: Power Balances

Constraints are related with power balances and power traded in both DA and real time market (RT) and are described in previous researches [11], [12] as follows:

$$0 \le P_{t,s}^{+} \le \sum_v^V P_{t,v,s}^{B2G} \times \eta^{dsg} \quad (7)$$

$$0 \le P_{t,s}^{-} \le \sum_v^V P_{t,v,s}^{B2G} \times \eta^{dsg} \quad (8)$$

$$P_t^{EM} = \sum_v^V \left(P_{t,v,s}^{G2B} - P_{t,v,s}^{B2G}.\eta^{dsg}\right) + P_{t,s}^{+} \quad (9)$$

$$P_t^{EM} = \sum_v^V \left(P_{t,v,s}^{G2B} - P_{t,v,s}^{B2G}.\eta^{dsg}\right) - P_{t,s}^{-} \quad (10)$$

$$P_{t,v,s}^{B2R}.\eta^{dsg} = R_{t,v,s} \quad (11)$$

$$0 \le P_{t,v,s}^{G2B} + P_{t,v,s}^{B2G} \le P^{max} \times \left(1 - X_{t,v,s}\right) \quad (12)$$

$$0 \le P_{t,v,s}^{B2R} \le P^{max} \times \left(X_{t,v,s}\right) \quad (13)$$

$$0 \le P_{t,v,s}^{G2B}, P_{t,v,s}^{B2G} \quad (14)$$

Where:

- $P_{t,v,s}^{G2B}$, $P_{t,v,s}^{B2G}$ and $P_{t,v,s}^{B2R}$ represent the power trade between grid to batteries, batteries to grid and batteries to road (used to travel).
- η^{dsg} and η^{chg} represent discharging and charging efficiencies.
- $R_{t,v,s}$ and $X_{t,v,s}$ represent the energy consumption in road (while traveling) and the binary index that show while a vehicle is in a trip state respectively.

D. Constraints: State of Charge of Batteries

Constraints related to battery approach are widely described in previews researches so analytical modelling will be used [2], [3].

$$soc_{t,v,s} = soc_{t-1,v,s} \quad (15)$$

$$+\Delta t \times \left(P_{t,v,s}^{G2B}.n^{chg} - P_{t,v,s}^{B2G} - P_{t,v,s}^{B2R}\right) \quad (16)$$

$$0 \le \underline{SoC} \le soc_{t,v,s} \le \overline{SoC} \le BC^{ES} \quad (17)$$

$$soc_{t=0} = SoC_{s,v}^{init} \quad (18)$$

$$soc_{t,v,s}^{deg} \ge soc_{t-1,v,s} - soc_{t,v,s} \quad (19)$$

$$soc_{t,v,s}^{deg} \ge 0 \quad (20)$$

Where:

- $soc_{t,v,s}$ represent the state of charge of v EV battery in t time and s scenario of shortage.
- $\underline{SoC}$ and $\overline{SoC}$ represent the state of charge limits.
- $SoC_{s,v}^{init}$ is a random initial state of charge of day.

E. Constraints: PQP market election

Constraints related to both the DA and RT markets are meticulously selected, and transform this model into a Multi Index Linear Programing effectively.

As shown in [10], the DA market could be represented by a price quantity probability analysis with a b price and quantity probability set; therefore, the present investigation will use these data.

$$DAEM = \Delta t \sum_t^T \sum_b^B (\lambda_b - \lambda_{b-1}) \times \left(P_t^{EM} \times PQP_{t,b}\right) \quad (21)$$

$$RTEM^{\uparrow} = \Delta t \sum_t^T \sum_s^S \sum_b^B \begin{matrix} \pi_{t,s} \times (\lambda_b - \lambda_{b-1}) \times \\ \left(P_{t,s}^{-} \times PQP_{t,s,b}^{\uparrow}\right) \end{matrix} \quad (22)$$

$$RTEM^{\downarrow} = \Delta t \sum_t^T \sum_s^S \sum_b^B \begin{matrix} \pi_{t,s} \times (\lambda_b - \lambda_{b-1}) \times \\ \left(P_{t,s}^{-} \times PQP_{t,s,b}^{\downarrow}\right) \end{matrix} \quad (23)$$

$$P_b^{PQP} - M^{big} \times PQP_{t,b} \le P_t^{SYS} + P_t^{EM} \quad (24)$$

$$P_t^{SYS} + P_t^{EM} \le P_b^{PQP} + M^{big} \times \left(1 - PQP_{t,b}\right) \quad (25)$$

$$P_b^{PQP} - M^{big} \times PQP_{t,s,b}^{\uparrow} \le P_t^{SYS} + P_t^{EM} + P_{t,s}^{-} \quad (26)$$

$$P_t^{SYS} + P_t^{EM} + P_{t,s}^{-} \le P_b^{PQP} + M^{big} \times (1 - PQP_{t,s,b}^{\uparrow}) \quad (27)$$

$$P_b^{PQP} - M^{big} \times PQP_{t,s,b}^{\downarrow} \le P_t^{SYS} + P_t^{EM} - P_{t,s}^{+} \quad (28)$$

$$P_t^{SYS} + P_t^{EM} - P_{t,s}^{+} \le P_b^{PQP} + M^{big} \times (1 - PQP_{t,s,b}^{\downarrow}) \quad (29)$$

Where:

λ_b and P_b^{PQP} are calculated from DA market historic data in base to cumulative distribution function (CDF), generating that way a Price-Quantity-Probability (PQP) function.

$PQP_{t,b}$, $PQP_{t,s,b}^{\uparrow}$ *and* $PQP_{t,s,b}^{\downarrow}$ are binary variables that allowed a step of PQP in equations from (24) to (29), for usage in equations (3) to (5) resulting in equations (21) to (23), finally M^{big} is a scalar value that allows the algorithm of step selection.

III. STUDY CASE

Based on [10], [11] and applied to a generic case, in order to achieve applicability, a 2x2 effect of travel pattern scenarios on the daily cost of EVAs was described as an input set of 500 EVs. However, regarding TESLA Model X EVs, the battery capacity was adjusted to BCES=100kWh, also using a fast charge lvl3 DC-DC, this tesla vehicle has a power value of 100kW, the value of m is adjusted to [0.0006,0.0017], but degradation costs in contrast to previous investigations have decreased its value to a range of 100-140 $/MWh.

A. Constraints: PQP market election

$\pi_{t,s}$ probabilities of shortage-overage in RT market, which is applied in Lima, Peru. Santa Rosa electric substation node values are shown in Fig. 1 corresponding to April 2019 historic data, and the P_t^{SYS} data correspond to 04 April 2019 that for EVAs would be calculated based in historical data. Likewise, PQP energy market is represented in “Fig. 2”.

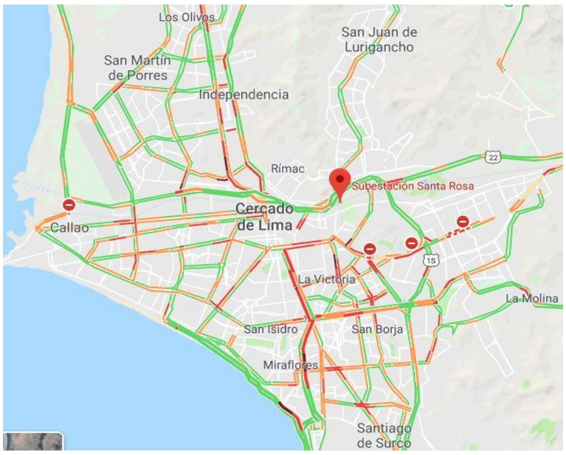

Fig. 1 Lima, Peru (Google Maps) – Traffic

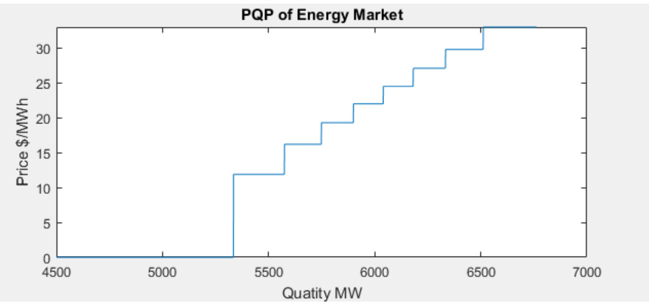

Fig. 2 PQP of Energy Market

IV. RESULTS AND DISCUSSION

A. Optimization model

The travel patterns used in the present optimization model were categorized as normal distributions for travel time and average vehicle speed, the values of which are shown in Table I.

Table I: Scenarios characterization

Scenarios Description	μ	σ
Time Traveling 1 scenario [h]	0.5	0.75
Time Traveling 2 scenario [h]	0.75	0.75
EV Speed 1 scenario [km/h]	30	15
EV Speed 2 scenario [km/h]	40	10

B. Objective Function: Costs

Compared to [10], [11], and as it was expected due to technology development, specifically in the CES battery degradation costs that were reduced to a range of 100-140 $/MWh, the energy traded in the energy markets could operate in the V2G model since the costs show a negative value that results in a cost per unit ("p.u.") greater than 1, as it is shown in "Fig. 3".

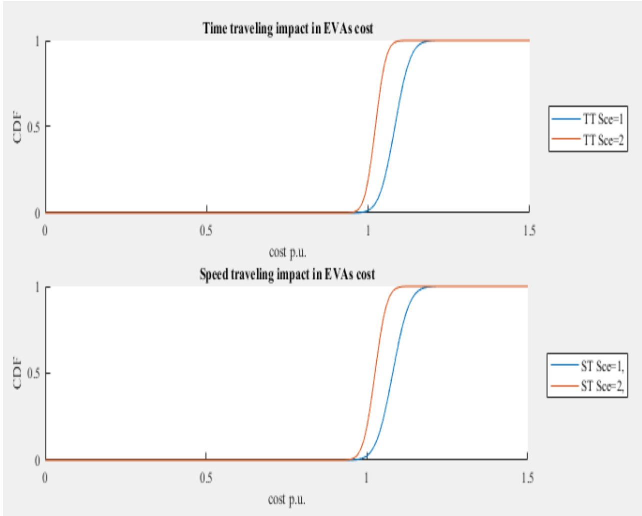

Fig. 3 CDF analysis of scenarios

Table II: Daily costs for travel patterns

Scenarios Description	Total Cost (positive for buying and negative for selling)
(TT. Sc 1;Speed Sc 1)	-946.67
(TT. Sc 1;Speed Sc 2)	-891.1
(TT. Sc 2;Speed Sc 1)	-886.66
(TT. Sc 2;Speed Sc 1)	-848.81

C. Constraints: Power Balances

As expected, the negative values of energy traded represent the sale of energy by EVAs to the national interconnected power system, as shown in Fig. 4(a). In addition, daily prices in the energy market have changed their values as presented in Fig. 4(b), the probability that the shortage and excess of energy will generate additional energy that is sold in the DA market can also be seen in Fig. 4(b).

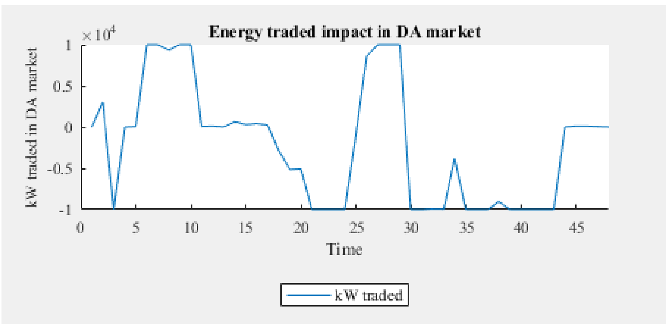

Fig. 4(a) Results for Analysis in first scenario of time traveling and first scenario of EVs speed – Energy traded in DA market

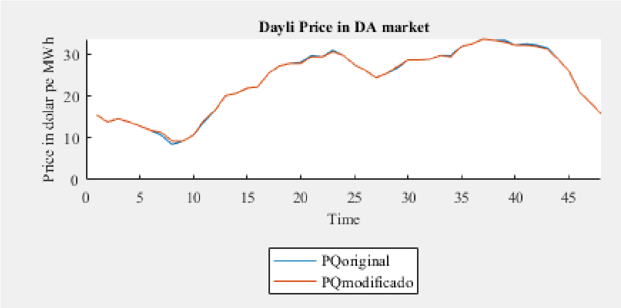

Fig. 4(b) Results for Analysis in first scenario of time traveling and first scenario of EVs speed – Daily price in DDA market

D. Constraints: Power Balances

For Power balance showed in results, the maximum, minimum and total capacity of the ESS is calculated and presented in Fig. 4(c), as well as the State of charge, which is a calculation based in State of charge of each EV controlled by EVAs.

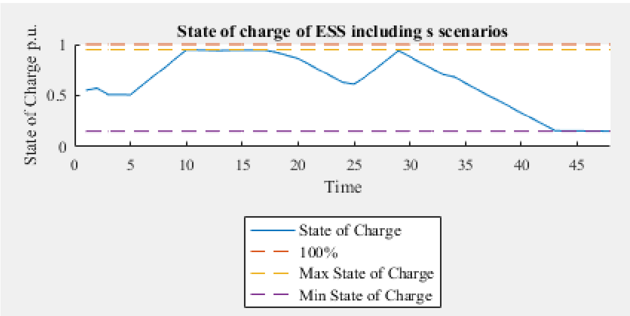

Fig. 4(c) Results for Analysis in first scenario of time traveling and first scenario of EVs speed – Description of State of charge

1) Total capacity of energy storage system (100%): It is calculated according to each EV adding all BCES.

2) *Max State of Charge condition:* If all electric vehicles are the same model, the percentage of the maximum state of charge of the battery will be multiplied by the total capacity of the EVA energy storage system. Otherwise, the maximum state of charge of the EES is calculated by adding all the maximum states of charge of each EV in EVA.

3) *Min State of Charge condition:* If all EVs are the same model, the same percentage of minimum battery charge will be multiplied by the total capacity of the EVA energy storage system. If not, the minimum state of charge of the EES will be calculated by adding all the minimum states of charge of each EV in the EVA.

4) State of Charge: The state of charge of the global EES of EVA is calculated by summing all the states of charge of each VE in EVA.

E. Constraints: PQP market election

As a result of the PQP analysis specifically in the DA energy market (rather than in the RT market), a better marginal cost performance could be generated in the energy markets, as shown in Fig. 4(d), when energy market prices are lower than those of the absence of EVA Group participation.

Fig. 4(d) Results for Analysis in first scenario of time traveling and first scenario of EVs speed – Variation in Energy prices triggered by EVAs insertion

V. CONCLUSIONS

Every company intending to invest in the core EVA business would be located in a specific location with a different travel pattern for the vehicle fleet, this is the main reason why this research analysis has been initiated, which concludes that each travel pattern scenario has its own impact on the cumulative cost distribution function. But according to the analysis developed, the reduction of battery degradation costs leads to a V2G share for the EVAs in the energy markets (DA and RT markets), which generates a substantial benefit for the EVA owners in the market for combustion engine vehicles.

EVAs' presence leads to a variation of the energy price in the market, which in each calculated scenario represents a better Distributed Network Operability, and a potential reduction in marginal cost performance.

Eventually this better evaluated V2G would assist in the independent investment of EVAs to obtain a better financial analysis for each EVA, regardless of location a study of travel patterns of the vehicle fleet could complement this research to obtain as detailed an analysis as possible.

Future research should compare an analysis of investment cost and other operating costs with the revenues from the sale of energy in the energy markets, in order to provide a better profit analysis and financial analysis for EVA owners; in addition, the corresponding centralized relationship of SCDMS with the interaction of EVAs should be analyzed.

REFERENCES

1. A. J. Cheng, B. Tarroja, B. Shaffer, and S. Samuelsen, "Comparing the emissions benefits of centralized vs. decentralized electric vehicle smart charging approaches: A case study of the year 2030 California electric grid," *J. Power Sources*, vol. 401, pp. 175–185, Oct. 2018.
2. M. Mohiti, H. Monsef, and H. Lesani, "A decentralized robust model for coordinated operation of smart distribution network and electric vehicle aggregators," *Int. J. Electr. Power Energy Syst.*, vol. 104, pp. 853–867, Jan. 2019.
3. M. Shafie-Khah, P. Siano, D. Z. Fitiwi, N. Mahmoudi, and J. P. S. Catalao, "An Innovative Two-Level Model for Electric Vehicle Parking Lots in Distribution Systems With Renewable Energy," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1506–1520, Mar. 2018.
4. L. Wang, S. Sharkh, and A. Chipperfield, "Optimal decentralized coordination of electric vehicles and renewable generators in a distribution network using A∗ search," *Int. J. Electr. Power Energy Syst.*, vol. 98, pp. 474–487, Jan. 2018.
5. A. Ahmadian, M. Sedghi, B. Mohammadi-ivatloo, A. Elkamel, M. Aliakbar Golkar, and M. Fowler, "Cost-Benefit Analysis of V2G Implementation in Distribution Networks Considering PEVs Battery Degradation," *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 961–970, Apr. 2018.

6. K. Mahmud, G. E. Town, S. Morsalin, and M. J. Hossain, "Integration of electric vehicles and management in the internet of energy," *Renew. Sustain. Energy Rev.*, vol. 82, no. 3, pp. 4179–4203, Feb. 2018.
7. S. Pirouzi, J. Aghaei, T. Niknam, H. Farahmand, and M. Korpås, "Exploring prospective benefits of electric vehicles for optimal energy conditioning in distribution networks," *Energy*, vol. 157, pp. 679–689, Aug. 2018.
8. L. Baringo and R. Sánchez Amaro, "A stochastic robust optimization approach for the bidding strategy of an electric vehicle aggregator," *Electr. Power Syst. Res.*, vol. 146, pp. 362–370, May 2017.
9. A. Perez-Diaz, E. Gerding, and F. McGroarty, "Coordination and payment mechanisms for electric vehicle aggregators," *Appl. Energy*, vol. 212, pp. 185–195, Feb. 2018.
10. M. R. Sarker, Y. Dvorkin, and M. A. Ortega-Vazquez, "Optimal Participation of an Electric Vehicle Aggregator in Day-Ahead Energy and Reserve Markets," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 3506–3515, Sep. 2016.
11. M. R. Sarker, H. Pandžić, K. Sun, and M. A. Ortega-Vazquez, "Optimal operation of aggregated electric vehicle charging stations coupled with energy storage," *IET Gener. Transm. Distrib.*, vol. 12, no. 5, pp. 1127–1136, Mar. 2018.
12. H. Yang, S. Zhang, J. Qiu, D. Qiu, M. Lai, and Z. Dong, "CVaR-Constrained Optimal Bidding of Electric Vehicle Aggregators in Day-Ahead and Real-Time Markets," *IEEE Trans. Ind. Informatics*, vol. 13, no. 5, pp. 2555–2565, Oct. 2017.
13. A. Delgado, "Social conflict analysis on a mining project using shannon entropy," in *Proceedings of the 2017 IEEE 24th International Congress on Electronics, Electrical Engineering and Computing, INTERCON 2017*, 2017.
14. R. R. Desai, R. B. Chen, and W. Armington, "A Pattern Analysis of Daily Electric Vehicle Charging Profiles: Operational Efficiency and Environmental Impacts," *J. Adv. Transp.*, vol. 2018, pp. 1–15, 2018.
15. A. Delgado, "Citizen criminality assessment in lima city using the grey clustering method," in *Proceedings of the 2017 IEEE 24th International Congress on Electronics, Electrical Engineering and Computing, INTERCON 2017*, 2017.