Reducing Probability of Transformer Failure by Managing EV Charging in Residential Parking Lots

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***Abstract*—The power of electric vehicle (EV) chargers is considerable and high penetration of EVs may lead to overloading and thermal stress for utility transformers. Large buildings usually are connected to the grid through a transformer. By managing EV charging in the building parking lots, the probability of transformer failure may be reduced. We propose a controller to manage the charging of the EVs to reduce the probability of transformer failure without the involvement of distribution grid operator. In order to test the proposed framework, a use case is developed using real and synthesized data from College Station, TX, United States.**

***Index Terms*—Electric vehicle, electric transformer, loss of life, hazard of failure, fuzzy control.**

I. Introduction

Electric vehicles (EVs) provide clean and environmental-friendly features and the increased public awareness have caused considerable increase in EV deployment [1]. This increase can cause repetitive utility transformer overloading and lead to accelerated ageing and increased probability of failure. Distribution transformers are not usually equipped with elaborate overload protection and monitoring devices and this overloading stress may remain undetected until it leads to transformer failure.

Apartment complexes are subject to this increased penetration of EVs. Due to cultural, financial, and social similarities in the residents of an apartment complex, the rapid increased penetration of EVs in some affluent neighborhood is quite likely. If the number of residential dwellings in an apartment complex is high enough, one transformer may be assigned for the whole building. Therefore, the charging of all EVs in the building can be managed using a single EV charging management system.

The adverse impact of EV charging on the transformer life is studied in [2], [3] and it is shown how increased penetration of EVs may lead to accelerated ageing of transformers and its economic impact is quantified. The impact that different EV penetration levels can have on transformers is studied in [4] and it is illustrated that even low level penetration can be troublesome. Deploying PV generation and battery energy storage to mitigate the transformer loss of life is introduced in [5] and [6]. The methods introduced in [5], [6] require the presence of PV generation and battery energy storage in the consumer location which may not be readily available and is costly to provide. In [7] and [8], a rule-based method is proposed in order to mitigate the impact of EV charging on transformer by peak shaving. In the authors' published work [9], a framework is proposed to manage the transformer risk of failure as well as loss of life using a charging scheduling system in the consumer location and a decision-support tool in the grid operator location. They interact in real-time to manage the charging. In the system proposed in the authors previously published work in [9], it is assumed that only one EV at a time can be charged in each building. Thus, this method cannot work in a parking space where several EVs need to be charged at the same time. Also, a communication infrastructure between the building and grid operator is needed. Structure and functionality of the controller in [9] is serving an operating condition for one residential building with one charging spot. The charging necessity factor as well as the decision-making algorithm used in [9] led to unready EVs in multiple occasions in the case study. In this paper, this index and the decision-making algorithm are revised to address the issue when multiple EVs are involved, which significantly changes the structure and functionality of the controller.

The main contribution of this paper is in developing the scheduling system for a residential apartment building parking with multiple EVs. Here, we include the capability of managing the charging of multiple EVs at the consumer location when a transformer is assigned specifically to the apartment building without a need for consumer-operator communications and operator decision tool. The economic impact of implementation of the proposed solution for several levels of penetration of EVs is studied. The method is tested using a realistic use case that is developed by deploying real and synthesized data.

The remainder of the paper is organized as follows. Transformer loss of life and hazard of failure are quantified in

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section II. In section III, the mitigation solution is explained. The case study and results are illustrated in section IV. Finally, the conclusions are outlined in Section V, followed by the references.

II. PROBABILITY OF TRANSFORMER FAILURE

In this paper, the probability of failure is quantified using the hottest spot temperature and Arrhenius-Weibull method [10]. In this method, firstly, the hottest spot temperature (θ_H) is calculated using the method proposed in IEEE Standard C57.91 [11]. The hottest spot temperature is used to calculate the loss of life as shown in (1).

$$Loss\ of\ Life = \frac{\sum_{n=1}^{N}[e^{(\frac{15000}{110+273}-\frac{15000}{\theta_H+273})}\Delta t_n]\cdot Analysis\ Time}{\sum_{n=1}^{N}[\Delta t_n]\cdot Insulation\ Life} \quad (1)$$

In this equation, Δt_n is the duration of the time step and N is the number of time steps. Analysis time is the duration of each time interval in which the loss of life is calculated. The insulation life is the expected life of the insulation from the beginning of transformer operation. The hazard function also can be defined as shown in (2).

$$H(t\,|\,\theta) = \frac{f(t)}{1-F(t)} \quad (2)$$

where H(t|θ) is the hazard function at time "t", the hottest spot temperature is θ, f(t) is the probability density function and F(t) is cumulative distribution function. The probability functions are determined using Weibull distribution and Arrhenius relationship. Due to lack of space, the method is explained only briefly in this section. More details can be found in [9]-[11].

When a transformer is purchased, the money paid for the transformer can be distributed in time-steps until the expected life is reached using equivalent cost of operating as explained in [9]. Transformer value (TV) at each moment is the value of the transformer cost of operation for the rest of its life from that moment and can be calculated using (3). In this equation, the initial transformer value is represented by equivalent hourly cost of operating the transformer and then the equivalent hourly cost is correlated to the transformer value at the end of the time step.

$$TV(t+1) = TV(t)\cdot\frac{(1-\frac{1}{(1+r)^{R(t+1)}})}{(1-\frac{1}{(1+r)^{R(t)}})} \quad (3)$$

where TV(t) is the transformer value at time t, r is the interest rate, and R(t) is the remaining life of the transformer at time t. In addition to loss of life using the transformer value, failure cost (FC) can be calculated using (4).

$$FC(t) = H(t\,|\,\theta)\cdot TV(t) \quad (4)$$

The total cost of the impact for each time step can be found using (3) and (4) as summarized in (5).

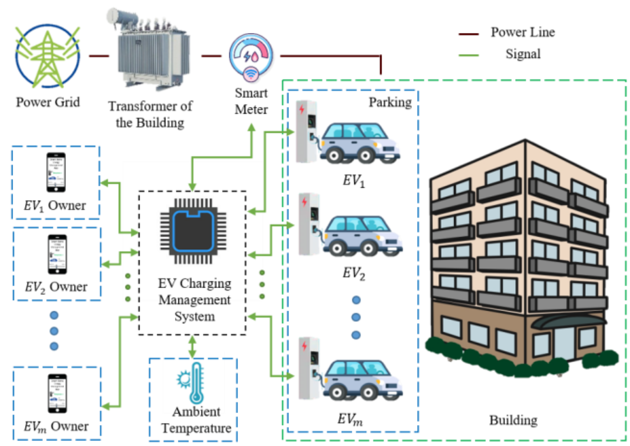

Figure 1. Schematic of the proposed architecture and controller

$$Cost = \overbrace{(TV(t+1)-TV(t))}^{Impact\ of\ Loss\ of\ Life} + \overbrace{(FC(t+1)-FC(t))}^{Impact\ of\ Failure\ Probability} \quad (5)$$

III. MANAGEMENT OF EV CHARGING

The proposed architecture is shown in Figure 1. There are n charging slots in the parking lot and the number of EVs connected to the chargers at time "t" is m(t). EV owners are in communication with the EV Charging Management System and receive the status of EV charging and can send their inputs. EV chargers send the request to charge to the management system and receive charging control signals from the system. The system also receives the transformer loading from the smart meter as well as the ambient temperature from an online real-time source. EV charging management system consists of several blocks as shown in Figure 2. The blocks are explained in details as follows.

A. EV Owner Inputs Preprocessor

This block receives the input data from each EV owners and calculates an index namely Charging Necessity Factor (CNF). It will send CNF and Comfort Level (CL) to the Fuzzy blocks.

1) Comfort Level (CL)

EV owners are able to select the comfort level from the available 11 levels which are numbers from 0 to 10. Comfort level 0 means that the customer selected the least level of comfort and highest level of saving, and the opposite is meant for level 10.

2) Estimated time of the next departure

This is the estimation of the next time of departure, which is determined by the EV owner.

3) Required state of charge (RSOC) for the next trip

Required state of charge needed for the next trip until the vehicle gets to a charging spot again. It is a number in percent.

After receiving all three inputs, the input preprocessor can calculate the CNF as shown in (6). CNF is an index that represents the risk of not having the vehicle ready with enough charging at the time the EV owner needs to depart.

$$CNF = \frac{(RSOC - SOC)\cdot BC}{TUD \cdot P_{Ch}} \quad (6)$$

where BC is the battery capacity in kWh, TUD is time until departure and P_{Ch} is the power of the EV charger.

B. Fuzzy Logic Blocks

Fuzzy logic is a powerful and effective control tool that has been used in many industries including the utilities [12]. Fuzzy logic is used in this paper to provide decision making using non-numerical and imprecise information. Considering that the factors used in the proposed method are based on comfort of consumer and availability of EVs, which can be considered non-numerical and imprecise, Fuzzy logic is a suitable option to be used for this purpose. The functions used in Figure 3 are calculated in real-time. Hence, their values are valid in real-time and will change when the operating condition change in time. In this paper, Fuzzy logic is used to introduce the customers' selection of CL as well as CNF into the decision-making process. In the fuzzification layer of the Fuzzy block, four levels of risk are defined for CNF and comfort level are defined as extreme, high, medium, and low. The fuzzy blocks fuse the two inputs of the fuzzification layer and calculates an index namely EV Participation Factor (EVPF) for EV "i" which is a number between 0 and 10 and represents the (un)availability of EV as well as the (dis)interest of EV owner in participating in the charging management. Higher EVPF will lead to higher charging price for the EV. The characteristics and rules of the implemented Fuzzy system are further explained in the authors' previously published paper [9].

C. CNF Checker

If time until departure is smaller than the needed time for EV to get to the required charging level, CNF will be bigger than 1. This can be used to determine whether the EV can participate or has to be charged. The role of CNF Checker is to check whether the CNF of the EV calculated by Inputs Preprocessor is bigger than one and if it is, the associated EVAF should be removed from the inputs and the EV is marked as unavailable for participation. The number of EVs available for participation is assumed to be p in Figure 2.

D. Transformer Probability of Failure Evaluation

Using the formulation introduced in Section II, the cost of transformer loss of life and failure is quantified by this block using the information of transformer loading and ambient temperature. It is then sent to the charging controller.

E. Charging Controller

The charging controller receives EVPF values for all EVs currently getting charged as well as the cost calculated by the transformer probability of failure evaluator. Using the algorithm shown in Figure 3, it selects the EVs for which the charging should be delayed for the time step. In this figure, "i" represents the "i"th EV. "Cost(i)" is the cost associated with transformer loss of life and probability of failure if the charging of EVs 1 to i is delayed. Inc(i) is the charging credit given to the EV owner for EV participation in the mitigation program, which can be used to decrease the charging cost of an EV. The calculated "i" using the algorithm shows that the charging of the first i-1 EVs should be delayed for the timestep.

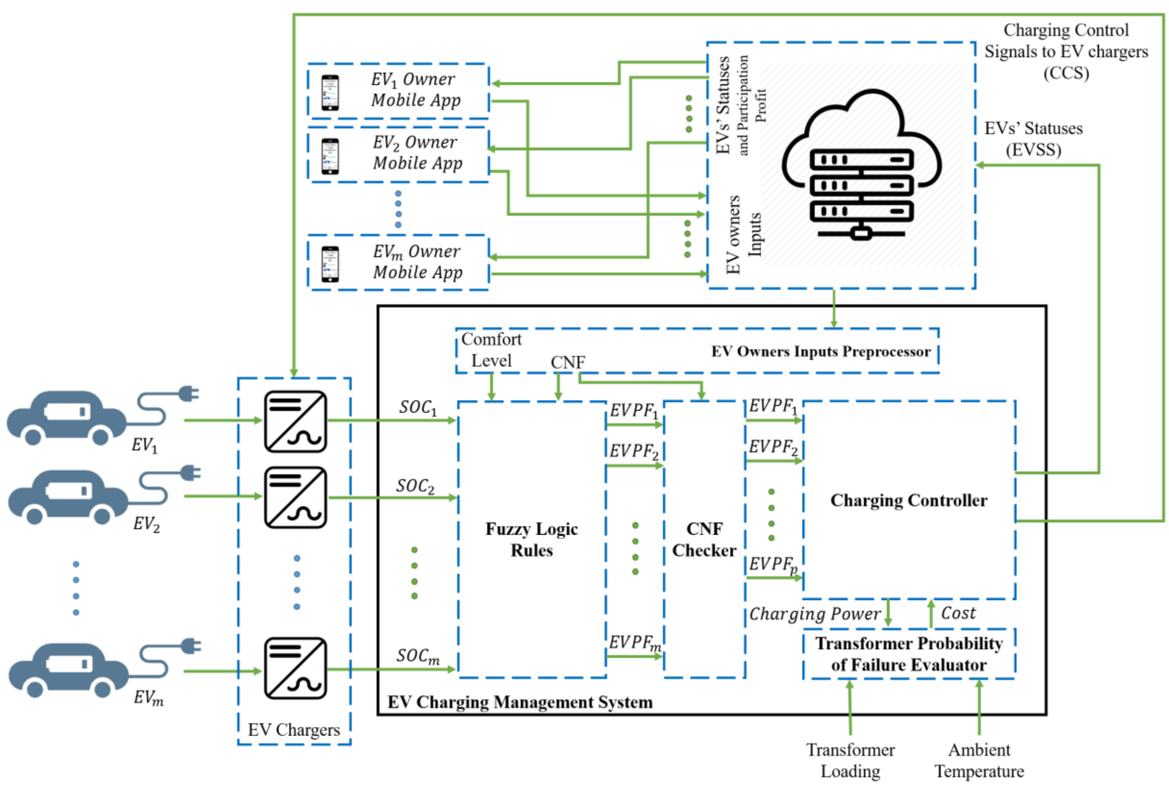

Figure 2. Schematic of the proposed framework and controller

IV. CASE STUDY AND RESULTS

The location for the experiment is considered to be College Station, Texas, United States. A one-year scenario is developed to test the proposed method. City of College Station ambient temperature data for one year is extracted from [13]. The EV loading data are synthesized using the available data of many trips [14]. The load data is generated using [15]. A separate CL is randomly generated for each EV owner in each time step. The characteristics of the transformer used for this study are shown in Table I. It is assumed the building is a residential apartment complex with 50 apartments. It is assumed there are 30 consumers with the low level, 15 with the base level and 5 with the high level of loading based on the levels introduced in [15]. The characteristics and details as well as differences between the three load levels can be found in [16].

TABLE I. CHARACTERISTICS OF THE TRANSFORMER

Nominal power	200KVA
Winding thermal time constant	7 minutes
Oil thermal time constant	114 minutes
Expected life in 100°C hottest spot temperature	180000 hours
Age at the start of the study	5 years
Replacement Costs	~20000$

For this case study, seven different scenarios are simulated as listed below. According to [14], the average number of vehicles for each household in the state of Texas is 2.6.

The test scenarios are:

A. No EV.

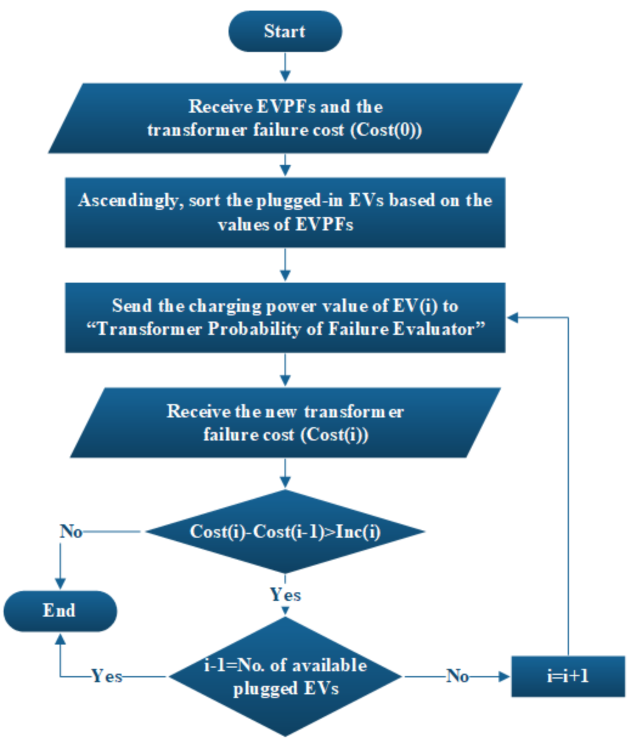

Figure 3. Charging controller algorithm.

B. 10% EV Penetration without charging management.
C. 10% EV Penetration with charging management.
D. 30% EV Penetration with no charging management.
E. 30% EV Penetration with charging management.
F. 50% EV Penetration with no charging management.
G. 50% EV Penetration with charging management.

In this case study, two types of EVs are randomly assigned to the EV owners. The characteristics of the EVs are shown in Table II. The incentive paid to the EV owners for their participation is calculated using (7).

$$Incentive_i(t) = EVPF_i(t) \cdot Electricity\ Price \qquad (7)$$

TABLE II. CHARACTERISTICS OF THE EVS.

	Battery Capacity (kWh)	Range with full charge (miles)	Full charge time (Hours)
Chevy Bolt EV	60	238	9.3
Nissan LEAF	60	226	8

As it can be seen in Figure 4, an increase in EV penetration in the building affects the building daily load curve unevenly where the increase in electricity consumption is higher in the evening. Also, the increase in the load is considerable in comparison to the load profile of the scenario without EVs. The 30% EV penetration almost doubles the electricity consumption of the building during peak hours. Another observation is that the average load profile in scenario A is well below the nominal rated power of the transformer. The transformer rating is selected intentionally to illustrate that increase of EV penetration will have conspicuous impact even when the transformer is over-sized.

The load profile of scenario G with 50% EV penetration and the management is shown in Figure 4 together with scenarios A and F, which correspond to the scenarios with no EVs and 50% EV penetration with no management, respectively. As illustrated in Figure 4, the proposed charging management system could effectively shave the peak by distributing the charging time of EVs to idle hours. The numerical results for all scenarios can be found in Table III. The results prove that the proposed solution could mitigate the transformer loss of life and reduce probability of failure. The most dramatic impact is

TABLE III. RESULTS FOR ONE YEAR USE CASE SCENARIOS

Scenario	Transformer probability of failure (%)	Economic impact of transformer failure ($)	Paid incentives ($)
A	8.7	1057	0
B	15.41	2087	0
C	10.11	1276	244
D	35.5	5261	0
E	16.94	2246	1684
F	77.97	18143	0
G	22.62	3099	5681

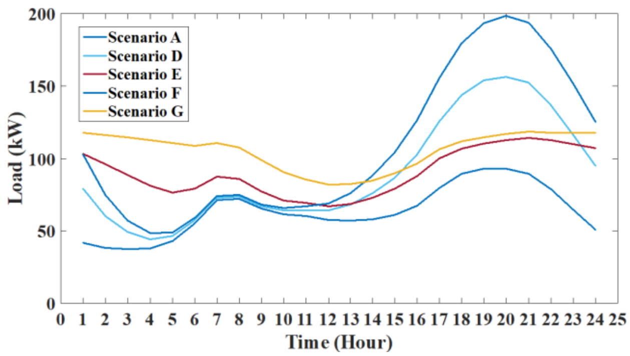

Figure 4. Average daily load profiles of scenarios A, F, and G.

for scenario F with no management where the chance of transformer failure is 78% while the proposed management system could reduce this probability to 23%. The total cost of each scenario which is the sum of economic impact of failure and paid incentives is decreased for all scenarios when the proposed management approach is deployed.

The profit of deploying the proposed controller for each scenario can be calculated by decreasing the cost of the no management scenario for a specific level of penetration from the scenario in which the controller is used for that specific level of penetration. The Incentives paid to the consumers is increased to $8517 when all EV owners decided to set the maximum CL all the time. The profit for this case is reduced to $6211 from $9363. The more interesting result came out from scenario E for which the paid incentive is increased to $2805 and the profit decreased to $152 from $1331. It shows that the consumer behavior can play an important role, particularly when the penetration of EVs is not high. Further study on consumers behavior and its role in determining the incentive is essential.

V. Conclusions

The paper proposes a charging management system for apartment complexes that schedules the charging of EVs in the associated parking area to reduce the probability of transformer failure. The outcomes of the proposed approach are:

- A Fuzzy logic-based controller is designed to generate EV participation factor based on the customer comfort level as well as the time and distance of the next EV trip.
- The proposed algorithm that schedules the charging of the connected EVs will reduce the cost of transformer failure.
- One-year use case scenarios developed to demonstrate the benefits of the proposed management system use real and synthesized data.
- The use case test results show that the proposed approach could effectively reduce the probability of transformer failure by making delays in EV charging and paying incentives to the EV owners in return.
- As an example, the probability of transformer failure is reduced by more than 55% for the scenario in which the penetration of EVs is 50%.
- For all scenarios, deployment of the proposed approach led to profit that increases for higher EV penetration levels. The lowest and highest profit was for 10% and 50% EV penetration which was $576 and $9363, respectively.

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