RISK-BASED RESIDENTIAL DEMAND SIDE RESPONSE

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Abstract

The advances in communication and utilization of internet of things enable residential dwelling occupants to manage their assets to provide services to the grid through demand response programs. However, it is essential that the comfort of the consumers is not affected and the programs do not require extensive manual management of the controller settings to keep the program attractive for the consumers. In this paper, a risk-based framework that automates management of the demand side response interactions between consumers and distribution system operator is proposed. A Fuzzy logic controller that optimizes time of operation of consumers' energy assets to minimize the risk to the consumers is defined in this paper. A case study is developed in which an unexpected increase in electric vehicles (EV) penetration causing a risk of overloading of distribution transformers is managed in an automated way using a demand side management program that utilizes the controller. The risk-based optimization results in the residential demand side response that successfully mitigates the stress on utility power transformers and yet meets the consumer expectations about the EV charging service availability.

1 Introduction

Due to an increase in penetration of distributed generation and change of the demand with the appearance of on-site battery energy storage and electric vehicles, more flexibility is needed to account for the demand change. Demand side management which meets this change from a passive to an active consumer is an option that can be considered when dealing with a flexible load [1].

The recent developments in communication infrastructure and rise of the internet of things (IoT) enables the residential consumers to provide services to the grid by adjusting and coordinating the time of use of their assets. This can be beneficial for the grid which receives the services and for the consumers which can be reimbursed through demand response program incentives. According to [2], the main reasons that residential consumers are not interested in participating in demand response programs are: 1) not wasting time tracking their electricity usage, and 2) the discomfort that can be caused due to remote control of their demand. Therefore, in demand response programs, it is essential to minimize the human interactions and the discomfort caused by the participation.

Current demand response programs can be divided into two main categories: a) price-driven, and b) incentive-driven methods [3]. For price-driven approaches, time of use [4], critical peak [5], and real-time pricing programs [6] are proposed. The main disadvantage of such programs is that they can include neither unexpected events nor undesirable operating conditions (e.g. time of use pricing) or they need continuous tariff tracing by consumers (e.g. real-time pricing).

There are several incentive driven programs such as direct load control [7], emergency demand response programs [8], and demand bidding [9]. Direct load control is intrusive and may cause discomfort of the consumers. Emergency demand response is only available in emergency situation and does not deploy the resources efficiently otherwise. Demand bidding requires extensive consumer attention and reaction based on the grid condition. The mentioned drawbacks may make such programs unsuitable for residential consumers.

In this paper, the risk is defined and quantified for different assets as a metric to evaluate how managing the assets impacts the comfort of the consumers. We propose a participation factor index to be used by the grid operator when deciding which assets will experience a risk from the consumers behaviour and how to incentivize the consumers to reduce the risk to the asset. Our contribution is the Fuzzy logic controller that calculates the risk level based on the proposed index.

The rest of the paper is organized as follows: In section 2, the risk for different assets is defined and quantified. The proposed on-site controller is explained in section 3. In section 4, use case is explained and the results of implementing the proposed controller in the use case are shown. Finally, the conclusions are outlined in section 5, followed by references.

2. Risk Assessment

The residential assets which are considered in this paper are as follows:

- Electric vehicle
- Washer and dryer
- HVAC
- Refrigerator and freezer

Each of these assets has its own specific characteristics and the risk of their unavailability should be assessed individually.

1.1 Electric Vehicle

In EV charging, it is important that an EV has enough battery charge for the planned trip at the time of departure. If the EV does not have enough charge for the next trip, the EV is not deployable because the EV user has to rely on some other transportation means. This leads to two factors being important for the risk assessment: a) the characteristics of the next trip, and b) the charging time. In addition to these factors, another index, namely the "comfort level" that represents the EV user's risk tolerance is defined. The inputs which are used in the risk assessment are:

- EV state of charge (SOC)
- Required state of charge for the next trip (RSOC)
- Estimated time of next departure

Before sending the inputs to the Fuzzy controller, they should be processed to provide a single input for the fuzzification layer. The risk of EV not having enough battery charge can be defined as:

$$R_{EV} = \frac{(RSOC - SOC)\cdot BC}{TUD \cdot P_{Ch}} \quad (1)$$

where BC is the battery capacity in kWh and P_{ch} is the rated power of the EV charger.

1.2 Washer and Dryer

The inputs that the user should provide for the washer and dryer are listed below:

- Load size
- Washing temperature
- Type of washing cycle
- Drying temperature
- The time when the load should be washed and dried

Load size, washing temperature, and type of washing cycle are used to calculate the washing time time T_w. The load size as well as drying temperature are used to determine the drying time T_D. The time left until the task is be done is designated as TU_{WD}. The risk associated with not having the load washed and dried on time is:

$$R_{WD} = \frac{T_W + T_D}{TU_{WD}} \quad (2)$$

Washing should be done before drying and there can be a gap between when washing is done and when drying is started.

1.3 HVAC

The inputs of the HVAC control system are as follows:

- Desirable temperature.
- Time when nobody occupies the dwelling.

The risk analysis for the HVAC is simple, because it is solely based on deviation of the dwelling temperature from the desirable temperature determined by the user. The time that takes for the HVAC to increase or decrease the temperature to reach the desirable temperature is yet another important input. The risk associated with HVAC can be calculated as follows:

$$R_F = \frac{|T_R - T_D|}{|T_a - T_R|\cdot \sigma_F \cdot P_{HVAC}} \quad (3)$$

where T_R, T_D, and T_a, are room, desirable, and ambient temperature respectively. σ_F is the building insulation constant and is defined as the temperature change caused by HVAC in an hour when the temperature difference between the inside and outside is one degree Celsius. P_{HVAC} is the rated power of HVAC. Definition of σ_F is inspired by the thermal transfer equation. Thermal transfer equation is shown in (4) [10].

$$Q = \frac{A\cdot k\cdot \Delta T}{L} \quad (4)$$

where A is the contact surface, k is the heat conductivity, ΔT is the temperature difference between inside and outside, and L is the thickness of walls. Using (4), σ_F can be defined as shown in (5):

$$\sigma_F = \frac{A\cdot k}{L} \quad (5)$$

1.4 Refrigerator and freezer (R&F)

In R&F, risk assessment depends on the goods inside and what is the required temperature for keeping the goods at the required temperature. For instance, one may keep medicine inside the refrigerator or freezer that can be made unusable if kept at higher temperature than required. If R&F fail to provide this condition, the medicine can be considered as a risk for the user. Using this information, the cycle of R&F motor operation can be adjusted in a way that it decreases the temperature to a lower level than needed so that in the near future when reduction of load is needed or there is an outage, the goods inside remain at desirable temperature. The inputs to the controller of this unit are:

- Maximum acceptable temperature for freezer ($T_{F,S}$)
- Maximum acceptable temperature for refrigerator ($T_{R,S}$)

The risk for freezer and refrigerator can be quantified using (3) and (4), respectively.

$$R_F = \frac{T_F - T_{F,S}}{(T_a - T_F)\cdot\sigma_F} \quad (3)$$

$$R_R = \frac{T_R - T_{R,S}}{(T_a - T_R)\cdot\sigma_R} \quad (4)$$

where T_a is the ambient temperature and σ is the insulation factor which is the time it takes for one degree increase in the inside temperature when there is a temperature difference between inside and outside. It may be given by the manufacturer or can be calculated by the controller. T_F and T_R are the real-time freezer and refrigerator temperatures respectively.

1.5 Comfort Level (CL)

The Comfort level is an index defined to determine the level of discomfort that the user can accept in return for incentives. In the concept of risk explained in this paper, the risk is associated with the level of discomfort tolerated by the user. Such risk can be defined for each asset individually.

3 Central Participation Controller

The separate risk assessments of owner's assets will be given to the central participation controller. The schematic of the central participation controller and its communications with other parts of the system are shown in Figure 1. The inputs set by the residents will remain unchanged unless they enter new settings to the controller.

The assets status is calculated based on the risk for each asset. The risk values will be used as inputs to the Fuzzy logic system. The membership function used to fuzzify all risk values is shown in Figure 2. This figure shows four risk levels, namely, "low", "medium", "high", and "extreme". Risk value of each asset as well as its comfort level are the inputs to a separate fuzzy logic system. However, the rules of the fuzzy inference system are the same for all the assets as shown in Table 1. The capital letters used in Table 1 refer to the membership degrees of outputs utilized for defuzzification as shown in Figure 3.

Table 1 Fuzzy logic inference system rules.

Risk \ CL	**Low**	**Medium**	**High**	**Extreme**
Low	D	E	F	G
Medium	C	D	E	F
High	B	C	D	E
Extreme	A	B	C	D

The outputs of the fuzzy logic systems are called assets participation factors (APF). APF_1 to APF_5 represent EV, washer and dryer, HVAC, and freezer, and refrigerator, respectively.

The participation factor calculator receives all APFs and categorizes them in 11 levels from zero to 10. The value of

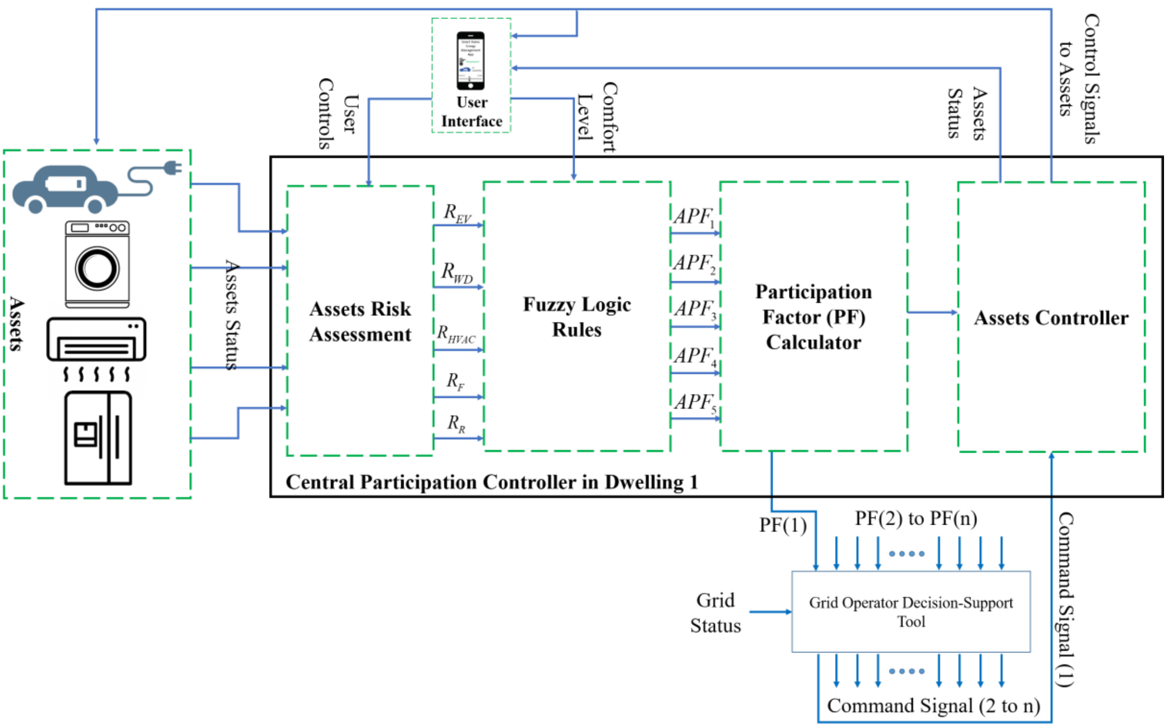

Figure 1 The schematic of the proposed controller

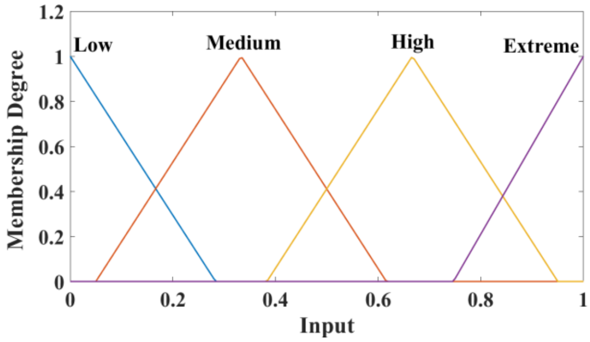

Figure 2 Membership function of inputs.

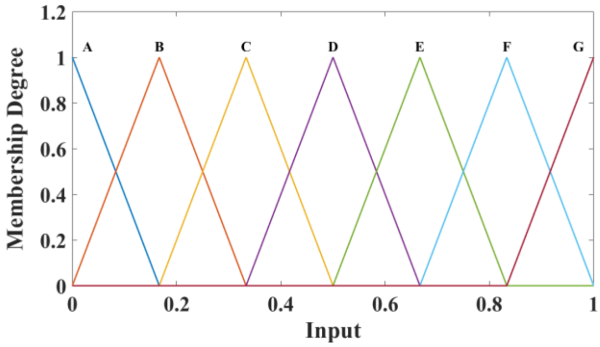

Figure 3 Membership function of outputs.

APFs are between 0 and 1. In participation factor calculator, APFs are multiplied by 10 and then rounded to the nearest integer. Assume the result is "*i*". Based on the result, the power of the asset is added to the value of the i-th member of a column matrix 1x11 called participation factor (PF). The values of the PF matrix members are reset at the beginning of each time-step (15 minutes in this study).

PFs are sent to the grid operator to be used in the decision-making process regarding deployment of the assets in the demand response program. When the decision is made, the command signals are sent to the controllers in the dwellings. The dwelling assets controller role is to disable or enable the assets depending on the signal received from the grid operator. In our case study, we assumed that the demand response is implemented to decrease the loss of life and probability of failure of the distribution transformers.

4 Case Study and Results

The experiment is designed based on the electricity consumption and temperature data of the City of College Station. Temperature data are obtained from [11]. In order to generate the load data, the load curves provided in [12] are used along with a probabilistic approach to logically randomize the asset time of deployment. The EV load is synthesized by analysing daily trip data provided in [13]. It is assumed that 30% of EV trips are done by all residents and during these trips the dwelling is assumed to be unoccupied. When nobody is in the residence, the HVAC as well as the washer and dryer are assumed not to be in use. For this case study, ten houses connected to a distribution transformer are considered and it is assumed that eight of them are using the proposed controller and are enrolled in the demand response program.

The service provided by the demand response program in this paper is aimed at reducing the loss of life and mitigating the probability of failure of the distribution transformer. The risk of this happening is caused by rapid deployment of EVs, and consequently, overloading of the transformer because it was not appropriately sized to handle the load of EVs in addition to the traditional dwelling's load. More details about the transformer overload can be found in [14-16]. Although in this case study the transformer loss of life and probability of failure mitigation are selected as the demand side services provided to the grid, the same approach can be used in selecting the participants for load reduction to provide other services.

In this use case, it is assumed that ten residential consumers are using the controller and they are all connected to the same transformer. The nominal power of the transformer is assumed to be 150kVA. Implementing the selected use case, we illustrate that deployment of the proposed controller could reduce the transformer loss of life and probability of failure considerably. The results are shown in Table 2. In this table, scenario A is when the controller is not used and scenario B is when the controller is used to manage the demand response.

Table 2 Transformer loss of life and probability of failure.

Scenario	Loss of life (%)	Economic impact transformer ageing and failure ($)	Paid Incentives ($)
A	53.5	7579	0
B	3.1	3361	1342

The average daily transformer load profile before and after

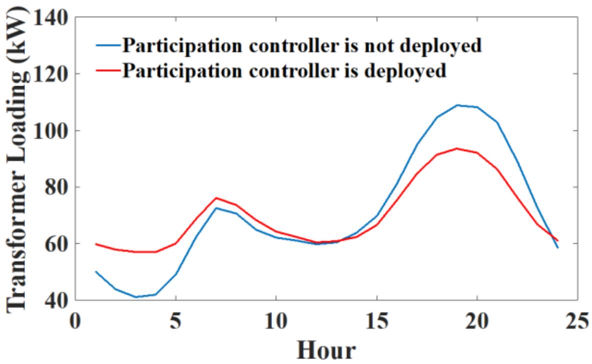

Figure 4 Transformer load profile.

deploying the controller to manage the demand response of the dwellings downstream from transformer is illustrated in Figure 4. It can be seen in this figure that the controller managed to shave the peak and move the load from the peak hours to late night hours when the demand is lower.

4 Conclusion

This paper proposes a risk-based evaluation of the assets in a residential dwelling for the purpose of participation in a demand response program. The focus is to cause minimal discomfort for the consumer when the assets are deployed to provide services to the grid through a demand response program. The main outcomes of the proposed approach are:

- The risk posed to the consumer from deployment of the dwelling assets through participation in demand response program is quantified in real-time.
- A fuzzy logic-based controller is developed to provide a participation factor to the grid operator to decide which consumer asset should be deployed when service is needed.
- A use case scenario in which a distribution transformer is operating under periodical overloading for one year is developed to test the effectiveness of the proposed solution.
- The results show that deployment of the residential consumers' assets in demand response program can reduce transformer replacement cost for the electric utility and at the same time create income for the participating consumers.

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