A fuzzy queueing based model for controlling power demand of electric vehicle charging

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***Abstract*—The rapid penetration of electric vehicles may lead to peak problems in a traditional grid so that some of the smart grid research is focused on charging strategies for electric vehicles. The charging problem is suitable for using a queue structure, and fuzzy queueing can be implemented for this purpose. This paper presents a fuzzy queueing based model, which can also control the power demand of electric vehicle charging. A charging model should guarantee that all charging requirements can be satisfied before vehicles leaving the charging stations. Simulation results exhibit that the proposed model decreases average waiting time of vehicles and also the proposed model utilize charging stations better than a traditional queueing model.**

Keywords—Electric Vehicles; Fuzzy Queueing; Smart Grid

I. INTRODUCTION

The penetration of electric vehicles (EVs) is rapidly increasing because of technological developments and low carbon emission policies. Manufacturers are releasing new and competitive models every year, and EVs are already seen as a part of the solution for global warming. Nevertheless, with this technological shift, some new problems arise. The electricity infrastructure we use today is not robust for a scenario in which a large number of vehicles want to be charged simultaneously. Due to their charging requirements, the integration of a vast number of EVs will be significant for the power demand of electric grids. That's why some of the smart grid research is focused on charging strategies for electric vehicles.

The problem related to scheduling or controlling EV charging may reduce the peak loads and the operational costs of a grid so that this issue have been studied by various researchers [1], [2]. Some of them used stochastic models to model and investigated a fleet of EVs. Clayton copula, Gaussian copula, and non-parametric copula were used to model the load profile [3], [4]. Other studies in the literature investigated optimization methods and dynamic programming [5]. An improved particle swarm optimization and the genetic algorithm was also combined to solve the optimization problem of charging and discharging [6]. In another study, the problem was tried to be solved only by using a genetic scheduler structure [7]. The Joint Searching (JS) scheduling algorithm is used with time-of-use pricing to maximize the profit of the charging stations [8]. The main problem of these studies is the high computational cost so that it was difficult to obtain a practical and feasible solution. Stochastic models are computationally faster, and they are more influential in making decisions based on predictions [3]. In a previous study, Munoz and Ruspini also used fuzzy queueing in EV charging [9]. The proposed study differs than this previous study by applying the fuzzy queueing method in a different way.

In this study, we prefer to use fuzzy queueing in the proposed solution. Fuzzy queueing is a robust method, which used to model queueing systems with a fixed number of servers, fuzzy arrival, and service rates [9]. Fuzzy queueing is a method with multiple parallel servers, which have finite or infinite system capacity and the arrivals to this system is managed by a possibility distribution [10]. The fuzzy queueing has been previously analyzed and described in various studies [11] - [13]. Since fuzzy queueing model in EV charging process is more promising and realistic than the traditional queueing model, it would be useful to do research on it [14].

This paper describes how to model the uncertainty in electric vehicle charging by using a fuzzy queueing based model. Unlike the previous studies in the literature, in this study not only uncertainty is modeled but also load control is carried out, so that power demand of the grid is controlled during EV charging process. Another contribution is the application of a fuzzy queueing in a different way to the vehicle charging process. It has been shown in the simulations that the proposed method produces better results than a traditional queueing method, and the proposed method utilizes charging stations better.

The rest of this paper is organized as follows. In Section II we explain preliminaries that are used to construct the proposed charging model and problem definition is given. In Section III efficiency of the proposed model is evaluated. We finally conclude the paper in Section IV.

II. THE PROPOSED MODEL

There are many uncertainties in the charging process of electric vehicles when real world situations are considered. An optimization should be done by considering various uncertainties, such as the number of simultaneous EVs to be connected to the grid or how fast the charge should be completed. In modeling the uncertain real-world problems, the fuzzy queues play a significant role.

EV charging problem is suitable for using a queue structure. Queue structure is concerned with modeling systems where some customers wait for a service. Fuzzy queues are used to represent the situations, which are difficult for traditional queueing methods. The EV charging process can be more suitably described by linguistic terms, such as urgent, fast or slow rather than probability distributions.

A. Fuzzy Set Theory

Uncertainty can be modeled with various approaches, and one way of doing this is using the fuzzy set theory, which formulates uncertainty by incorporating the linguistic variables. Fuzzy sets have elements with degrees of membership. A triangular fuzzy number can represent a triple with the following membership function:

$$\mu_A(x) = \begin{cases} 0 & x \leq L \text{ or } x \geq H \\ (x\text{-}L)/(M\text{-}L) & L \leq x \leq M \\ (x\text{-}H)/(M\text{-}H) & M \leq x \leq H \end{cases} \quad (1)$$

In this membership function of the fuzzy set A; L, M and H values denote low, moderate and high charging desires respectively, and L<M<H. This function is represented in Fig. 1. The triangular fuzzy number is denoted by (L, M, H) triple, and it becomes a non-fuzzy number when all values equal to each other.

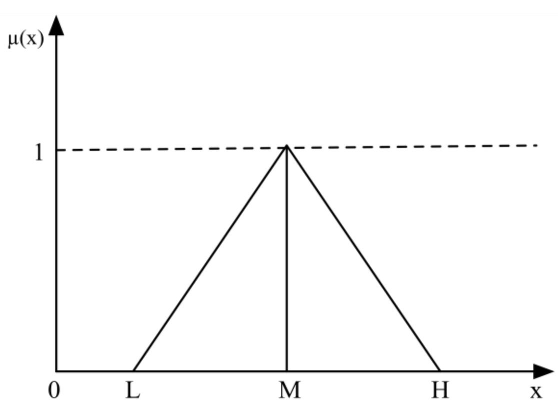

Figure 1. Membership function of the triangular fuzzy set.

B. Fuzzy Queueing Based Model

In this study, we use the fuzzy queueing model for EV charging. In this model λ denotes arrival rate of EVs to a charging station with Poisson distribution. The fuzzy service time of charging station is denoted by μ. The proposed fuzzy queueing model aims to have the least load on the grid while appropriately serving EVs. The λ rate is state independent because arrival rate does not depend on how many vehicles are already waiting in a charging station.

In the system there are total C charging stations, the total load is T and the maximum allowed load per charging station is M. If the system reaches the maximum allowed load, new arrivals have to wait. In the proposed queue model service rate and arrival rate of customers are fuzzy decision variables. Thus, service rate and arrival rate are described by linguistic terms, such as low, moderate or high instead of probability functions.

When there are N EVs in the system, then the rate of departure from charging stations is,

$$\mu_d = N\mu \text{ for } 0 \leq N < C \quad (2)$$

$$\mu_d = C\mu \text{ for } C \leq N \text{ and } T \leq M. \quad (3)$$

Little's Law explains the average number of customers, their effective arrival rate and service time. According to Little's Law, expected number of EVs in the system E_N is defined as follows.

$$E_N = \lambda E_W \quad (4)$$

Let A_k denotes the number of EVs at the k^{th} charging station forming a queue.

$$E(A) = \sum_{n=1}^{\infty} n a_n \quad (5)$$

E_N and E_W values are calculated by using the Markov process.

$$E_N = \frac{[\lambda E(A^2)]}{\mu[\mu\text{-}\lambda E(A)]} + \frac{\lambda E[A(A-1)]}{2[\mu\text{-}\lambda E(A)]} + \frac{\lambda(\mu+\tau)E(A)}{\mu\tau} - L_V \quad (6)$$

where A is a fuzzy set, τ denotes time taken to start charging, and L_V denotes the number of leaving EVs. L_V is calculated as

$$L_V = \frac{\lambda}{\mu} \quad (7)$$

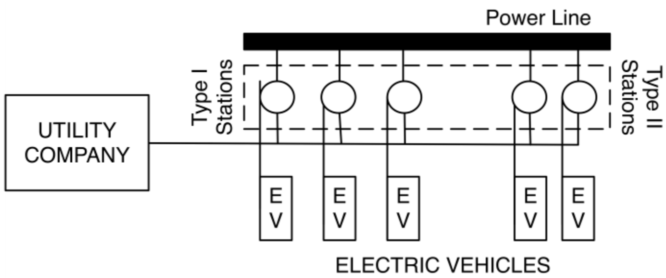

Figure 2. Entities of the problem space.

Finally, expected waiting time in the queue is denoted as E_W and expected occupation time for a charging station is denoted as E[S]. These values are calculated as follows,

$$E_W = \frac{\lambda E(\mathrm{A})}{\mu[\mu\text{-}\lambda E(\mathrm{A})]} + \frac{E[\mathrm{A}(\mathrm{A}-1)]}{2E(\mathrm{A})[\mu\text{-}\lambda E(\mathrm{A})]} + \frac{1}{\tau} \tag{8}$$

$$E[S] = \frac{\tau + \lambda E(\mathrm{A})}{\tau[\mu\text{-}\lambda E(\mathrm{A})]} \tag{9}$$

C. Problem Definition

EV charging problem can be defined as finding a balance between the grid load and total waiting time of EVs in the queue of stations. Grid load shouldn't be increased too much to cause peaks, and total waiting time of an EV shouldn't affect the daily routines of EV owners. As a result of a limited number of charging stations and limited allocated power resource, the problem can be formulated as finding the best resource allocation to organize the charging process.

As illustrated in Fig. 2 there are three entities in this problem: EVs, stations and the utility. Charging stations aim to serve the largest number of EVs while EVs aim to satisfy their charging demands. As the total number of charging stations is limited, only a portion of EVs being charged simultaneously in the charging stations. A model should guarantee that all charging requirements can be satisfied before EVs leaving the charging stations. Finally, the priority of the utility is preventing peak occurrences in the grid.

III. Simulation Results

In the simulation environment, charging stations have the first come first served (FSCF) principle, and jockeying is not allowed for the EVs as stations can be geographically away from each other. Charging stations work simultaneously, and priority is assigned to EVs according to their charging demands. There are two assumptions for the simulation environment, which simplify the construction of the simulation environment and do not affect the outcome of this study.

- EV batteries are assumed to be charged at the same rate.
- All EV batteries are assumed to have the same capacity.

Simulations have been conducted to evaluate the fuzzy queueing based charging model. Two different types of charging stations were used in these simulations. The properties of these charging stations according to SAE standards are given in Table I [15]. AC Level 2 charging stations are used to utilize fast charging.

In the simulation environment, there are total 20 charging stations formed by 15 AC Level 1 charging stations and 5 AC Level 2 charging stations. The total number of electric vehicles is 200, charging utilization is 100, and inter-arrival time is taken as 0. Service time depends on the state of charge of electric vehicle batteries, and service rate is determined by the SAE charging properties.

In the first simulation environment, the proposed model is compared with the traditional queueing model according to the average waiting time. Average waiting time of each EV is calculated by dividing total waiting time by the total number of vehicles. As it is seen in Fig. 3, it can be seen that the proposed model achieved a lower average waiting time than the traditional model. As the number of EVs increased, the performance gap also increased. This result indicates that proposed model can better organize the vehicle charging process. Finally, a sudden increase has been observed in the average waiting time for both models when the number of EVs is greater than 140. The reason is due to the resource limitations, which brings a difficulty to the both models in making an optimization.

In the second simulation environment, the number of EVs served by each charging station is analyzed for both models. There are again 200 EVs and 20 charging stations in the simulation environment. In Fig. 4, it is observed that the proposed model utilizes charging stations in a better way than the traditional queueing model. In this simulation, a more homogeneous workload for charging stations also indicates that the available resources are used in a more efficient way, which is also among one of the goals of this study.

TABLE I. SAE CHARGING PROPERTIES

Type	Voltage (V)	Peak Current (A)	Average Charging Time (Hour)
AC Level 1	120	16	7-17
AC Level 2	240	31	3-7

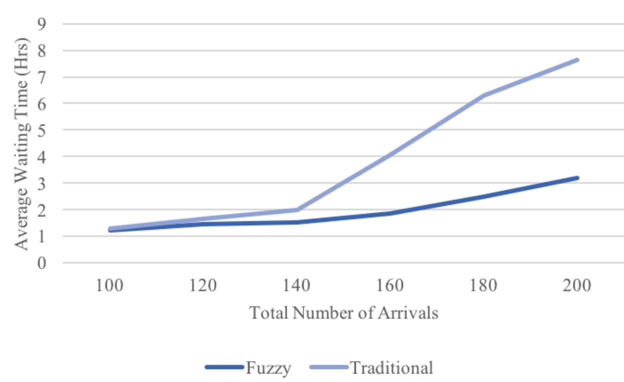

Figure 3. Comparison of average waiting time.

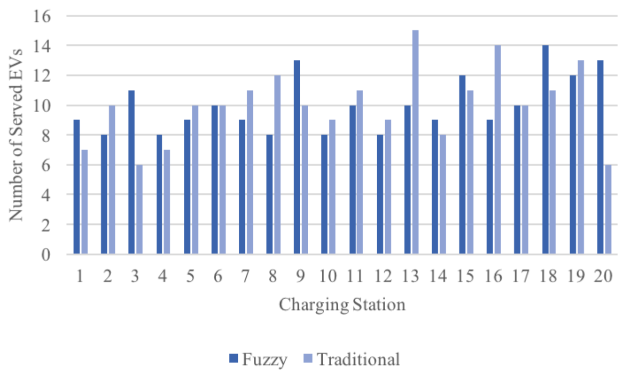

Figure 4. The number of EVs served by each charging station.

IV. CONCLUSIONS

Development of intelligent management structures for EV charging stations is an important research area in smart grid studies because penetration of a high number of EVs would likely lead to various problems in traditional grids. In this paper, we present a fuzzy queueing based model for controlling power demand of EV charging. In real world application, parameters in an EV charging system may be fuzzy and, therefore, the system performance measures should also be fuzzy. The simulation results show that the proposed model achieves a better performance than a traditional queueing model and it also shows a better performance in the utilization of charging stations. The proposed method can be expanded to the demand management problems in hybrid renewable energy systems.

The limitation of the proposed model is the lack of integration of control strategies of the utility. For this reason, in future studies, we plan to extend our research by incorporating dynamic electricity pricing mechanisms.

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