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Electrical Vehicles Charging Coordination by Fuzzy Logical System

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Abstract

Today, with the rapid technological development, interest in electric vehicles is also increasing. This raises the question of what the effects of the vehicles on the electric power network will be. In this article, the adverse effects of charging scenarios of electric vehicles' batteries on the electric power network are examined and fuzzy logic based solutions are proposed to prevent or reduce the effects of charging electric vehicles during peak hours. In this article a fuzzy logic system that is providing the cheapest charging prices, also reducing the impact on the load curve of Turkey's electrical network is provided.

Key Words

Electrical Vehicles, Fuzzy Logic, Least Squares Method, Load

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1. INTRODUCTION

Over the past decade, transportation systems and their usage have witnessed constant forward leaps. Consequently, concerns about effective consumption of renewable energy started to take place. Using clean technologies does not only regard being renewable but also having advantages about being environmental, economical and technically advanced, this make distribution companies increase their net profits. (Sadeghi & Kalantar, 2015) Governments also support using of Plug-in Electric Vehicles (PEVs) as transportation systems by subsidizing them in tax cuts. Although electrical vehicles were introduced in the 1800s, they couldn't become popular because of their lower range and cheaper oil prices. Nowadays, PEVs are more desirable because of their higher range capability, clean technology, less noise, higher safety, low maintenance and cost effectivity. ("Advantages and Disadvantages of Electric Cars - Conserve Energy Future," 2014) As a result, over one million PEVs have been sold all over the world. (teslaccessories, 2017)

Plug-in Hybrid Electrical Vehicles (PHEVs) were produced as an alternative to PEVs to achieve better fuel and electricity consumption. Both electric/battery motor system and conventional internal combustion engine are combined in one vehicle by PHEVs. (Poullikkas, 2015) Vehicle to grid (V2G) technology is also an alternative to achieve better performance. V2G technology encourages the charging of the vehicles off-peak hours and discharging them during peak hours. This is intended to optimize charging schedule for the behalf of PDN. (Andersen, Mathews, & Rask, 2009; Richardson, 2013; Sovacool & Hirsh, 2009)

Current renewable energy sources (RES) are not sufficient for the increasing demand on electricity let alone fueling extra PEVs. Increasing access of PEVs to Power Distribution Networks (PDN) as shown by some simulations that it has been causing some problems. (Luo, Zhu, Wan, Zhang, & Li, 2016; Salah, Ilg, Flath, Basse, & Dinther, 2015) Studies in both rural and urban areas using power distribution of UK, which is heavily loaded already, reveal that charging PEVs is varying in density. (Neaimeh et al., 2015) Studies in South Korea (Arias & Bae, 2016; Arias, Kim, & Bae, 2017), forecast PEVs' electrical demand using weather conditions and real-world traffic distribution data of different periods such as: weekdays, weekends, summers and winters; in commercial and residential sites. For each different period, different charging demand was revealed. (Arias & Bae, 2016) Fast charging stations were examined in morning, afternoon and evening as a part of feasibility study for the investment of installing energy storage systems and renewable energy sources. (Arias et al., 2017) The study on PEV users in Ireland shows that most of them charge their vehicles in the evening at home when the highest demand of electricity occurs. (Morrissey, Weldon, & O'Mahony, 2016) During peak hours, simulations of charging in New England, New York and Texas indicates that unscheduled charging will affect the peak load only by % 1.9 by 2025. (Harris & Webber, 2014) But studies in (Apostolaki-Iosifidou, Codani, & Kempton, 2017) shows that charging and discharging will cause power losses vary from %12 to %36. Studies concludes that impacts of PEVs to PDNs varies according to lots of types of different inputs.

So many studies have revealed the disadvantages of charging PEV and showed how to eliminate them. When the charging is organized load curve can be smoothened, power loss can be reduced, node voltage drop can be decreased and at the same time transport system such as vehicle velocity, road length and waiting time can be more efficient. (Luo et al., 2016) Uncoordinated charging can worsen Voltage Unbalanced Factor (VUF). A study in (Farahani, 2017) shows that VUF can be minimized by selecting of PEVs' point of connection (phase a, b or c), the state of PEVs (charging or discharging) and rating power of charging/discharging by using Particle Swarm Optimization. Charging or discharging priorities can be organized through seven operating modes and it can achieve smoothness on the power load curve. (Khemakhem, Rekik, & Krichen, 2017)

Some studies (Hu, Zhan, Zhang, & Song, 2016; Moon & Kim, 2017; Soares, Ghazvini, Borges, & Vale, 2017) were conducted to balance charging by proposing optimal electricity price. In (Soares et al., 2017), prices proposed for different price-sensitive customer classes considering electricity Demand Respond (DR). In (Moon & Kim, 2017), mismatches between loads and costs were solved for the benefits of both users and operators. In (Hu et al., 2016), two different pricings were proposed to flatten the power load; when PEVs cooperate with other PEVs, the other occurs when there is no cooperation. Simulations were made in low voltage distribution in Ankara (Turkey) show that there will be different types of penetrations and load demands. Hence, there will be need for a multi-tariff system for EVs. (Temiz & Guven, 2016)

A novel pricing system using Fuzzy Logic was introduced in this study because of the shortcomings of the studies mentioned before. Fuzzy Logical System is considered to calculate optimal pricing of different levels of each battery State of Charge (SOC), motor power and the amount of power needed from the interconnected power system plus the specification of each period of a day according to the consumed power. In this study, the users were encouraged to charge their vehicles at the optimal hours within a day from the PDN by inspectional multi-pricing system. It is assumed that this new pricing system is more inspectional to use because of users' needs like battery SOC and motor powers are considered as well as PDN.

2. MATERIALS AND METHODS

2.1. Fuzzy Inference System

Fuzzy Inference System (FIS) is sets of rules which is shaped by classes of objects that have unsharp boundaries. The rules are characterized by membership functions whose values range between zero and one unlike binary/traditional rules whose values are only zero or one. Briefly, reasonably blended inputs are answers to a problem that are certainly yes, possibly yes, cannot say, possibly no or certainly no. One of the most used fuzzy model which is used in this study too is Mamdani Fuzzy inference model. Rule structures can be seen below.

Rule 1: if a1 is X1 and b1 is Y1 … then c is Z1

Rule 2: if a2 is X2 and b2 is Y2 … then c is Z2

Rule 3: if a3 is X3 and b3 is Y3 … then c is Z3

⋮

Rule k: if ak is Xk and bk is Yk … then c is Zk.

where a and b are first and second input variables respectively and c is the output variable and k is the numbers of the rules. By optimization techniques or an expert's knowledge, determination of membership function's type, size, locations and shapes may be defined. FIS is very useful in some fields like control systems, route planning or image processing etc. (Di Nola, Lettieri, Perfilieva, & Novák, 2007; Zadeh, 1965, 1975)

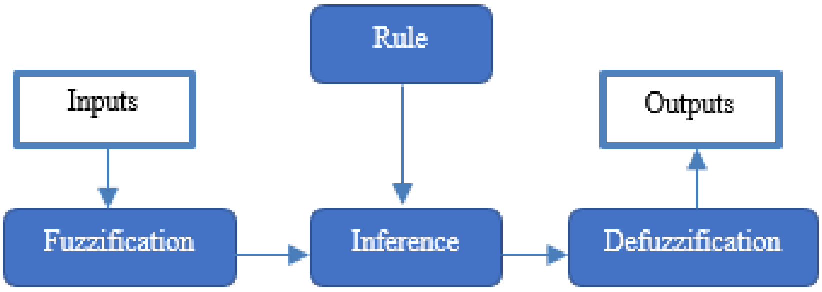

Figure 1: General Structure of Fuzzy Inference System

2.2. Least Squares Method

Least square method is used to minimize the variation between values of unknown parameters, β_0, $\beta_{1,\ldots}$ these values are concluded from the regression function model and empirical evidences.

The least squares method is expressed mathematically by the following equation.

$$Q = \sum_{i=1}^{n}[y_i - f\left(\vec{x_i}; \hat{\vec{\beta}}\right)]^2 \qquad (1)$$

As mentioned earlier, while β_0, $\beta_{1,}\ldots$ are optimization variables, x_1, x_2,… estimator values are used as coefficients. To point out the fact that the estimated values of the parameter are not the same as the actual values, the estimates are shown by $\beta_0{}^{\wedge}$, $\beta_1{}^{\wedge}$,… For linear models, the least squares method is usually computed analytically. On the other hand, for nonlinear models, the simulation should be done using almost recursive numerical algorithms.

When a linear model is expressed like this,

$$y = \beta_0 + \beta_1 x + \varepsilon$$

1. The partial derivative of Q is calculated according to β0 and β1,
2. Each partial derivative is made to equal to 0
3. The output system is calculated by two variables and two equations

The formulas described are valid only for the straight-line model, but the relationship to the parameter estimators remains similar for more complex models, including both statistically linear and statistically non-linear models.

2.3. Proposed Model

As it seen in Figure 2, meaningful relationship can be seen between load and price. In the present study, it was attempted to derive the charging price characteristic for PHEV by using engine power through load information. Thus, it is aimed to reduce the negative effect of the PHEV on the PDN to minimum level by means of the to-be-price routing and to achieve a better load demand curve.

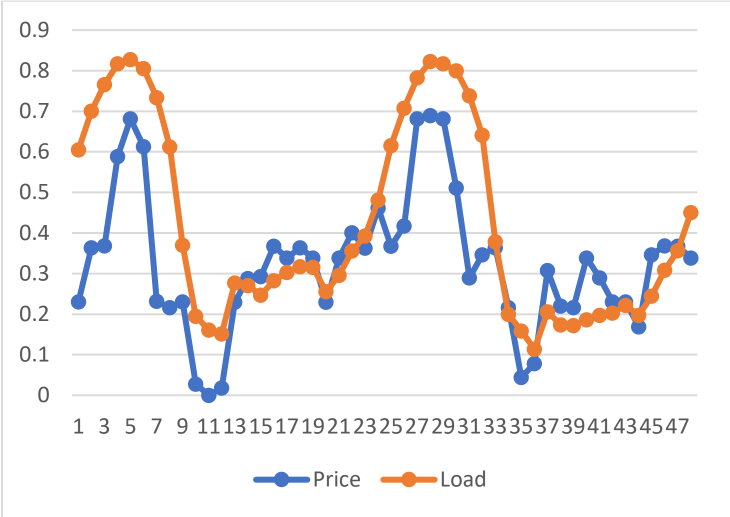

Figure 2. Load / Price Relationship Graph

This study suggests a brand new friendly pricing system for both users and PDN by using three different FISes on three different PEV classes. PEV classes are sorted according to their engine powers. Engines that are below 85 kW, 85-120 kW and above 120 kW are classed by Turkish taxation system. For each one of three PEV classes, battery SOC and power demand from PDN in each hour within a given day 24 are taken as inputs to determine price for each case, the output for the proposed FIS can be seen in Fig. 4. Altough those inputs are identical for three FISes, outputs (price) change for each FIS.

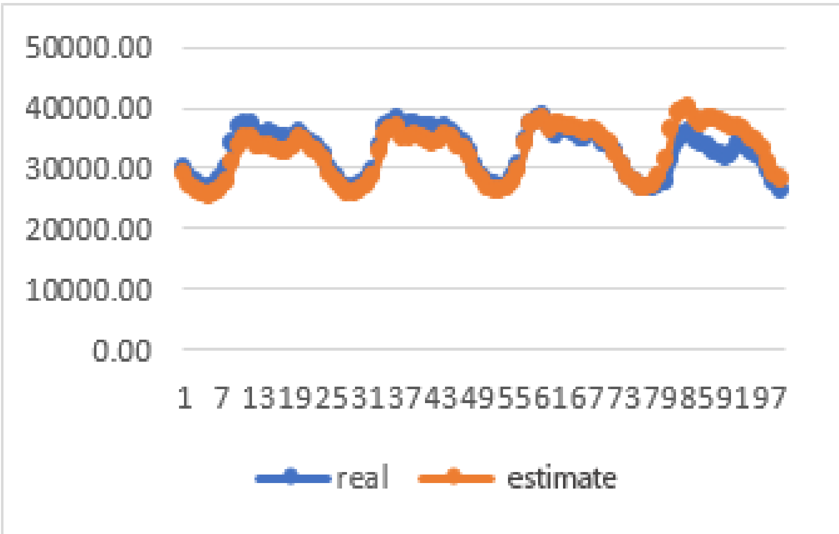

Figure 3. Real / Estimate Load Relationship Graph

The proposed system uses the values calculated for seven days by the least square method, while changings in the hourly load consumption amount as the input parameter.

Output (price) is determined from inputs (Battery SOC and Power Load of PDN) by fuzzy rules and membership functions that can be seen in Fig. 5.

Battery SOC Membership function (%) can be seen on Fig.5.A. Battery charge is rated by 9 out of %100. The other input which is Power Load of PDN can be seen in Fig. 5.B. Energy Exchange of Turkey has been measuring national hourly electricity consumption. This data enables comparing between hours of a day to analyse consumption intensity and ranking it between 1 (lightest) to 7 (heaviest). Finally, the output (price) gets labelled in seven different linguistic abbreviations: very cheap (VC), cheap

(C), normal cheap (NC), normal (N), normal expensive (NE), expensive (E) and very expensive (VE). Price membership functions are attained by both trial-and-error and comparison between other FISes that belong to two other engine-power classes.

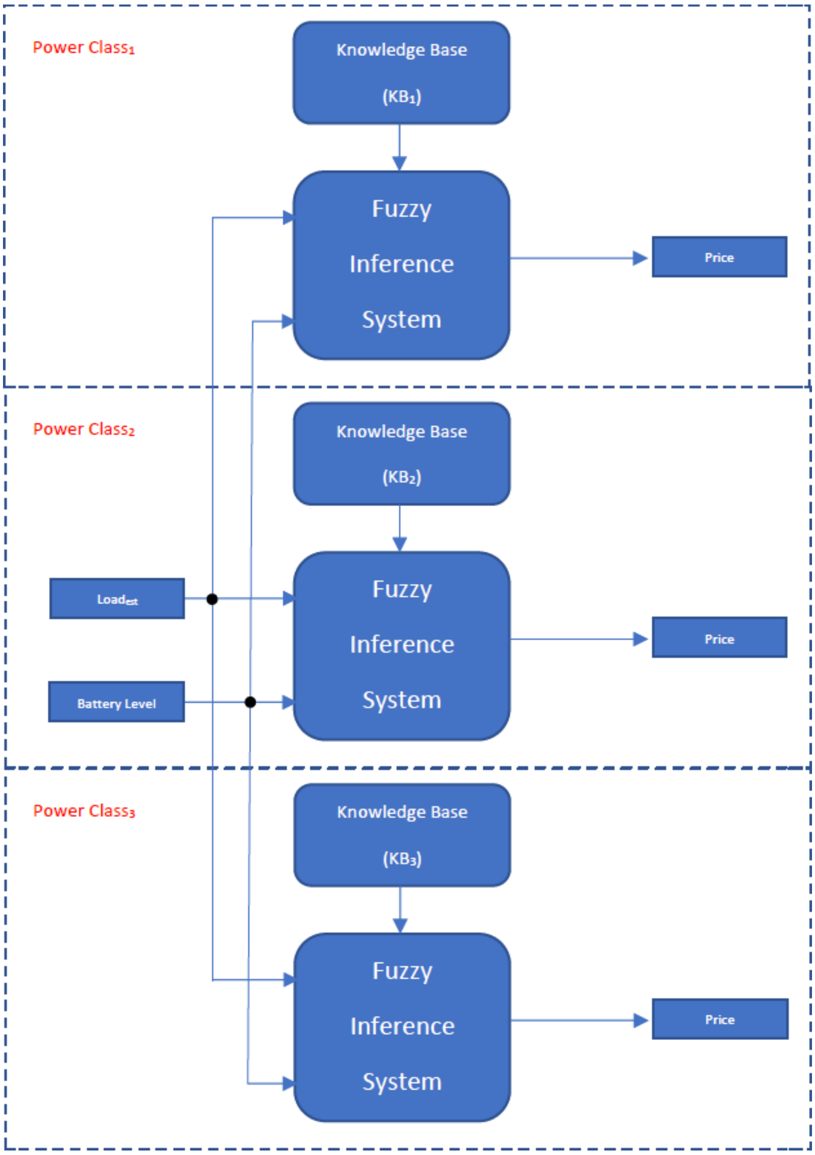

Figure 4. General View of Proposed System Framework

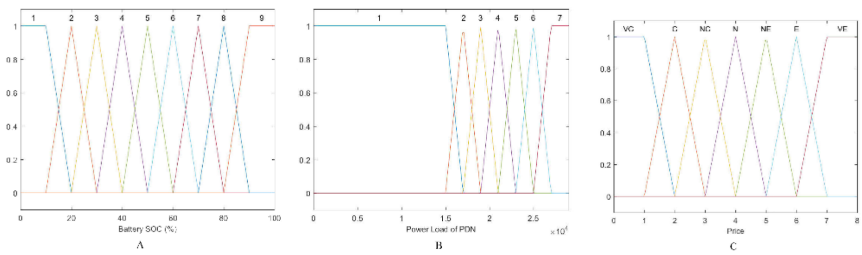

Figure 5. Membership Functions of the Inputs and the Output

3. RESULTS AND DISCUSSION

A separate load balancing profile was created for the three different engine power classes by the proposed system. During the training and test phase of this system, electrical power consumption amounts and battery charge values are noted on an hourly basis between 2015-2017.

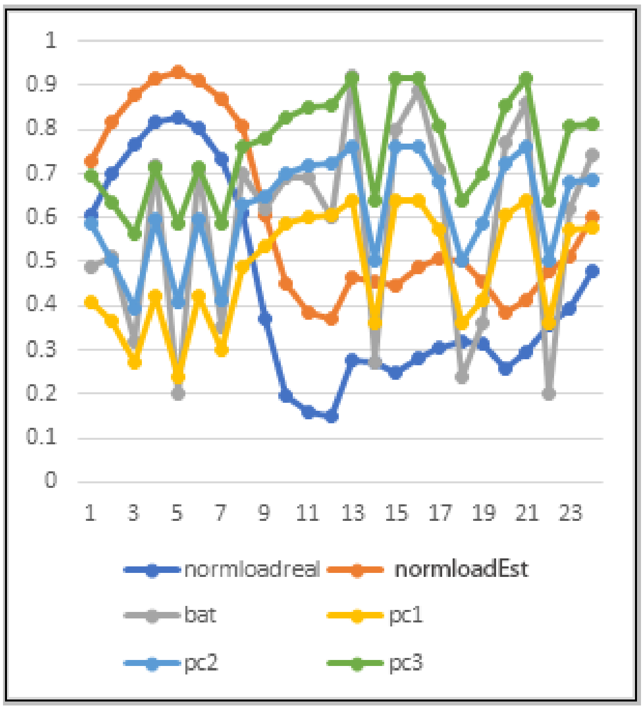

Figure 6. Graph of Price Recommendation for Electrical Vehicles

As can be seen from the Figure 6, the load estimation using the least square method showed a meaningful correlation with the real load graph. The results for three different engine power classes show a significant relation between engine powers and price values. When PHEV's battery SOC is taken into account by the proposed system, it generates deterrent price proposals at times when the effect of the electric charging on the PDN is intense. Likewise, when the vehicle has a low load level compared to the same battery SOC it also suggests encouraging charging prices.

4. CONCLUSION

This study developed price mechanism for PEV users to dynamically coordinate their charging taking in consideration battery SOC, engine powers and PDN. These criterias are used as inputs for a FIS which outputs an optimal price. The strategy was to prioritize those inputs for all variations of each one of them considering of both users and PDN; for PDN: it is expected to flatten the power load curve, for users: it leads them to charge their PEV from PDN during suitable intervals in order to reduce electricity bill. This pricing mechanism outputs, which are economic to the users and nonexhaustive to the PDN. Through these measurements, it was noticed that the output is synchronized with the power load curve which can be seen on Energy Exchange of Turkey daily. By making normalization, this incentive price mechanism has become applicable to any future price revaluation.

In Turkey, distribution companies need approval for their long-term investment plans. Until now, they have presented their plans based on forecasted load growth without any EV penetrations. This study will also help and guide distribution companies to have accurate planning. This study helps coordinating both private and public charging infrastructures in Turkish context and can also be applied to other emerging EV markets.

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