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A New Incentive-Based Optimization Scheme for Residential Community With Financial Trade-Offs

ZHEN NI, (Member, IEEE), AND AVIJIT DAS, (Student Member, IEEE)
Electrical Engineering and Computer Science Department, South Dakota State University, Brookings, SD 57007, USA

Corresponding author: Zhen Ni (zhen.ni@sdstate.edu)

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ABSTRACT Demand-side management and incentive-based optimization have the potential to improve energy efficiency of modern smart homes and smart communities. Existing approaches only refer to consumers' comfort level to thermal-related electric appliances. Other controllable appliances may not be included in the incentive designs, and the total community power consumption is somehow neglected. Thus, the involvement of residents' participation is limited. To address this issue, we propose a new incentive-based residential energy optimization system to manage community demand reduction requests efficiently and, meanwhile, reward consumers with multi-level financial incentives and guaranteed comfort. A new design of comfort indicator is used, which considers both thermal and major controllable electric appliances based on the consumers' comfort level. We integrate a genetic algorithm to solve this optimization problem, i.e., to minimize the reward costs for the utility (according to maximize the consumers' comfort level). As an alternative approach, the mixed integer programming technique is also employed if the objective function includes a certain piecewise linear decision variable. Simulation studies on both 10-house and 100-house cases show that the proposed approach is outperformed two existing approaches in terms of reward incentives, comfort levels, and the number of active appliances.

INDEX TERMS Community energy optimization, financial incentives, genetic algorithm, comfort indicator, demand response, and residential energy management system.

NOMENCLATURE

N	Total number of households.
$P_{AC,i}$	Power rating for the air conditioner of resident i, kW.
$S_{AC,i,t}$	Status of the air conditioner of resident i at time t.
$1_{\{.\}}$	Indicator function which represents the value should be 1 if the conditions are met.
$S^c_{AC,i,t}$	Controller status of the air conditioner of resident i at time t.
$To_{r,i,t}$	Initial room temperature of resident i, °F at time t.
$LR_{a,i}$	Room temperature loss rate of resident i.
$TA_{a,i}$	Ambient temperature for the air conditioner of resident i, °F.
a_i	Effect of the air conditioner of resident i, °F/kW.
$T_{Low,i}$	Low temperature defined by resident i, °F.
$T_{High,i}$	High temperature defined by resident i, °F.
$P_{WH,i}$	Power rating for the electric water heater of resident i, kW.
$S_{WH,i,t}$	Status of electric water heater of resident i at time t.
$S^c_{WH,i,t}$	Controller status of the electric water heater of resident i at time t.
$To_{w,i,t}$	Initial tank temperature for the electric water heater resident i, °F at time t.
$T_{WH,L,i}$	Low temperature for the electric water heater defined by resident i, °F.
$T_{WH,H,i}$	High temperature for the electric water heater defined by resident i, °F.
$LR_{w,i}$	Tank temperature loss rate of resident i.
$TA_{w,i}$	Ambient temperature for the electric water heater of resident i, °F.
e_i	Effect of the electric water heater of resident i, °F/kW.

$P_{h,CD,i}$	Cloth dryer heating rated power of resident i, kW.
$S_{CD,i,t}$	Control signal from community energy management system for the cloth dryer of resident i at time t.
$P_{m,CD,i}$	Cloth dryer motor rated power of resident i, kW.
$T_{CD,i,t}$	Operation status of the clothes dryer of resident i at time t.
$P_{h,DW,i}$	Dish washer heating rated power of resident i, kW.
$S_{DW,i,t}$	Control signal from community energy management system for the dish washer of resident i at time t.
$P_{m,DW,i}$	Dish washer motor rated power of resident i, kW at time t.
$T_{DW,i,t}$	Operation status for the dish washer of resident i at time t.
$P_{EV,i}$	Electric vehicle rated power of resident i, kW.
$S_{EV,i,t}$	Status of the electric vehicle of resident i at time t.
$p_{cri,i,t}$	Critical loads of resident i, kW at time t.
TA_i	Total number of appliances of resident i.
$NA_{i,t}$	Total number of active appliances of resident i at time t.
$CP_{i,t}$	User defined number of active appliances should be turned on at time t.
R_1, R_2 and R_3	Reward rates, $cents/kW.5minutes$.
$P_{total,i,t}$	Power consumption capacity of resident i, kW at time t.
$P_{c,i,t}$	Total power consumption of resident i, kW at time t.
$P_{L,i}$	Lower bound of the power consumption defined by resident i, kW.
w_1, w_2 and w_3	Weights of comfort indicator.
$RW_{i,t}$	Total reward cost of resident i at time t, \$.
M	Large enough constant.
$v_{i,t}$	Binary variable.
η	Weight of objective function.
l	Priority number.

I. INTRODUCTION

Due to the increasing penetration of intermittent distributed energy resources and the ever-increasing electricity demand, community energy optimization becomes a critical issue in peak hours. Demand side management (DSM) is one popular solution to solve this problem. The main objective of DSM is to encourage users to consume less power during peak hours and shift their needs to off-peak hours [1]. According to [2], in the U.S.A., residential load demands consume 38% of total electricity energy consumption. Involving residents and encouraging them to participate in certain energy management and optimization schemes becomes a critical issue in modern smart home and smart community area.

In the existing literature, demand response (DR) can be categorized into price-based demand response (PBDR) and incentive-based demand response (IBDR) programs [3]. Generally, various techniques are used in the PBDR program, such as time-of-use, critical peak pricing, peak load reduction pricing, and real-time pricing [4]–[13]. Many residential customers are risk-averse, and they are not making decisions about electricity consumption on a daily or hourly basis. Also, equity problems might arise from time-dependent retail rate schemes, such as the day shift versus the night shift. Because of these issues, time-varying retail rate schemes still face obstacles in many regions when it comes to large-scale deployment [14].

According to [15], the IBDR programs are responsible for 93% of peak load reduction in the U.S. today. In recent years, the utility companies started to conduct IBDR programs to increase their revenues by aggregating residential demands [16], [17]. Fifty-five utility companies across the U.S.A. offer IBDR programs to their residential customers [18]. The IBDR program is based on DSM and the participants are financially rewarded according to their quantified contributions during peak hours. It can also be described as an incentive payment program to reduce usage of electricity when the grid reliability is jeopardized [3]. The consumers who participated these programs reported that their comfort levels were affected and the incentives are not attractive enough [18]. Hu *et al.* [18] and Perfumo *et al.* [19] investigated DR programs where the aggregated demands are controlled by adjusting the temperature settings of the thermostatically controllable loads, i.e., air conditioner. Khalid *et al.* [20], Ghazvini *et al.* [21], [22], Cole *et al.* [23], Das and Ni [24], Anandalaskhmi *et al.* [25], Ni *et al.* [26], and Paudyal *et al.* [27] proposed different methods to minimize the peak hour load demands, to minimize the operational cost of the utilities and to maximize the benefits of the program participants. In [28]–[30], decentralized coordination techniques for DR aggregation are presented. These studies mainly focused on off-line algorithms, which are more suitable for day-ahead markets. The aggregated costs of the decentralized coordination techniques are usually higher than the centralized coordination techniques [31]. The DR problem considering residential appliances with mixed-integer operating constraints is proposed in [32]. The DR problem is only formulated for inelastic residential appliances which is a limitation in practice.

Pipattanasomporn *et al.* [9], Shao *et al.* [33], and Haider *et al.* [34] propose DR schemes that consider both controllable and non-controllable residential appliances for minimizing the peak-hour load demand and operational cost of the utility. A centralized DR framework with consumers' responsiveness for different pricing strategies are presented in [35]. In [36], an incentive-based demand reduction bidding strategy is proposed for the consumers. They propose an algorithm based on dynamic programming technique to maximize the profit of the energy service provider. A hierarchical residential load management system using particle swarm optimization is proposed to optimize the load and the customer comfort index (comfort parameters are temperature, illumination, and indoor air quality) in [37]. Ozturk *et al.* propose a branch and bound algorithm based technique for minimizing the cost of scheduling consumer load according to the environment/social factors. In the aforementioned literature, maximizing consumers' comfort levels while minimizing the operational cost of the utility are not well-organized. Specially, for the calculation of consumer comfort level, major residential electric appliances are not taken into consideration which may misguide the controller in terms of consumer comfort level.

Motivated by the above mentioned references, we propose a new residential energy optimization scheme to address demand reduction requests (DRRs) efficiently. Compared to prior works [18], instead of considering only thermal-related electric appliances, the proposed energy optimization scheme considers all the residential home electric appliances (both controllable and critical loads) in demand response. The problem is formulated to minimize the sum of total reward cost for utility and comfort indicator (CI) for consumers. Note, minimizing CI is to maximize the comfort level of the consumers. Genetic algorithm (GA) approach is used as a general approach to solve the non-linear residential demand optimization problem considering operational constraints. As an alternative approach, mixed integer programming (MIP) technique is also investigated which is applicable for the proposed optimization scheme due to piecewise linear objective/reward function. The performance of the proposed approach is compared with the existing approaches in [18] and [25] in terms of total financial rewards from the utility and average comfort level of the residents. For participants, the proposed strategy can 1) distribute financial rewards according to their quantified participation in the DR events, and 2) maintain their comfort level based on their energy consumption preferences. For the utility, the proposed strategy can 1) execute the DRRs by controlling residential appliances, and 2) minimize the total reward costs of the utility by performing DRRs. By benefiting both users and the utility, the proposed strategy is expected to attract more participants and further utilize the potential capability of controllable residential demand-side resources.

The rest of this paper is organized as follows. The model description of the residential appliances is presented in Section II. The proposed optimization scheme is described in Section III. The solution designs are demonstrated in Section IV. The simulation setup and results analysis are carried out in Section V. Finally, the conclusion is provided in Section VI.

II. MODEL DESCRIPTION OF THE RESIDENTIAL APPLIANCES

Residential appliances can be classified into two types: 1) controllable or non-critical loads and 2) uncontrollable or critical loads. The controllable loads have high potential to participate in the DR events and earn rewards. The controllable appliances are controlled by the community energy management system (CEMS), which is responsible to change the status of the controllable appliances in response to the specified DRR by the utility.

A. AIR CONDITIONER MODEL

Air conditioner (AC) is one of the major controllable residential appliances. The power consumption of the AC depends on the operating status of the AC. If the status is ON, it consumes the rated power; if the status is OFF then the power consumption is zero. The power consumption equation of the AC for resident i at time t can be expressed as [9],

$$p_{AC,i,t} = P_{AC,i} S_{AC,i,t}. \tag{1}$$

where, $S_{AC,i,t}$ represents the ON/OFF status, and $S_{AC,i,t} = 1_{\{T_{Room,i,t} > T_{High,i}\}}$.

The indoor air temperature of the house with the ACs can be estimated as [18],

$$T_{r,i,t} = To_{r,i,t} - LR_{a,i}(To_{r,i,t} - TA_{a,i}) - a_i p_{AC,i,t}. \tag{2}$$

where, the parameters $LR_{a,i}$, a_i, and $p_{AC,i,t}$ are different for each resident.

B. ELECTRIC WATER HEATER MODEL

The power consumption of the electric water heater (EWH) for resident i at time t can be calculated as [9],

$$p_{WH,i,t} = P_{WH,i} S_{WH,i,t}. \tag{3}$$

where, $S_{WH,i,t}$ represents the ON/OFF status and $S_{WH,i,t} = 1_{\{T_{WH,i,t} < T_{WH,L,i}\}}$.

For estimating the water temperature in EWH at time t, the equation can be written as [18],

$$T_{w,i,t} = To_{w,i,t} - LR_{w,i}(To_{w,i,t} - TA_{w,i}) + e_i p_{WH,i,t}. \tag{4}$$

where, the parameters $LR_{w,i}$, e_i, and $p_{WH,i,t}$ are different for each resident.

C. CLOTH DRYER AND DISHWASHER

The cloth dryer (CD) and dishwasher (DW) are task-based appliances. In these appliance models, two power consumption parts need to be considered, one is for motor part and another one is for heating coils. The CEMS controls these appliances by turning OFF the heating coils without interrupting the motor part to ensure that these appliances can resume its operation without the residents' action. The power consumption equation of the cloth dryer for resident i at time t can be expressed as [33], [34],

$$p_{CD,i,t} = P_{h,CD,i} S_{CD,i,t} + P_{m,CD,i} T_{CD,i,t}. \tag{5}$$

Like the CD, the power consumption equation of the DW can be written as,

$$p_{DW,i,t} = P_{h,DW,i} S_{DW,i,t} + P_{m,DW,i} T_{DW,i,t}. \tag{6}$$

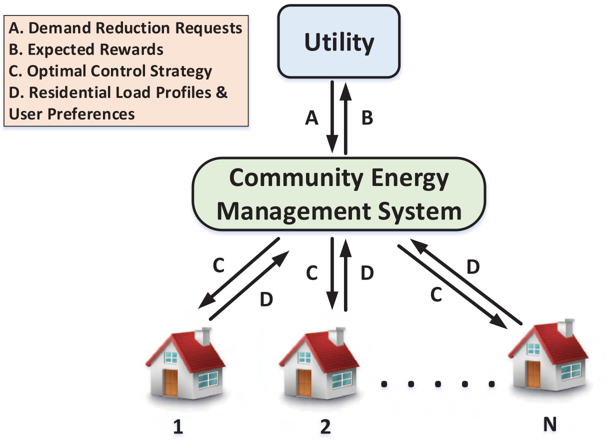

FIGURE 1. The community energy management system model and information flow.

In this paper, we assume that the DW consumes the rated power during its operation. In reality, the power consumption of this type of appliance may differ with different cycles but we can always average the power consumption in a period of time.

D. ELECTRIC VEHICLE MODEL

The power consumption by the electric vehicle (EV) for charging, can be written as [9],

$$p_{EV,i,t} = P_{EV,i}S_{EV,i,t}. \tag{7}$$

For electrical vehicles, we consider only normal charging mode and assume that the electrical vehicles consume the rated power during the active mode.

E. CRITICAL LOADS

The critical loads (CLs) of the household may include refrigeration, freezing, cooking, lighting and other non-controllable electric appliances. A random profile which has a maximum value of 2 kW and a minimum value of 1 kW is selected in the simulation program [9]. The uniform probability distribution is used for the random profile.

III. PROPOSED OPTIMIZATION SCHEME

A. OVERVIEW OF THE OPTIMIZATION SCHEME

The proposed model and information flow chart are illustrated in Figure 1. In the proposed design, the CEMS serves as an agent who receives DRRs from the utility and executes the DRRs by controlling residential appliances. According to the design, the utility sends DRR signal to the CEMS (signal - A) and every household of the community sends residential load profiles and their preferences (signal - D) to the CEMS. Then, the CEMS generates the optimal control strategy (signal - C) for residential appliances based on users' preferences and sends the estimated rewards to the utility (signal - B).

B. DESIGN OF COMFORT INDICATOR, INCENTIVES AND OBJECTIVE FUNCTION

1) COMFORT INDICATOR DESIGN

When the utility sends the DRR signal to the CEMS, distributing that DRR to the community residents in consideration of their comfort level is the most critical issue for the CEMS. In a community, residents have different user habits. During a DR event, it is very important to schedule the residential appliances in a proper way so that the utility can minimize their reward costs and maximize the comfort level of the residents. To address this issue, in this paper, we propose a CI term for each resident which will measure the comfortability of the resident based on their user habit and preferences.

The proposed CI is designed considering three different items: i) CI for the air conditioner, ii) CI for the water heater, and iii) CI based on number of active appliances during optimization period. A weighted sum of normalized equation is used to aggregate the CI terms as,

$$CI_{i,t} = w_1 CI_{AC,i,t} + w_2 CI_{WH,i,t} + w_3 CI_{S,i,t}. \tag{8}$$

where the sum of the weights are assumed as 1.

The CI of the air conditioner at time t can be designed with a normalized equation as,

$$CI_{AC,i,t} = \left| \frac{2T_{r,i,t} - T_{Low,i} - T_{High,i}}{T_{High,i} - T_{Low,i}} \right|. \tag{9}$$

If the $CI_{AC,i}$ value is getting high, the resident i will start feeling uncomfortable and vice versa. This formula is similar as the CI in [18]. Similarly, the normalized equation of the CI of water heater for resident i at time t can be written as,

$$CI_{WH,i,t} = \left| \frac{2T_{w,i,t} - T_{WH,L,i} - T_{WH,H,i}}{T_{WH,H,i} - T_{WH,L,i}} \right|. \tag{10}$$

During peak hours, the comfort level of the resident also depends on the number of appliances he/ she can use. In the peak time period, users want to best use their appliances, and load curtailment may hamper their daily lives. We introduce an appliance status based CI as,

$$CI_{S,i,t} = \left| \frac{TA_i - NA_{i,t}}{TA_i - CP_{i,t}} \right|. \tag{11}$$

where, the number of active appliances $NA_{i,t}$ for resident i can be calculated as,

$$NA_{i,t} = \sum_i S_{i,t}. \tag{12}$$

The active appliance status set $S_{i,t}$ for resident i at time t can be expressed as,

$$S_{i,t} = \{S^c_{AC,i,t}, S^c_{WH,i,t}, S_{CD,i,t}, S_{DW,i,t}, S_{EV,i,t}, S_{cri,i,t}\}. \tag{13}$$

where, the status for all critical loads $S_{cri,i,t}$ is assumed as 1 (ON).

In this paper, the CI is designed in such a way that the value of CI greater than 1 represents the resident is uncomfortable and the value of CI less than or equal to 1 represents the resident is comfortable.

According to the optimization scheme, the controller distributes the available energy of the utility to the community residents based on their load profiles, preferences and comfort levels. The energy distribution of the utility can also be defined as power limit of the resident. If the power consumption of the resident is higher than the optimized power limit, then the controller turns off the appliances based on the priority list of the resident to make the power consumption within the power limit. When the room temperature and water temperature are within the defined range, then the CEMS turns off the AC and the EWH appliances and allocates the power consumption of these appliances to other appliances to keep the consumer in his/her comfort zone. The comfort level of the thermostatically controllable loads depends on the temperature. Since we incorporated the number of active appliances in the CI during the optimization period, if the temperature of these appliances can be maintained within the consumers' comfort zone then these appliances can be assumed as active appliances. To address this issue, during the DR event, if the room temperature and water temperature of the house are within their comfort zone, then the controller statuses ($S^c_{AC,i,t}$ and $S^c_{WH,i,t}$) of these appliances are assumed as 1, though the statuses of these appliances ($S_{AC,i,t}$ and $S_{WH,i,t}$) are 0. The relationship can be expressed as,

$$S^c_{AC,i,t} = \begin{cases} 1, & \text{if } T_{Low,i} \leq T_{Room,i,t} \leq T_{High,i} \\ S_{AC,i,t}, & \text{otherwise} \end{cases} \tag{14}$$

$$S^c_{WH,i,t} = \begin{cases} 1, & \text{if } T_{WH,L,i} \leq T_{WH,i,t} \leq T_{WH,H,i} \\ S_{WH,i,t}, & \text{otherwise} \end{cases} \tag{15}$$

According to the relationship, the controller status of the AC and the controller status of the EWH output 1 if the room temperature and water temperature are within the resident's comfort zone and output the same value as the status of these appliances ($S_{AC,i,t}$ and $S_{WH,i,t}$) for other temperature conditions.

2) REWARD DESIGN

The relationship between $CI_{i,t}$ and the reward rates can be designed with a hierarchical structure as,

$$RWR_{i,t} = \begin{cases} R_1, & \text{if } CI_{i,t} \leq 1 \\ R_2, & \text{if } CI_{i,t} > 1 \text{ and } compromise_i = 1 \\ R_3, & \text{if } CI_{i,t} > 1 \text{ and } compromise_i = 0 \end{cases} \tag{16}$$

The reward rate structure is adopted from [18]. The participant needs to share information of the residential load profiles, comfort temperature setting for temperature-dependent appliances, priority list of the appliances (if any), and whether he/she is willing to compromise comfort by curtailing the loads. The lowest and highest rewards are R_1 and R_3, respectively. In the reward structure, the $compromise_i$ represents if the resident is willing to compromise his/her comfort level or not. The $compromise_i = 1$ represents that the resident is willing to compromise. If any resident is not willing to compromise his/her comfort level ($compromise_i = 0$), then he/she will get a higher reward if the CEMS curtails any load from him/her. Any resident may intentionally choose $compromise_i = 0$ to gain more financial benefits with the expectation to receive the highest reward rate, R_3. However, the emergency cases may occur very rarely such that the resident may not have much chance to receive R_3 reward while losing opportunities to receive R_2 rate.

According to the reward structure, if the $CI_{i,t}$ value is less than 1, the user will be rewarded at R_1 rate. If the $CI_{i,t}$ value is greater than 1 and $compromise_i = 1$, then the user will receive reward at R_2 rate. And R_3 reward is for the users who do not want to compromise ($compromise_i = 0$) and whose $CI_{i,t}$ value is greater than 1. To be fair for all the residents, the CEMS keeps a record of the DRR participation history for every resident. If multiple residents have same CI values, the CEMS will choose the resident with a lower DRR contribution history to maintain a fair and equal opportunity for all the residents.

The reward rate structure can be written as [18], [40],

$$RWR_{i,t} = R_1 v_{i,t} + R_2(1 - v_{i,t})com_i + R_3(1 - v_{i,t})(1 - com_i). \tag{17}$$

where, $v_{i,t}$ is a binary variable and com_i is representing $compromise_i$.

3) OBJECTIVE FUNCTION

The objective is to minimize total reward cost for the utility while maximizing the comfort level of the residents (thereby minimizing comfort indictor). The objective function can be expressed as,

$$y_t = \min_{P_{c,i,t}, v_{i,t}} \left\{ \sum_{i=1}^{N} RW_{i,t} + \eta \sum_{i=1}^{N} CI_{i,t} \right\}. \tag{18}$$

subject to the constraints as,

$$\sum_{i=1}^{N} (P_{total,i,t} - P_{c,i,t}) \geq DRR. \tag{19}$$

$$P_{L,i} - P_{c,i,t} \leq M(1 - v_{i,t}). \tag{20}$$

$$P_{L,i} - P_{c,i,t} > -M v_{i,t}. \tag{21}$$

$$RW_{i,t} = (P_{total,i,t} - P_{c,i,t}) RWR_{i,t}. \tag{22}$$

$$P_{c,i,t} = \sum_{l=1}^{NA_{i,t}} P_{i,t}. \tag{23}$$

where, the constraint (19) represents the total load reduction of the community at time t should be equal or higher than the DRR. The constraints (20) and (21) represent the relationship between the two variables $P_{c,i,t}$ and $v_{i,t}$, and $P_{L,i}$ and M are known values. The equation for calculating rewards for each house is presented in equation (22). Note, the reward function in equation (22) is a piecewise linear function because the reward rate $RWR_{i,t}$ in equation (17) is a discrete value and the variable $v_{i,t}$ is a binary variable. If the reward rate $RWR_{i,t}$

is continuous then the reward function will also be a continuous function. The equation (23) represents the total power consumption of resident i in kW at time t, and the appliance power consumption set can be expressed as,

$$P_{i,t} = \{p_{AC,i,t}, p_{WH,i,t}, p_{CD,i,t}, p_{DW,i,t}, p_{EV,i,t}, p_{cri,i,t}\}. \tag{24}$$

The time frame of this optimization problem is set as $\tau = \{0, \Delta t, 2\Delta t, \ldots, T\}$, where $\Delta t = 5$ minutes and T represents the total time period.

IV. SOLUTION DESIGNS

The optimization problem is formulated with non-linear objective function subject to the linear constraints. In this section, two different optimization techniques are investigated as the solution designs of the proposed optimization scheme. First, the integration of the GA approach is demonstrated to solve this non-linear optimization problem. Second, the MIP technique is investigated as an alternative solution of the proposed optimization scheme which requires the reformulation of the problem statement. In this section, the conventional optimization approaches are also demonstrated for comparative study.

A. INTEGRATION OF GENETIC ALGORITHM IN CEMS

The GA optimizes based on a natural selection process that mimics biological evolution where the algorithm repeatedly modifies a population of individual solutions [41]. In recent years, the GA is used for optimization in many applications on smart grid [42]–[45]. The steps to minimize equation (18) based on residents load profiles are summarized as follows,

- Step 1: The algorithm starts by initializing a random population with K individuals. In the population, each individual contains $2N$ variables and the power consumptions of N houses consider as N variables ($P_{c,i,t}$). Another N individuals represent the binary variables ($v_{i,t}$) for N houses where the binary variables are shaped based on the constraints.
- Step 2: The value of fitness function (objective function refer to equation (18)) for each individual of the current population is calculated. Then, the relative fitness of each individual is calculated as,

$$RF(k) = \frac{y_t(k)}{\sum_{k=1}^{K} y_t(k)}. \tag{25}$$

  An individual is selected, called *elite*, which has lowest relative fitness then others (since minimization problem). Then, four highest relative fitness individuals are selected and replaced by the *elite* individual.
- Step 3: In this step, rest of the individuals are used for *crossover* and *mutation*. In every generation, four individuals are selected by using linear bias function for crossover. After crossover, the offsprings are used for random mutation process. The mutation process is used to find the global minima without getting trapped into the local-minima. Then, the children are added to the current population and the fitness of the children are evaluated by using the fitness function. Later, four individuals of the population with highest relative fitness are eliminated and the remaining populations are sent to the next generation (iteration).
- Step 4: The algorithm stops when the average change in the fitness value is found less than the defined function tolerance value. When the algorithm meets the stopping criteria, it generates the outputs of the power consumption ($P_{c,i,t}$) and the binary variable ($v_{i,t}$) for all the houses. After getting the output values, the CEMS schedules the appliances based on the user's priority.

Finally, the proposed CEMS calculates the total financial rewards as well as the comfort level for each house and goes to the next time step. The design parameters of GA are presented in Section V.

B. ALTERNATIVE SOLUTION: MIXED INTEGER PROGRAMMING

The MIP is a technique suitable for optimization problems which involves both continuous and discrete variables [46]. The MIP method can be an alternative technique to solve the proposed residential energy optimization problem. In this paper, we used mixed integer linear programming (MILP) technique as a MIP method. This method is applicable because we have one continuous and one binary variables for each house. For example, by substituting equations (17) and (22) in equation (18), the objective function for house i can be written as,

$$\min_{P_{c,i,t}, v_{i,t}} \Big\{ P_{total,i,t}\{(R_1 - R_3)v_{i,t} + R_3\} - V_{new,i,t}(R_1 - R_3) - P_{c,i,t}R_3 + \eta CI_{i,t} \Big\}. \tag{26}$$

where we introduce a new variable $V_{new,i,t}$, replacing the non-linear term $P_{c,i,t}v_{i,t}$. In this specific design, $v_{i,t}$ is a binary variable, therefore, we can rewrite the objective function with $V_{new,i,t}$ and add two new constraints for this new variable as [47],

$$0 \le V_{new,i,t} \le v_{i,t} P_{total,i,t} \tag{27}$$

$$-P_{total,i,t}(1 - v_{i,t}) \le P_{c,i,t} - V_{new,i,t} \le P_{total,i,t}(1 - v_{i,t}) \tag{28}$$

where both constraints are developed considering that the new variable $V_{new,i,t}$ should be either equal to zero (if $v_{i,t} = 0$) or equal to $P_{c,i,t}$ (if $v_{i,t} = 1$). Note, the MILP is not feasible to solve the objective function if the variable $v_{i,t}$ is not a binary variable. That is to say, the objective function in equation (18) will be a nonlinear function if $RWR_{i,t}$ is a continuous function.

C. CONVENTIONAL SOLUTIONS

The first conventional solution is adopted from [25]. According to the conventional strategy, at each time step, if the total

TABLE 1. Load profiles and personal preferences of the ten residential houses.

House No.	AC $P_{AC,i}$ (kW)	WH $P_{WH,i}$ (kW)	CD $P_{h,CD,i}$ (kW)	DW $P_{h,DW,i}$ (kW)	EV $P_{EV,i}$ (kW)	CLs $p_{cri,i}$ (kW)	User Preferred Load	Total Power Rating (kW)	Lower Bound ($P_{L,i}$) (kW)	Com
1	1.4	4.0	3.4	2.9	4.0	1.1	CD	17.3	10.4	0
2	1.2	3.9	3.7	2.7	0	1.3	0	13.3	6.9	1
3	1.5	3.5	3.8	3.0	3.8	1.3	DW	17.4	9.8	0
4	1.6	3.8	0	2.6	0	1.1	0	9.3	6.7	0
5	1.3	3.1	3.1	0	3.6	1.4	0	12.8	6.1	1
6	1.2	3.4	3.5	2.8	0	1.2	CD	12.6	9.8	1
7	1.1	3.9	3.7	0	3.8	1.5	EV	14.3	10.6	0
8	1.5	3.8	0	2.9	4.0	1.7	0	14.1	7.2	1
9	1.5	4.0	3.3	2.6	0	1.1	DW	13.0	9.7	0
10	1.3	3.2	3.2	0	3.6	1.2	0	12.8	6.0	1

power consumption of the community is higher than the available power, then the system assigns the deviation Δ equally among the N number of residents. Note, the deviation Δ is the difference between the total power consumption and the available power. According to this strategy, the power consumptions of the residents are expected to reduce by Δ/N. Later, the system estimates financial rewards for each resident based on their participation in the event and sends the information to the utility.

Another solution is from a most recent work [18]. In [18], a CI for measuring thermal comfort level of the residents is proposed and only air conditioner is used as a residential appliance to validate their approach. The energy optimization problem is solved by mixed integer quadratic programming algorithm using BONMIN solver in general algebraic modeling system.

V. SIMULATION SETUP AND RESULTS ANALYSIS

The simulation is conducted for 10-house and 100-house residential communities. The case studies are compared with existing approaches in terms of number of active appliances, reward incentives and comfort levels.

A. SIMULATION SETUP FOR 10-HOUSE RESIDENTIAL COMMUNITY

In the community of ten houses, each resident has different personal preferences and load profiles. Six different appliances are used where AC, EWH, CD, DW and EV are considered as controllable loads and CLs are treated as non-controllable loads. The power ratings of the appliances are generated randomly according to the ranges in [9], [18], and [33]. In this paper, the power rating of the unavailable appliances is defined as 0. The total power demand of the community is calculated as 136.9 kW.

For each house, the CLs, AC and EWH are set as first, second and third priority loads, respectively. These three loads are considered as highest priority loads for all houses. The load profiles and personal preferences of ten residents are summarized in Table 1. The lower bound of power consumption in each house is the sum of the power rating of the highest priority loads and the user preferred controllable loads (e.g., in house 1 of Table 1, CD is user preferred load). The lower bound of power consumption in a house represents if the CEMS curtails any controllable loads from these appliances, the utility has to pay higher rewards (R_2 or R_3) to the consumer. In this paper, the priority numbers of the other appliances (except highest priority loads and user preferred loads) are defined randomly.

In the experiment, the time duration of each DRR is set to five minutes. The advantage of using this time interval is to prevent the discomfort caused by performing a single DRR with a long time period. At the beginning of each short DRR, the sensor of each house sends the feedbacks to the CEMS which will help to optimize the system based on the resident's preferences.

For the 10-house residential community, the GA is implemented with $K = 50$ populations where two-point crossover is used with 10% mutation rate. The simulated binary crossover technique is also investigated as an alternative technique for the GA crossover [48], [49]. The strategy for determining the reward rates can be varied case by case. In this paper, the reward rates R_1, R_2 and R_3 are assumed as 20, 40, and 60 cents/ (kW.5min), respectively. For the traditional approach [25], a reward of 40 cents/ (kW.5min) is used which is the median value of the proposed reward rates. Simulation results are presented in the rest of this section.

B. DRR1: APPROXIMATELY 40% DEMAND REDUCTION

In this experiment, the utility sent 55 kW DRR to the CEMS for 20 minutes which is approximately 40% of the total power demand of the community. The results of the residents' comfort levels and the reward distributions are shown in Table 2. The comfort percentage (%) represents the percentage of time when the power consumption was within the residents' comfortable ranges.

The results show that all the residents were within their comfortable power consumption ranges, and, the comfort percentage is 100% for all houses with reward R_1 rate. House 8 received the most financial rewards due to their broad comfortable power range. Note power range refers to the difference between the total power rating (kW) and the lower bound (kW). In the community, a participant who has a higher comfortable power range, has higher chance for high rewards. Here, the higher comfortable power range represents that the

TABLE 2. **DRR1 results for ten houses.**

House No.	Average Power (kW)	Rewards (% comfort) ($)	House No.	Average Power (kW)	Rewards (% comfort) ($)
1	10.80	5.20 (100%)	6	8.85	3.00 (100%)
2	7.88	4.34 (100%)	7	9.35	3.96 (100%)
3	12.32	4.06 (100%)	8	6.03	6.46 (100%)
4	3.90	4.32 (100%)	9	7.68	4.26 (100%)
5	6.60	4.96 (100%)	10	6.83	4.78 (100%)

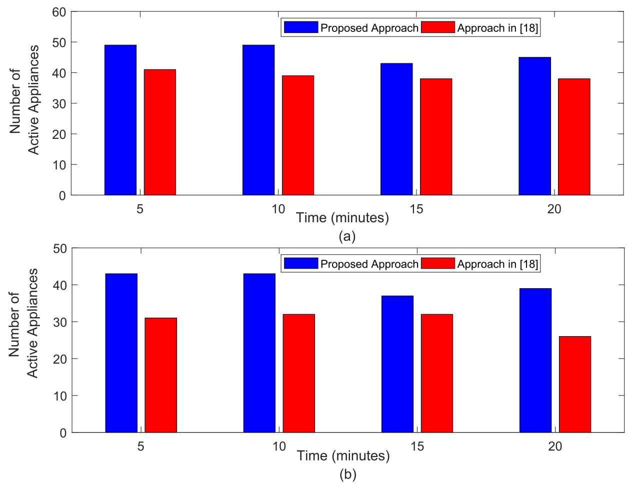

FIGURE 2. **The figures (a) and (b) represent the result comparisons in terms of number of active appliances for DRR1 and DRR2, respectively.**

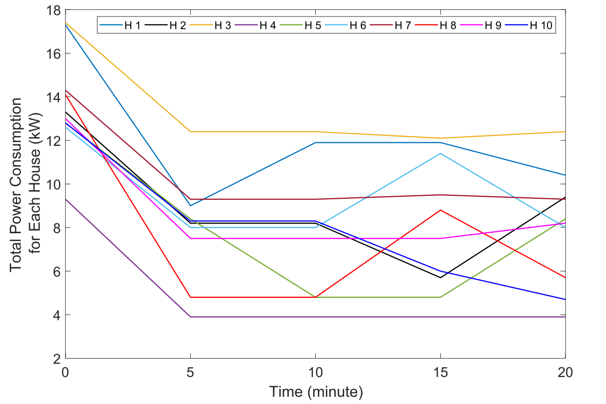

FIGURE 3. **Total power consumption of each house over the time interval for DRR1.**

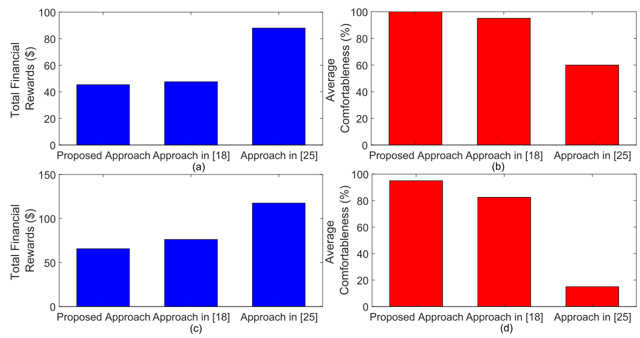

FIGURE 4. **Result comparison in terms of total financial rewards and average comfortableness. The figures (a) and (b) represent the result comparison for DRR1 in terms of total financial rewards and average comfortableness, respectively. The figures (c) and (d) illustrate the result comparison for DRR2 in terms of total financial rewards and average comfortableness, respectively.**

resident gives freedom to the utility to curtail a higher amount of loads.

Figures 2(a) and 2(b) show the comparison of the number of active appliances between the proposed approach and existing approach in [18]. In each time step, the proposed approach outperformed the existing optimal framework. The results show that the proposed approach is distributed the available energy to the residential appliances more efficiently than the existing framework. The total power consumption of each house over the time interval for DRR1 is also presented in Figure 3. According to the Figure 3, all the residents are using their appliances before the DR event at time 0. When the DRR1 is applied, the CEMS curtails the loads from the houses according to minimize the reward costs of the utility and maximize the overall comfort level of the community. During the DR event, specially between five minutes and twenty minutes, the power fluctuations are observed due to the comfort level adjustment of the houses. For the comfort level adjustment, sometimes the CEMS curtails loads from one house and allocates that energy to another house to maximize the comfort level of the community. From Figure 3, it is also observed that the power consumption curve for house 4 remains flat during the DR event. For house 4, their number of controllable appliances is comparatively lower than others. They also have a large temperature comfort margin for AC and EWH than others. Because of this reason, during the DR event, the CEMS maintain their comfort level by allocating energy to their DW and critical loads.

The result comparisons in terms of total financial rewards and average comfortableness are presented in Figures 4(a) and 4(b). In [18], during the optimization period, the framework dedicates energy to the thermostatically controllable loads though the temperatures are in residents' comfort zone. Due to this reason, sometimes the framework violated the comfort margin of the residents and the utility had to pay reward to the residents. Sometimes, the framework curtails the task-based user preferred loads because other appliances are not considered in the CI, which costs higher rewards for the utility. In [25], the proposed technique assigns the energy deviation equally among all the residents of the community. Sometimes the existing technique curtails user preferred loads which hurts the residents' comfort levels. According to the results, for 40% of load curtailment, the proposed approach outperformed the existing approaches [18], [25].

Furthermore, we also compare the optimization results between GA and MILP. Both approaches achieve the same optimization results ($45.34 for the total rewards) and 100% average comfortableness. MILP seems to have a faster computation time than GA in this case. Note, MILP is only

TABLE 3. DRR2 results for ten houses.

House No.	Average Power (kW)	Rewards (% comfort) ($)	House No.	Average Power (kW)	Rewards (% comfort) ($)
1	9.35	6.36 (100%)	6	7.27	4.26 (75%)
2	4.67	8.96 (100%)	7	9.35	3.96 (100%)
3	8.53	7.10 (100%)	8	2.85	9.00 (100%)
4	3.90	4.32 (100%)	9	7.68	4.26 (100%)
5	2.47	10.48 (75%)	10	4.33	6.78 (100%)

feasible when equation (22) is a piecewise linear function (i.e., the reward function is a discrete-value function). If the reward function is a continuous function, then equation (18) will be a nonlinear objective function and so MILP will not be feasible.

C. DRR2: APPROXIMATELY 55% DEMAND REDUCTION

In this case, the utility sent 75.30 kW DRR to the CEMS for 20 minutes which is approximately 55% of the total power demand of the community. The results of residents' comfort levels and the reward distributions are shown in Table 3.

According to the results, during the 20 minutes, the CI values for houses 2 and 5 were higher than 1 in two different five-minute time intervals, respectively. The proposed approach allocated R_2 rate to them, because both of them are agreed to compromise. The result comparison in terms of number of active appliances are presented in Figures 2(a). Like DRR1, the number of active appliances using the proposed approach is higher than the existing optimal framework. According to the results, the proposed approach can still allocate residential energy efficiently at high DRR request.

The results obtained from the proposed approach are also compared with the existing approaches in terms of the total financial rewards in dollars and the average comfortableness in percentages. The results are illustrated in Figures 4(c) and 4(d). The increase in DRR may lead to a dramatic rise in terms of reward costs. Because, for a large amount of load curtailment, the CEMS has no way without violating some residents' comfort levels to reduce enough demand. The affected residents will be rewarded at R_2 or R_3 rate. According to the results, the proposed approach showed better performance for both cases compared to the existing approaches at 55% of load curtailment.

D. RESULTS COMPARISON FOR DIFFERENT DRRs WITH DIFFERENT TIME LENGTHS

The proposed approach is also tested for different DRRs with different time lengths using the ten residents system and compared with the existing approach in [18]. The three dimensional results of the proposed and the existing approaches are illustrated in terms of total financial rewards and the average comfortableness in Figures 5 and 6, respectively.

According to Figure 5, for both approaches, with the increasing of time lengths and the DRR, the total reward costs rise sharply. The results show that up to 40% of load curtailment, the existing approach showed competitive

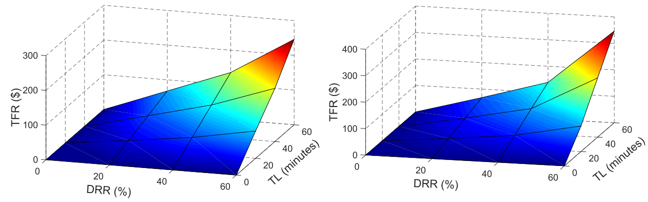

FIGURE 5. Total financial rewards for different DRR with different time length using the proposed approach (left) and the existing approach (right). Here, *TFR*, *DRR*, and *TL* represent total financial rewards, demand reduction rate and time length, respectively.

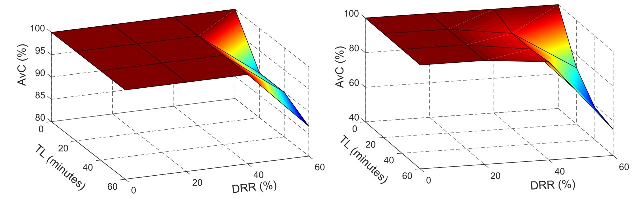

FIGURE 6. Average comfortableness for different DRR with different time length using the proposed approach (left) and the existing approach (right). Here, *AvC*, *DRR*, and *TL* represent average comfortableness, demand reduction rate and time length, respectively.

TABLE 4. Power rating ranges of each appliances.

Appliances	Power Rating (kW)
Air conditioner	1.1-1.6
Water heater	3.2-4.5
Dish washer	1.8-3.1
Cloth dryer	3.4-4.1
Electric vehicle	3.6-4.0
Critical loads	1.0-2.0

performance with the proposed approach. With high DRR, the proposed approach showed better performance than the existing approach. For example, the maximum financial rewards of the proposed and existing approaches are found as $246.16 and $346.44, respectively. In Figure 6, the results show that, at up to 20% of demand reduction rate, both approaches performed same in terms of average comfortableness. With the increasing load curtailments and time lengths, the comfort level of the residents dramatically fall for both approaches. For example, the minimum average comfortableness of the proposed and existing approaches for 60% of load curtailment are observed as 86.67% and 55%, respectively.

E. SIMULATION STUDY OF A 100-HOUSE RESIDENTIAL COMMUNITY

The proposed approach is also tested for 100 residents. The power ratings of the appliances are randomly generated according to the ranges in [5], [9], [18], [39], and [50]. The power rating ranges for the appliances are summarized in Table 4.

In this case, the simulation is conducted for 100 runs. For each run, the power rating of the appliances is generated randomly within the defined ranges for 100 houses, and the total financial rewards and the average

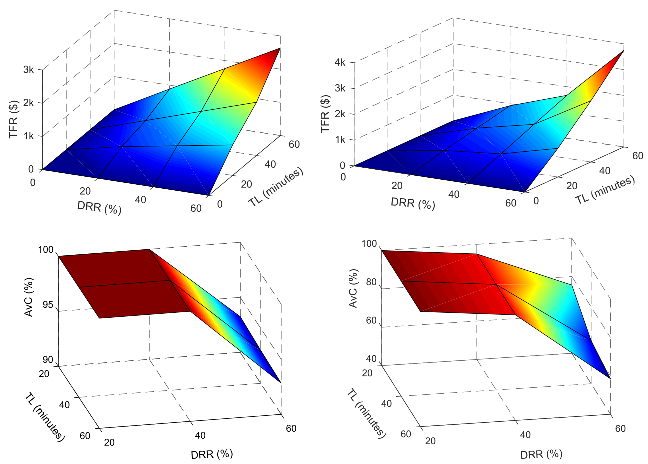

FIGURE 7. Total financial rewards for different DRR with different time length using the proposed approach (top-left) and the existing approach (top-right) [18] for 100-house residential community; Average comfortableness for different DRR with different time length using the proposed approach (down-left) and the existing approach (down-right) [18] for 100-house residential community. Here, *TFR*, *AvC*, *DRR*, and *TL* represent total financial rewards, average comfortableness, demand reduction rate and time length, respectively.

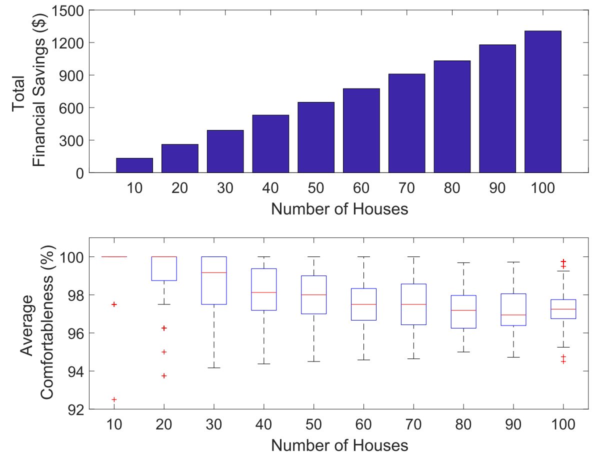

FIGURE 8. Total financial savings and average comfortableness of the community for different number of houses.

comfortableness are calculated using the proposed technique. After 100 runs, the statistical estimated value of the total financial rewards and average comfortableness are obtained by Monte Carlo simulation technique in [51]. According to Figure 7 (top row), the total financial rewards of the system increase sharply as the time length and the DRR increases. For all cases, the reward cost value of the proposed approach is less than the existing approach [18]. The maximum value of the reward costs for 60% of load curtailment using the proposed approach and the existing approach are obtained as $2637.4 and $3748.7, respectively. In terms of average comfortableness, no effect is observed up to 40% of load curtailment with different time lengths for the proposed approach, while the average comfortableness of the existing approach is decreasing after 20% of load curtailment. The minimum value of the average comfortableness for 60% of load curtailment using the proposed approach and the existing approach are obtained as 92.83% and 58.48%, respectively. According to the results, the proposed approach outperformed the existing framework in terms of both average comfortableness and total financial rewards of the system.

In addition, we conduct the simulations by varying the number of houses. For this case study, we consider the DRR 50% of the total power demand of the community with 20 minutes of time period. For the total financial savings, we calculate the cost of the community demand before and after the optimization scheme considering 60 cents/(kW.5min) as the base price of the electricity for each run. Then we calculate the average financial savings by subtracting the total financial cost before and after the optimization scheme at the end of 100 runs. The result in terms of total financial savings is presented in the first subplot of Figure 8. The results show that the total financial savings increase with the addition of number of houses. For the average comfortableness of the community, we present a box plot over the 100 runs to analyze the comfort level of the community from a statistical viewpoint. The results in terms of average comfortableness are illustrated in the second subplot of Figure 8. In the figure, on each box, the red color central mark indicates the median, the top and bottom edges of the box indicate the 75th and 25th percentiles, respectively. The outliers are represented individually by + symbol. For example, for a 40-house resident system, the box plot shows that the median average comfortableness for 100 runs is approximately 98% where the minimum value is approximately 94%, and the maximum value is about 100%. The results also show that the proposed optimization scheme can schedule the appliances efficiently with the addition of number of houses and maintain the average comfort level of the community above 92%. According to the results it can be concluded that the utility can earn more benefit using the proposed optimization scheme and maintain satisfactory comfort level of the community with the addition of number of houses.

VI. CONCLUSION

A new residential community energy optimization scheme is proposed to distribute DRRs efficiently while considering consumers' comfort levels and rewarding the participating consumers with financial incentives. A multilevel reward structure is designed to show the trade-off between consumers' comfort levels and reward incentives. A new CI is designed to measure the comfort level of the residents where both thermal and other major residential electric appliances are taken under consideration. Both GA and MIP formulation is investigated to solve the optimization problem and the performance of the approaches are reported in terms of total reward the utility, average comfortableness and computation time. The GA approach is used as a general approach to solve the proposed optimization problem. The MIP approach is used as an alternative solution of the residential energy optimization problem for the case when the objective function is piecewise linear. The performance of the proposed optimization scheme was validated using different DRRs with different time lengths, and the simulations were studied under both 10-houses and 100-houses benchmark systems. The results were compared with two existing approaches. The proposed approach outperformed them in terms of number of active appliances, total reward cost of the utility, and average comfortableness of the residents in the community.

In the future, we will investigate the performance of the proposed optimization scheme for a large scale residential community and design the CI for the residential consumers considering different weather conditions. We also analyze the performance of the proposed optimization scheme for real-time residential load profiles and continuous reward functions over 24-hour time period.

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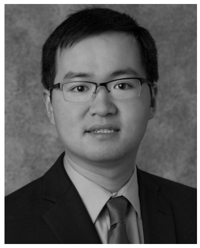

ZHEN NI (M'15) received the B.S. degree from the Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan, China, in 2010, and the Ph.D. degree from the Department of Electrical, Computer and Biomedical Engineering, The University of Rhode Island (URI), Kingston, RI, USA, in 2015. He is currently an Assistant Professor with the Department of Electrical Engineering and Computer Science, South Dakota State University, Brookings, SD, USA.

His current research interests include computational intelligence, smart grid, machine learning, and cyber-physical systems. He received the URI Excellence in Doctoral Research Award in 2016, the Chinese Government Award for Outstanding Students Abroad by the Chinese Government in 2014, and the Second Prize of Graduate Student Poster Contest by the IEEE Power and Energy Society General Meeting in 2015. He has been actively involved in numerous conference and workshop organization committees in the society, including the General Co-Chair of the IEEE CIS Winter School, Washington, DC, USA, in 2016.

AVIJIT DAS (S'16) received the B.Sc. degree in electrical and electronic engineering from American International University-Bangladesh, Bangladesh, in 2013, and the M.S. degree in electrical engineering from South Dakota State University (SDSU), Brookings, SD, USA, where he is currently pursuing the Ph.D. degree in electrical engineering. His research interests include power system operation and optimization, grid integration of renewable energy systems, distributed generation, smart grid, and computational intelligence.