IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 19, 2021, accepted March 5, 2021, date of publication March 9, 2021, date of current version March 17, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3064895

Optimal Management of a Distribution Feeder During Contingency and Overload Conditions by Harnessing the Flexibility of Smart Loads

ZUNAIB MAQSOOD HAIDER[1], KHAWAJA KHALID MEHMOOD[2], SAAD ULLAH KHAN[3], MUHAMMAD OMER KHAN[4], ABDUL WADOOD[5], AND SANG-BONG RHEE[6]

[1]Department of Electrical Engineering, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan
[2]Department of Electrical Engineering, The University of AJ&K, Muzaffarabad 13100, Pakistan
[3]Department of Electrical and Computer Engineering, Air University, Islamabad 44000, Pakistan
[4]Department of Electrical Engineering and Technology, Riphah International University, Faisalabad Campus, Punjab 38000, Pakistan
[5]Department of Electrical Engineering, Air University Islamabad, Kamra Campus, Kamra 43570, Pakistan
[6]Department of Electrical Engineering, Yeungnam University, Gyeongsangbuk do 38541, South Korea

Corresponding authors: Abdul Wadood (wadood@au.edu.pk) and Sang-Bong Rhee (rrsd@yu.ac.kr)

This work was supported by the ''Development of Modular Green Substation and Operation Technology of the Korea Electric Power Corporation (KEPCO)''.

ABSTRACT Due to an increase in penetration of intermittent distributed energy resources (DERs) in conjunction with load demand escalation, the electric power system will confront more and more challenges in terms of stability and reliability. Furthermore, the adoption of electric vehicles (EVs) is increasing day by day in the personal automobile market. The sudden rise in load demand due to EV load might cause overloading of the potential transformer, undue circuit faults and feeder congestion. The objective of this paper is to develop a strategy for distribution feeder management to support the implementation of emergency demand response (EDR) during contingency and overload conditions. The proposed methodology focuses on management of smart home appliances along with EVs by considering demand rebound and consumer convenience indices, in order to reduce network stress, congestion and demand rebound. The developed scheme ensures that the load profile is retained below a certain level during a demand response event while mitigating demand rebound impacts. Simultaneously, the mitigation of consumers' convenience level violation, information of smart loads and homeowners' objective of serving critical loads are also considered during the event. The effectiveness of the developed approach is assessed by simulating a node of a distribution network of 300kW, consisting of 9 distribution transformers serving the associated homes. In this study, the smart loads such as an air conditioner/heater, an EV, a clothes dryer, and a water heater are also modeled and simulated. Furthermore, the simulation results are compared with an already developed de-centralized approach, and a simple fair distribution approach to evaluate and validate the effectiveness of the designed methodology. It is exhibited by the analysis of the results that the developed approach reduced the demand rebound following a demand response event and minimized the congestion at distribution transformer during overloading condition while maintaining the consumers' comfort.

INDEX TERMS Demand rebound, distributed energy resources, electric vehicles, feeder congestion, load profile, network Stress.

NOMENCLATURE

Acronyms

DER	Distributed energy resources
DFLM	Distribution feeder load management
DR	Demand response
EDR	Emergency demand response
EV	Electric vehicle
FA	Feeder agent
HEMS	Home energy management systems
HLA	Home load agent
SOC	State of charge
TA	Transformer agent

The associate editor coordinating the review of this manuscript and approving it for publication was Md. Rabiul Islam.

Variables

δl	Interval length (hour)
δr	Amount of required energy (Btu/$^\circ F$) to raise the temperature of the room by $1^\circ F$
$A_{s,tank}$	Water heater unit surface area (ft^2)
C_{HVAC}	Rating of the heating unit (Btu/h)
$H_{j,G}$	Rate of heat loss of a home (Btu/h)
K	Number of customers associated with a transformer
L_{GO}	Load limit assigned to feeder agent by grid operator
N	Number of transformers connected to a feeder node
R_{bat}	Battery rated capacity (kWh)
$R_{H,tank}$	Heating resistance of water heater tank ($ft^2.^\circ F.h/Btu$)
Rw_j	Hot water flow rate during time slot j (gpm)
t_{air}	Temperature of surrounding air of WH unit ($^\circ F$)
$t_{j,ac}$	Temperature of room during time slot j ($^\circ F$)
$t_{j,wh}$	Temperature of hot water during time slot j
T_{pr}	Power of the battery discharged during traveling (kWh)
$t_{wh,inlet}$	Temperature of water at water heater tank inlet ($^\circ F$)
$TR_{cap,i}$	Transformer $i \in N$ rated capacity
U_{tank}	Volume of WH tank
W_{ac}	HVAC unit rated demand (kW)
$W_{coil,cd}$	Power required by the heating coil of CD unit
W_{EV}	EV charger rated power (kW)
W_{FD}	Instantaneous power demand at a distribution feeder node
$W_{home,i,k}$	Total load (kW) of a home $k \in K$ assoicated with transformer $i \in N$
$W_{TR,i}$	Instantaneous load (kW) at a transformer i

I. INTRODUCTION

In electrical systems and markets, the instantaneous balance between supply and demand is always needed, which makes the objective of creating functioning electricity markets more complex. Nevertheless, power sector is focusing on the integration of more distributed energy resources (DERs) for its daily operation [1]. The replacement of fossil-fuel based conventional generation units with renewable alternatives poses threats of its own, particularly due to inherent intermittent nature of solar and wind energy [2], [3]. In order to compensate the intermittency in solar and wind power, there is a need to incorporate more flexible resources into the grid operation. For reliable operation and economical supply, power networks require higher utilization efficiency and an adequate capacity. However, their low load factor is projecting the ordinary utilization efficiency. Moreover, electric power systems are dealing with a lot of challenges including limited energy resources, aging of the infrastructure, customer satisfaction [4], and abrupt load growth due to interconnection of electric vehicles (EVs). As the share of EVs is increasing rapidly in the personal automobile market [5], their interconnection with the power system can jeopardize its stability. Some of the foreseeable challenges are overloading of the transmission and distribution network, voltage sag, line losses and abrupt growth in load demand [6]– [9]. The growth in electricity demand and aging of the transmission and distribution infrastructure require massive investment in terms of replacement and expansion. Therefore, the electric utilities are looking for suitable solutions to cope with future demands and it is necessary to develop market clearing mechanisms and physical controls to maintain stability. However, due to development of smart home energy management systems (HEMS), advanced information technologies, smart energy meters and demand response (DR) enabled appliances, the share of EV load can be made transparent up to a remarkable extent and can defer the up-gradation of the existing power network.

In previous studies, researchers have widely used emergency demand response (EDR) at the transmission or sub-transmission level. However, there are very few studies focusing EDR utilization at the distribution level. Emergency demand response (EDR) is a type of demand response program utilized under abnormal operating conditions of power system such as overloading, contingencies etc. In [10], the authors implemented a centralized event driven EDR at sub-transmission level. The proposed strategy considered cost based objective function and executed by converting the non-linear optimization problem into linear optimization problem in order to use piece-wise linear method. The authors in [11] suggested an analytical hierarchy process based EDR implementation at transmission level. The synthesized approach proposed a methodology based on the objective of minimizing incentive payments and maximizing economic benefit during a demand response event. A methodology is formulated in [12] at the transmission level to implement EDR as a mixed integer linear problem. This study focused on the minimization of fuel cost during a DR event. The authors implemented the proposed approach using CPLEX 11.0 solver and GAMS environment. In [13], the authors proposed a centralized framework at the transmission level. The proposed strategy depends on the load/generation forecast. The objective of this study is to maximize utilization efficiency of the energy storage devices and minimize the operation cost. A methodology is developed in [14] at transmission level to deal with the optimal dispatching problem using BAT algorithm. The developed method proposed a dispatched model with a focus on minimizing the operation cost of micro turbines along-with the reduction in pollutant emission. An EDR strategy has been developed in [15] to use residential loads during contingencies in a distribution network. However, the appliances characteristics are not considered in this study and are modeled as lumped loads. Therefore, the analysis of the effect of the design approach on consumers' daily life is not conceivable. The implementation of EDR at transmission level uses aggregated load curve and considers customers' load as a lumped load. The objectives are mainly focused to minimize the operational cost and flattening of load curve. Whereas the EDR strategies at distribution level analyze the consumers' convenience and consider the characteristics of household appliances and their control for its implementation which are the key points in the acceptance of an EDR strategy. The acceptance and effectiveness of an EDR strategy at the distribution level is analyzed by the demand rebound, congestion and the effect on consumers' comfort. Therefore, the implementation of EDR at distribution level is quite complex.

To reduce power demand, some studies have suggested the approach to use dynamic pricing schemes. In [16], the authors proposed a residential demand response strategy to reduce the peak demand with the objective of minimizing utility supply cost by assuming cost as a homogeneous function in the total consumption of energy. The authors in [17] proposed a control strategy using dynamic demand response controller. The developed methodology is based on the electricity retail price to manage residential HVACs in order to reduce peak demand. The main objectives of this study are to reduce the peak demand and the curtailment in the operational cost of electricity. An average system cost minimization framework is investigated in [18] by developing an electricity retail price model considering market price information and load demand. The load is scheduled to minimize the cost of energy consumption bearing the market clearing price. A scheme to reward consumers for peak shaving is developed in [19], [20]. In these studies, consumers get benefit based on voltage improvement and load shift. Nonetheless, the load reshape can not be assured for its heavy reliance on homeowners' behavior. A sparse load shifting mechanism for the scheduling of smart household appliances considering price-based strategy is discussed in [21]. It is a centralized approach in which the characteristics of the appliances are not considered and suffers from the heavy dependence on consumers' behavior. A hybrid technique is proposed in [22] employing load shifting strategy for optimization of energy consumption patterns. In this study, a day-ahead scheduling is proposed through coordination of home appliances in order to minimize electricity cost. Dynamic programming method is used to solve the rescheduling problem which is modeled as a knapsack problem. The authors in [23] adopted the Markov decision process to formulate the demand response management problem of the interruptible loads. The management of interruptible loads is optimized considering the time of use tariff using deep reinforcement learning method. The objectives of this study are to reduce the operation costs and peak load. In [24], a home energy management system is proposed by the authors for scheduling of home appliances considering demand charge tariff. The authors minimized the one-day demand charge tariff and real-time pricing costs of a consumer comprehending operational dependencies of the home appliances. A reinforcement learning based residential demand response architecture is proposed in [25]. The authors employed the finite Markov decision process to formulate the scheduling problem of energy consumption. The objectives are the minimization of electricity bill and the dissatisfaction induced by the proposed demand response strategy. An incentive based integrated demand response model is developed in [26]. In this study, the energy substitution effect and the consumers' behavioral coupling effect is considered by the authors with the focus to reduce multi energy aggregator cost and consumers' dissatisfaction. A decentralized real-time demand response architecture is modeled in [27] by the authors in two phases to modify the residential load. In first phase, each consumer predicted a day-ahead raw demand to minimize the electricity cost. Whereas, in second phase, the consumers mitigated the variation between predicted and actual demand to minimize the penalty inflicted. In [28], a distributed optimization model is proposed by the authors to minimize the operational cost. The desired objective is obtained by efficiently utilizing the energy storage systems and finding the Nash-equilibrium considering a day-ahead charging-discharging scheduling and capacity trading. A hierarchical demand side management infrastructure is developed in [29] using artificial immune algorithm. In this study, the authors focused on minimizing the peak-to-average ratio of energy usage pattern and operational cost. In [30], the power sources are optimally distributed in the grid to minimize the energy cost. The generation planning is performed by solving a mixed-integer non-linear optimization problem considering power-flow losses. The developed approach depends on the grid structure and the demand. The authors in [31] proposed an optimal load control strategy using modified particle swarm optimization algorithm at distribution network level. The developed framework employed on-load tap changers and residential demand response for the management of voltage in unbalanced distribution networks. However, the price-based techniques depend heavily on the consumers' behavior and suffer from the rebound effect and coincident load shifting/shedding. Moreover, the aforementioned literature focus on the advance models for demand response implementation, but they are solely aimed to reduce the cost and consumers' dissatisfaction, ignoring the characteristics of household appliances and analysis of the demand rebound and congestion following a demand response event.

Researchers also have proposed several approaches to manage electrical vehicle (EV) charging to control abrupt growth in load demand. Some solely focused on centralized control of EV charging where a central control unit manages the EV charging, such as the authors in [32] developed a stochastic model for distribution system planning using multistage joint reinforcement of EV charging stations. The Markovian analysis is performed to determine the EV charging demand and a scenario matrix is formulated to minimize the operational cost and investment. The two case studies are performed in [33] by the authors to showcase the effectiveness of the approach proposed in [32] by applying it on IEEE 18-bus and IEEE 123-bus distribution systems. A mathematical model is developed in [34] for the calculation of charging price of electric vehicles. The authors presented a mechanism of EV charging regions in this study, where each region receives a non-discriminatory dynamic price signal and genetic algorithm is used to achieve the cost minimization objective. The coordinated charging model of electric vehicles is proposed in [6] by the authors to improve the load factor of the main grid. Therefore, the charging of EVs is scheduled in off-peak hours to achieve the desired objective. In [35], a relationship is explored between load factor, feeder losses and load variance. The authors proposed an optimal charging algorithm to minimize the distribution network losses considering coordinated charging strategy of electric vehicles. The difference in peak and valley load of the grid is optimized in [36] by developing a controlled strategy for EV charging. The authors implemented a two-stage model of peak-valley price and used genetic algorithm for its determination. In [37], a stochastic programming model is formulated by the authors for scheduling the EV charging of a public parking-lot using Stochastic Dual Dynamic-Programming. In this study, the results are first obtained in the offline-mode and then employed in the online-mode. A few studies have exploited the EV charging schemes at consumer premises with decentralized control. The authors in [38] focused on the minimization of load variance for the implementation of the proposed approach. The designed framework considered the topology of distribution network and iterative price-driven coordination among consumers and utility for the control of plug-in electric vehicles (PEVs). A resilient framework is proposed by the authors in [39] for decentralized control of dc parking lots. A scheme is presented to control the distributed generators incorporated with the parking lots for rapid charging of electric vehicles considering accurate sharing of oscillatory and dc power components. In [40], the authors used a shrunken primal dual sub-gradient algorithm for decentralized charging of electrical vehicles during overnight in order to achieve valley filling. The optimization problem formulated is a non-separable objective function considering distribution network constraints and individual charging requirements. A load shifting service is procured in [41] for decentralized charge and discharge scheduling of the plug-in electric vehicles. The authors employed mixed discrete programming to solve the time scheduling problem with the objective of flattening the demand curve. A non-cooperative game strategy is investigated in [42] considering the interaction mechanism between PEVs to minimize the energy cost of smart charging station. All PEVs coordinate with each other to achieve the desired objective by finding the generalized Nash equilibrium. The authors adopted Newton fixed-point approach for seeking the generalized Nash equilibrium. A multiple electric vehicle aggregators based strategy is implemented in [43] to flat the demand profile of the distribution network. The authors employed water-filling algorithm to cope with the peak demand and valley gap issues by charging and discharging of the electric vehicles. The benefits of decentralized strategies over centralized techniques have been discussed in [44]. However, the developed schemes solely focus on controlling EV demand while neglecting the characteristics of other controllable appliances.

Based on the literature review, there is a need of extensive research to implement EDR strategies for demand reshape at the distribution level especially by considering and analyzing congestion, demand rebound and consumer convenience indices. In this paper, an optimal decentralized approach has been developed to control the DR-enabled/smart household appliances including EVs. This study aims at restraining the instantaneous load demand by optimizing the demand rebound and the customers' convenience indices to minimize the adverse impacts of a demand response (DR) event. Pattern search algorithm is used to optimize the demand rebound index, whereas genetic algorithm is used to optimize the customers' convenience index. Demand rebound index helps in reducing the load demand following a DR event and customers' convenience index helps in maintaining the customers comfort and reduces the power system congestion. To implement the designed approach, this study proposes a decentralized strategy at a distribution feeder node level, a distribution low voltage transformer (TF) level and a home level to manage smart household appliances including EV, air conditioner/heater (HVAC), clothes dryer (CD) and water heater (WH). Whereas, critical loads e.g. cooking, plug loads and lighting loads are not controllable. The developed approach offers some advantages over previously proposed methods as customers have flexible choice to manage their smart loads and the proposed methodology does not require any prediction models for its operation. The main contributions of the paper are as follows:

1) A constraint optimal decentralized approach has been developed to administer the DR-enabled/smart household appliances including EVs by efficient and effective allocation of the available resources. The designed strategy is rigorous in perspective as it considers the objectives of feeder agent, transformer agent and home load agent to function appropriately.
2) In this paper, a new approach is proposed to reduce the customers dissatisfaction, system congestion and demand rebound by formulating the consumers convenience and demand rebound indices, and constituting the objective functions comprised of these indices.
3) The proposed framework is analyzed by obtaining the analytical results and extensive simulations are performed to validate the designed mathematical model. Furthermore, the results of the developed model are compared with a well-known resource allocation algorithm which exhibits a reduction of 53% and 40% in demand rebound and distribution transformer congestion, respectively along with the improvement in consumers dissatisfaction.

The rest of the paper is outlined as follows: in Section 2, the architecture of a distribution feeder load management (DFLM) strategy is explained. Section 3 discusses the mathematical modeling of the smart household appliances.

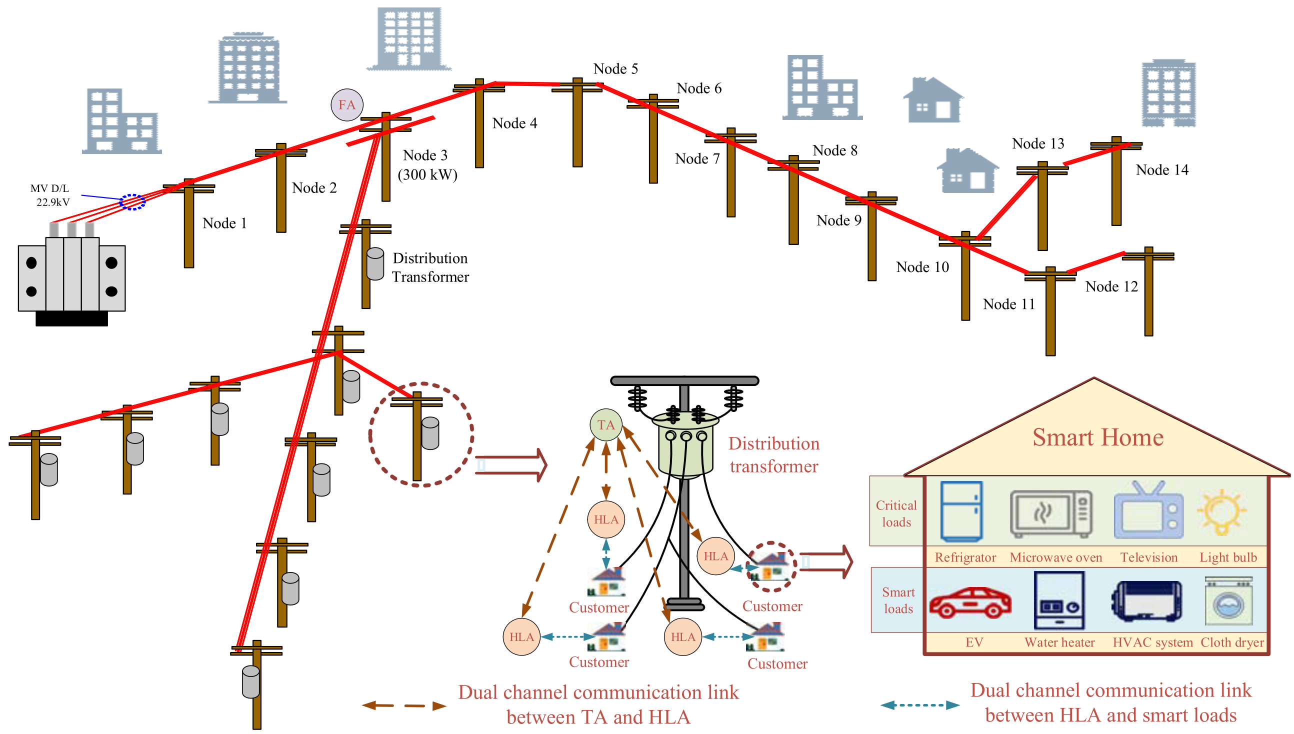


FIGURE 1. Distribution feeder load management architecture.

The mathematical formulation of the designed architecture is represented in Section 4. To showcase the effectiveness of the proposed approach, Section 5 presents a case study. Finally, the conclusions are described in Section 6.

II. INFRASTRUCTURE OF PROPOSED METHODOLOGY

This study introduces an automated distribution feeder load management (DFLM) infrastructure to manage responsive household appliances. The main objective is to optimally restrain the instantaneous load demand of each customer to a certain level during contingency or overload condition while mitigating demand rebound. The designed methodology is categorized and established at three levels as follows:

1) A distribution feeder node level supervised by a Feeder Agent (FA)
2) A distribution transformer level supervised by a Transformer Agent (TA)
3) A home level supervised by a Home Load Agent (HLA)

The designed DFLM infrastructure is presented in Fig. 1.

A. FA GOALS

A FA coordinates with the associated TAs of the distribution transformers connected with a feeder node to achieve its objectives. The objectives of FA are as follows:

1) To ensure that the total instantaneous load (kW) at a feeder node level is less than or equal to the load limit assigned by the grid operator during contingency. Mathematically, it is expressed in (1).

$$W_{FD} \leq L_{GO} \tag{1}$$

whereas

$$W_{FD} = \sum_{i=1}^{N} W_{TR,i} = \sum_{i=1}^{N} \sum_{k=1}^{K} W_{home,i,k} \tag{2}$$

2) Assign a load limit to each associated distribution transformer ($L_{TR,i}$, kW) during contingency condition to limit the power consumption in order to avoid the load-shedding. It is represented numerically as in (3).

$$L_{TR,i} = \frac{L_{GO}}{\sum_{i=1}^{N} TR_{cap,i}} \cdot TR_{cap,i} \tag{3}$$

B. TAs GOALS

TA coordinates with the HLAs of all the associated homes to achieve its goals. The objectives of TA are as follows:

1) To ensure that the total instantaneous load at a distribution transformer ($W_{TR,i}$, kW) is below a certain load limit during contingency/overload condition. In this work, the state of distribution transformer is considered either normal or critical, based on the following constraints:

$$W_{TR,i} = \sum_{k=1}^{K} W_{home,i,k} \leq TR_{cap,i} \quad \forall i = 1, \ldots, N \tag{4}$$

$$W_{TR,i} \leq L_{TR,i} \quad \forall i = 1, \ldots, N \tag{5}$$

In case of violation of any of the constraints mentioned in (4) and (5), the transformer state will change from normal to critical.

2) Optimally allocate demand restraining limit ($DTL_{home,i,k}$) to the associated homes during critical state, in order to minimize demand rebound. For this purpose, TA considers demand rebound index and the convenience factors of the homes.

C. HLAs GOALS

HLA works in pursuit of the home-owner's objectives. To accomplish its goals, the HLA coordinates with the associated TA, after a home-owner acknowledges the participation request from TA. The objectives of the HLA are as follows:

1) Ensure working of inflexible appliances (e.g. lighting loads, plug loads and cooking etc.) at all time.
2) Maintain total instantaneous load (kW) of a consumer ($W_{home,i,k}$) below its allocated demand restraining limit ($DTL_{home,i,k}$) as presented in (6).

$$W_{home,i,k} \leq DTL_{home,i,k} \tag{6}$$

3) Mitigate the violation of consumers' comfort level by changing the initial order of load priority, when the convenience level parameters are violating.
4) Turn-off least order loads during critical state after changing the priority order to make $W_{home,i,k} \leq DTL_{home,i,k}$ in accordance with (7).

$$W_{home,i,k} = \begin{cases} P_A - \sum_{m=x}^{d} P_m, & P_A > DTL_{home,i,k} \\ P_A, & otherwise \end{cases}$$
$$\text{where} \quad m = x, x-1, \ldots, 1 \tag{7}$$

where "P_A" represents aggregated instantaneous load of a consumer; "d" represents required number of the turn-OFF appliances to obtain $P_A \leq DTL_{home,i,k}$; "P_m" is the power required by the m-th priority appliance, and "x is the number of least priority appliance.

For each smart appliance, customers set two types of characteristics in the HLA: convenience level setting and appliance priority. The convenience level setting of a smart load is related to its set point value. For example, it is related to job finish time for EV and CD, whereas, it is related to the set point of temperature for WH and HVAC.

During critical state, the HLA monitors the current parameters of each smart appliance and adjusts the set points of temperature of WH and HVAC, considering their convenience level setting parameter. The HLA will change the order of appliances' priority if the parameter(s) of the appliance(s) are violating their convenience level setting(s).

D. INFORMATION EXCHANGE AND DESIGN STRATEGY

The overall strategy and coordination between a TA and an HLA is illustrated in Fig. 2. They coordinate with each other as follows:

Step 1: The TA waits for the signal from the FA specifying a load limit ($L_{TR,i}$, kW)

Step 2: The TA checks the state at transformer by comparing the total load ($W_{TR,i}$, kW) at transformer and the assigned load limit ($L_{TR,i}$, kW) or with the transformer rated capacity $TR_{cap,i}$.

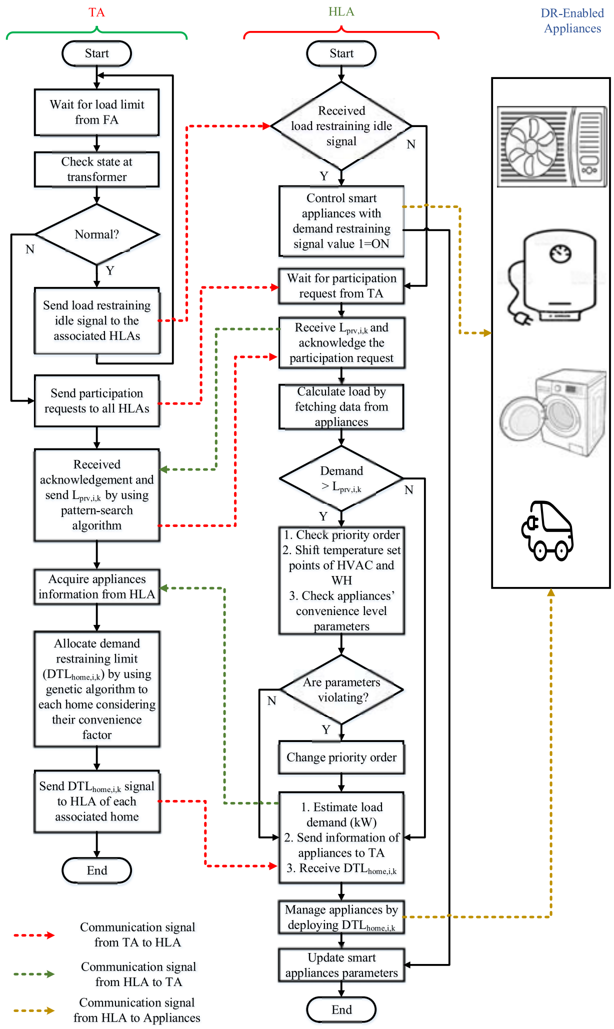


FIGURE 2. Signal coordination and strategy for a TA located at transformer and an HLA resided in a home.

Step 3: If the state at transformer is normal, the TA sends "load restraining idle signal" to the HLAs of all associated homes and the HLA controls all smart appliances with $C_{j,app} = 1$, where "$C_{j,app}$" represents demand restraining signal for a smart appliance, where "app" represents set of smart household appliances. Otherwise, TA forwards the participation requests to the associated HLAs.

Step 4: The HLA acknowledges the participation request with a set of required load demand consists of load demand of critical loads and load demand of all household appliances, and a relationship between demand rebound index and load demand. The TA allocates the provisional load limit ($L_{prv,i,k}$) to the associated HLAs considering the number of received acknowledgments by using pattern search algorithm.

The incentives will be given to the participated homes during normal operating state by offering low price of the consumed units, whereas, during critical state, the non-responsive homes will pay the penalty in the form of high price for each consumed unit.

Step 5: The HLA calculates the home demand (kW) by fetching data from household appliances.

Step 6: The HLA adjusts the set points of temperature for WH and HVAC considering their convenience level setting, if the home demand (kW) is more than $L_{prv,i,k}$. It also checks the convenience level parameters and load priority of each smart appliance and changes the priority order in case of violation of convenience level setting.

Step 7: The HLA estimates the instantaneous load (kW) of a home by deploying $L_{prv,i,k}$ and sends appliances' information to the TA.

Step 8: The TA assigns demand restraining limit ($DTL_{home,i,k}$) to the associated HLAs by using genetic algorithm in order to reduce network congestion and to minimize consumers' convenience factor.

Step 9: Finally, the HLA manages the smart appliances by switching-off least priority appliance(s) to assure that $W_{home,i,k}$ remains below the assigned $DTL_{home,i,k}$.

In the next section, the mathematical modeling of the smart home appliances is discussed.

III. MODELING OF SMART HOME APPLIANCES

In this paper, a methodology is designed to accommodate the smart household appliances including EVs during contingencies and to avoid overloading of the power distribution network equipment (e.g. transformer). The designed technique manages the smart appliances in a way to mitigate the demand rebound impacts. Therefore, it tends to reduce the required demand after contingency/overloading event.

During a contingency or overload condition, the HLA receives external signal from the TA to manage power consumption of smart household appliances including WH, EV, HVAC and CD. These appliances are considered as smart appliances and their mathematical models are developed as in [45]. All other household appliances are considered as inflexible/critical appliances which can not be controlled.

The physical models of smart household appliances are developed and modeled in this section to illustrate how they react to demand restraining request. A consumer has to set the convenience level and priority of every smart appliance in order to control it appropriately. Convenience level of an appliance is its least acceptable job finish time/set point of temperature. The HLA will dynamically change the preset appliances' priority order once it perceives that the convenience level settings are violating. The convenience level settings for WH and HVAC are represented in set points of temperature, whereas it is considered as process/task finish time for CD and EV. According to their own comfort, the consumers can change the appliances' setting at any time. The impacts of the behavior of home residents are also taken into account for modeling of the smart loads as considered in [45].

A. MODEL DEVELOPMENT FOR HVAC

In each time interval j, the power required ($R_{j,ac}$) by an HVAC system depends on the temperature set point ($t_{s,ac}$) and the current room temperature ($t_{j,ac}$). $R_{j,ac}$ is calculated as in (8).

$$R_{j,ac} = W_{ac}.E_{j,ac}.C_{j,ac} \tag{8}$$

where "$C_{j,ac}$" and "$E_{j,ac}$" represent demand restraining and state signals during time slot j for HVAC, respectively (0=OFF and 1=ON).

The HVAC is ON when the temperature drops belows a certain point and OFF when it exceeds the set temperature. The HVAC system remains in the previous state if $t_{j,ac}$ lies within the acceptable range. Mathematically, it is expressed in (9)

$$E_{j,ac} = \begin{cases} 0, & t_{j,ac} > (t_{s,ac} + t_{con,ac}) + \delta t_{ac} \\ 1, & t_{j,ac} < (t_{s,ac} + t_{con,ac}) - \delta t_{ac} \\ E_{j-1,ac}, & t_{s,ac} - \delta t_{ac} \leq t_{j,ac} - t_{con,ac} \leq t_{s,ac} + \delta t_{ac} \end{cases} \tag{9}$$

where "δt_{ac}" is the tolerance in room temperature, and "$t_{con,ac}$" represents the adjustment in set point of HVAC temperature during contingency/overload condition considering its convenience level setting.

The value of $C_{j,ac}$ depends on the contingency/overload situation. If the state at transformer is critical, then the value of $C_{j,ac}$ depends on the allocated demand restraining limit ($DTL_{home,i,k}$) and the HVAC priority. Otherwise, it remains 1=ON.

The calculation of room temperature for a time interval j is conducted as in (10).

$$t_{j,ac} = t_{j-1,ac} + \delta l.\frac{H_{j,G}}{\delta r} + \delta l.\frac{C_{HVAC}}{\delta r}.E_{j,ac}.C_{j,ac} \tag{10}$$

B. MODEL DEVELOPMENT FOR WH

In each time interval j, the power required ($R_{j,wh}$) by a WH system depends on the temperature set point of hot water ($t_{s,wh}$) and the current temperature of the water ($t_{j,wh}$). $R_{j,wh}$ can be obtained as follows:

$$R_{j,wh} = E_{j,wh}.W_{wh}.\eta_{wh}.C_{j,wh} \tag{11}$$

where "$C_{j,wh}$" and "$E_{j,wh}$" represent demand restraining and state signals for the WH, respectively (0=OFF and 1=ON), and "η_{wh}" represents efficiency of the unit.

The WH is ON when the temperature drops belows a certain point and OFF when it exceeds the set temperature. The WH system remains in the previous state if $t_{j,wh}$ lies within the acceptable range. Mathematically, it is expressed in (12).

$$E_{j,wh} = \begin{cases} 0, & t_{j,wh} > (t_{s,wh} + t_{con,wh}) + \delta t_{wh} \\ 1, & t_{j,wh} < (t_{s,wh} + t_{con,wh}) - \delta t_{wh} \\ E_{j-1,wh}, & t_{s,wh} - \delta t_{wh} \leq t_{j,wh} \\ & -t_{con,wh} \leq t_{s,wh} + \delta t_{wh} \end{cases} \tag{12}$$

where "δt_{wh}" is the tolerance in hot water temperature, and "$t_{con,wh}$" represents adjustment in the set point of WH temperature during contingency/overload condition considering its convenience level setting.

The value of $C_{j,wh}$ is dependent on contingency/overload situation. If the state at transformer is critical, then the value of $C_{j,wh}$ depends on the allocated demand restraining limit ($DTL_{home,i,k}$) and WH priority. Otherwise, it remains 1=ON.

The calculation of hot water temperature for a time interval j is conducted as in (13).

$$t_{j,wh} = \frac{t_{j-1,wh}.(U_{tank} - Rw_j.\delta l)}{U_{tank}} + \frac{t_{wh,inlet}.Rw_j.\delta l}{U_{tank}} + \frac{1gal}{8.34lb}.\left[E_{j,wh}.C_{j,wh}.\frac{3412Btu}{kWh} - \frac{A_{s,tank}.(t_{j,wh} - t_{air})}{R_{H,tank}}\right] .\frac{\delta l}{60\frac{min}{h}}.\frac{1}{U_{tank}} \tag{13}$$

C. MODEL DEVELOPMENT FOR CD

In a cloth dryer, there are two components which require power (kW): the heating coils, and a motor. The power consumption of heating coils is normally in the range of several kilowatts, whereas in contrast, the motor requirement is in the range of several hundred watts.

In each time interval j, the power required ($R_{j,cd}$) by a CD unit depends on the total time to finish the job ($Jt_{max,cd}$) and its aggregated turn-ON time ($Jt_{j,cd}$) which is determined as in (14).

$$R_{j,cd} = E_{j,cd}.C_{j,cd}.W_{coil,cd} + W_{mtr,cd}.E_{j,cd} \tag{14}$$

where "$C_{j,cd}$" and "$E_{j,cd}$" represent demand restraining and state signals for CD, respectively (0=OFF and 1=ON).

$C_{j,cd}$ manages the load demand (kW) of heating coils only. Therefore, once the operation of cloth dryer is started, the motor starts working and stops after the task is finished. If $Jt_{max,cd}$ is greater than $Jt_{j,cd}$, the heating coils turn-ON. Otherwise, the coils are OFF. It is represented in (15) as follows:

$$E_{j,cd} = \begin{cases} 0, & Jt_{j,cd} \geq Jt_{max,cd} \\ 1, & Jt_{j,cd} < Jt_{max,cd} \end{cases} \tag{15}$$

The value of $C_{j,cd}$ is dependent on contingency/overload situation. If the state at transformer is critical, then the value of $C_{j,cd}$ depends on the allocated demand restraining limit ($DTL_{home,i,k}$) and CD priority. Otherwise, it remains 1=ON.

Equation (16) represents the mathematical expression for calculation of $Jt_{j,cd}$ in each time interval j.

$$Jt_{j,cd} = E_{j,cd}.C_{j,cd}.\delta l + Jt_{j-1,cd}\Big|_{Jt_{0,cd}=0} \tag{16}$$

where "δl" represents the interval length (hour) and $Jt_{0,cd}$ represents the value of cloth dryer aggregated time at the time of plug-in.

D. MODEL DEVELOPMENT FOR EV

An EV charging model mainly consists of three components: plug-in time, charger rating, and battery state-of-charge (SOC). In each time interval j, the power required (kW) by an EV ($R_{j,EV}$) is related to the maximum state-of-charge ($SOC_{max,EV}$) and the current state-of-charge ($SOC_{j,EV}$) of the battery and can be obtained as follows:

$$R_{j,EV} = W_{EV}.S_{j,EV}.E_{j,EV}.C_{j,EV} \tag{17}$$

where "$S_{j,EV}$" represents the plug-in status during time slot j, where 1=plugged-in and 0=unplugged; "$C_{j,EV}$" and "$E_{j,EV}$" represent demand restraining and state signals for EV, respectively (0=OFF and 1=ON).

The charging state of an EV is described as follows:

$$E_{j,EV} = \begin{cases} 0, & SOC_{j,EV} \geq SOC_{max,EV} \\ 1, & SOC_{j,EV} < SOC_{max,EV} \end{cases} \tag{18}$$

The value of ($C_{j,EV}$) is dependent on contingency/overload situation. If the state at transformer is critical, then the value of $C_{j,wh}$ depends on the allocated demand restraining limit ($DTL_{home,i,k}$) and EV priority. Otherwise, it remains 1=ON.

The calculation for the initial SOC ($SOC_{0,EV}$) of an EV is expressed in (19).

$$SOC_{0,EV} = 1 - \frac{T_{pr}}{R_{bat}} \tag{19}$$

The value of $SOC_{j,EV}$ in each time interval j is determined using (20) as follows:

$$SOC_{j,EV} = SOC_{j-1,EV} + R_{j,EV}.\frac{\delta l}{R_{bat}} \tag{20}$$

where "$R_{j,EV}$" represents the load demand of an EV during time slot j, and "δl" represents the interval length (hour).

Gaussian probability distribution is used to find the arrival time of EVs and is expressed in (21). The standard deviation and the mean for distribution are 2.8 hours and 18 hour respectively [46]. The probability of home-arrival-time of EVs is represented in Fig. 3.

$$h(t, \sigma, \mu) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} \tag{21}$$

where "$h(t, \sigma, \mu)$" is the probability density of electric vehicles' home-arrival-time; "σ" represents the standard deviation for the distribution and "μ" represents the average value of EVs home-arrival-time.

The initial state of charge of EVs are determined by using the daily driving patterns. Fig. 4 represents the daily traveling distance in America in miles [47]. In this study, daily traveling distance for each EV is determined by using Monte Carlo Simulations.

The mathematical formulation of the designed approach is explained in the next section.

IV. MATHEMATICAL FORMULATION

This study focuses on optimal control of smart household appliances during critical state to reduce demand rebound. The grid operator seeks for reducing system stress and the customers prefer to have minimum impact of the designed strategies on their routine life. To reduce system stress and

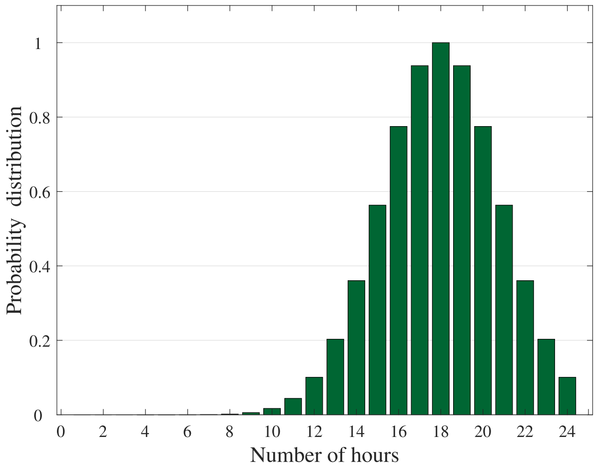


FIGURE 3. EVs home arrival time distribution.

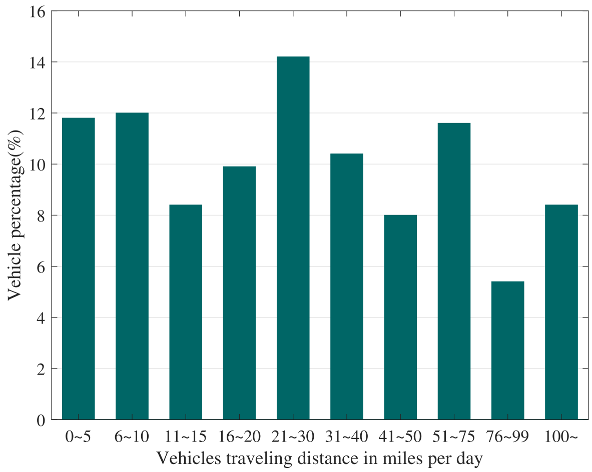


FIGURE 4. Vehicles driving distance in America.

demand rebound, a demand rebound index (DRBI) is developed and is minimized by using pattern search algorithm, whereas to fulfill consumers' objectives, the convenience factor of each home is minimized by using genetic algorithm and a demand restraining limit is assigned.

During critical state, the HLA acknowledges the participation request with the set of required load demand ($LD_{H,req,i,k}$) as indicated in (22) and a relationship ($DRBI_{H,i,k}(LD_{H,i,k})$) between demand rebound index at the home level ($DRBI_{H,i,k}$) and the load demand of home ($LD_{H,i,k}$).

$$LD_{H,req,i,k} \in \big[LD_{H,req,low,i,k} = D_{H,hist,crit,max,i,k} \quad LD_{H,req,max,i,k} = D_{H,hist,max,i,k}\big] \tag{22}$$

where "$LD_{H,req,low,i,k}$" is the load demand of a home $k \in K$ associated with transformer $i \in N$ to secure critical loads; "$LD_{H,req,max,i,k}$" is the total demand of a home; "$D_{H,hist,crit,max,i,k}$" and "$D_{H,hist,max,i,k}$" are the maximum required power of critical loads and the maximum required power of all the appliances in a home based on historical data of similar day, respectively.

$DRBI_{H,i,k}(LD_{H,i,k})$ is derived without the explicit knowledge from neighboring HLAs and TAs. It is related to the average home's historical demand profile ($D_{H,hist,i,k}$) of the same climate. By taking samples of $LD_{H,i,k}$ ranging from its lower bound ($LD_{H,req,low,i,k}$) to the upper bound ($LD_{H,req,max,i,k}$), and applying to (23), we can obtain different values of $DRBI_{H,i,k}$.

$$DRBI_{H,i,k} = \int_{t_{EN_{start}}}^{t_{EN_{end}}} \big(D_{H,hist,i,k} - LD_{H,i,k}\big)dt \quad s.t.\ D_{H,hist,i,k} - LD_{H,i,k} \geq 0. \tag{23}$$

An approximated $DRBI_{H,i,k}$ as a function of $LD_{H,i,k}$ is empirically indicated in (24) as a quadratic function by using polynomial regression as follows:

$$DRBI_{H,i,k}(LD_{H,i,k}) = a_{H,i,k} \cdot LD^2_{H,i,k} + b_{H,i,k} \cdot LD_{H,i,k} + c_{H,i,k} \tag{24}$$

where "$a_{H,i,k}$", "$b_{H,i,k}$", and "$c_{H,i,k}$" are the co-efficients of 4 quadratic function.

The demand rebound at the transformer level ($DRBI_{TR,i}$) is represented in (25) which depends on $DRBI_{H,i,k}(LD_{H,i,k})$ of all the associated homes.

$$DRBI_{TR,i} = \sum_{k=1}^{K} DRBI_{H,i,k}(LD_{H,i,k}) \quad \forall i = 1,\ldots,N \tag{25}$$

The TA minimizes the $DRBI_{TR,i}$ by using pattern search algorithm and allocates provisional demand limit ($L_{prv,i,k}$) to the associated homes. The objective function of this optimization problem is given in (26) as follows:

$$min\left(DRBI_{TR,i} = \sum_{k=1}^{K}\left\{a_{H,i,k} \cdot L^2_{prv,i,k} + b_{H,i,k} \cdot L_{prv,i,k} + c_{H,i,k}\right\}\right) \tag{26}$$

Subject to
Equality constraints

1) $\sum_{k=1}^{K} L_{prv,i,k} = L_{TR,i} \quad or \quad \sum_{k=1}^{K} L_{prv,i,k} = TR_{cap,i}$

Inequality constraints

2) $LD_{H,req,low,i,k} \leq L_{prv,i,k} \leq LD_{H,req,max,i,k}$
$\forall i = 1,\ldots,N$
$\forall k = 1,\ldots,K$

The HLA constructs a belief vector ($\boldsymbol{B_{H,i,k}}$) after receiving $L_{prv,i,k}$ as defined in (27).

$$[\boldsymbol{B_{H,i,k}}]_{X\times 1} = [\boldsymbol{CBN}]_{X\times Y}\cdot[\boldsymbol{PWR}]_{Y\times 1} \tag{27}$$

where "$X = \sum_{r=1}^{Y}\frac{Y!}{r!(Y-r)!}$" is the total number fo beliefs and "Y" is the total number of smart appliances.

"$[\boldsymbol{CBN}]_{X\times Y}$" represents a combination matrix of usage status of all smart loads and is given in (28).

$$[\boldsymbol{CBN}]_{X\times Y} = \begin{bmatrix} u_{app,1,1} & u_{app,1,2} & \cdots & u_{app,1,f} \\ u_{app,2,1} & u_{app,2,2} & \cdots & u_{app,2,f} \\ \vdots & \vdots & \ddots & \vdots \\ u_{app,e,1} & u_{app,e,2} & \cdots & u_{app,e,f} \end{bmatrix} \quad (28)$$

where "$u_{app,e\in X,f\in Y}$" is an appliance status which is either 0 or 1.

"$[\boldsymbol{PWR}]_{Y\times 1}$" is the vector consisting of rated load demand (kW) of all smart appliances given in (29).

$$[\boldsymbol{PWR}]_{Y\times 1} = [R_{app,1}, R_{app,2}, \cdots, R_{app,Y}]^T \quad (29)$$

where "$R_{app,z\in Y}$" is the power required (kW) by an appliance $z \in Y$.

The HLA sends the appliances' data and the load demand of home (LD_{prv}) considering belief vector and provisional demand limit ($L_{prv,i,k}$). The TA allocates demand restraining limit ($DTL_{home,i,k}$) to the associated homes by minimizing the convenience factor ($CI_{home,i,k}$) of the homes by using genetic algorithm and therefore, helps in reducing network congestion and in maintaining consumers' satisfaction.

The convenience factor of a home $k \in K$ ($CI_{home,i,k}$) is obtained from the convenience factor of smart household appliances. An appliance convenience factor ($CI(k)_{Appliance,i}$) is derived from its convenience level setting.

For each smart household appliance, its convenience factor is described as follows:

A. HVAC CONVENIENCE FACTOR

In a time interval j the convenience factor of HVAC ($CI(k)_{HVAC,i}$) of a home $k \in K$ associated with a distribution transformer $i \in N$ is determined by the ratio of the difference of its convenience setting for HVAC ($t_{con,ac}$) and actual room temperature ($t_{j,ac}$), and $t_{con,ac}$ as indicated in (30).

$$CI(k)_{HVAC,i} = \frac{t_{con,ac} - t_{j,ac}}{t_{con,ac}} \quad (30)$$

B. CONVENIENCE FACTOR FOR WH

In a time interval j, the convenience factor of WH ($CI(k)_{WH,i}$) of the k-th home associated with a distribution transformer $i \in N$ is determined by the ratio of the difference of its convenience setting for WH ($t_{con,wh}$) and actual hot water temperature ($t_{j,wh}$), and $t_{con,wh}$ as expressed in (31).

$$CI(k)_{WH,i} = \frac{t_{con,wh} - t_{j,wh}}{t_{con,wh}} \quad (31)$$

C. CONVENIENCE FACTOR FOR CD

In a time interval j, the convenience factor of CD ($CI(k)_{CD,i}$) of a home $k \in K$ associated with a distribution transformer $i \in N$ is determined by the ratio of the difference of its convenience setting remaining time ($Jt_{rem,cd}$) and remaining time to finish the job ($Jt_{j,cd}$), and actual convenience level setting ($Jt_{con,cd}$). It is expressed in (32) as follows:

$$CI(k)_{CD,i} = \frac{Jt_{rem,cd} - Jt_{j,cd}}{Jt_{con,cd}} \quad (32)$$

D. CONVENIENCE FACTOR FOR EV

In a time interval j, the convenience factor of EV ($CI(k)_{EV,i}$) of the k-th home associated with a transformer $i \in N$ is determined by the ratio of the difference of its convenience setting remaining time ($Rt_{rem,ev}$) and remaining time to finish the charging ($Rt_{j,ev}$), and actual convenience level setting ($Rt_{con,ev}$).

$$CI(k)_{EV,i} = \frac{Rt_{rem,ev} - Rt_{j,ev}}{Rt_{con,ev}} \quad (33)$$

As such, in a time interval j, a consumer's convenience factor ($CI_{home,i,k}$) is calculated as in (34).

$$CI_{home,i,k} = \frac{1}{Y} \cdot \Big[CI(k)_{HVAC,i} + CI(k)_{WH,i} + \cdots \cdots + CI(k)_{CD,i} + CI(k)_{EV,i}\Big] \quad (34)$$

where "Y" represents the number of plugged-in DR-enabled household appliances in a home $k \in K$ connected with transformer $i \in N$. The value of $CI(k)_{Appliance,i}$ for an appliance will be '0' if it is unplugged.

Now the objective function that is minimized by using genetic algorithm is expressed in (35).

$$min\left(\sum_{k=1}^{K} CI_{home,i,k} = \sum_{k=1}^{K}\Big\{CI(k)_{HVAC,i} + CI(k)_{WH,i} + CI(k)_{CD,i} + CI(k)_{EV,i}\Big\}\right) \quad (35)$$

Subject to

$$1)\ \sum_{k=1}^{K} DTL_{home,i,k} \leq L_{TR,i}\ or\ \sum_{k=1}^{K} DTL_{home,i,k} \leq TR_{cap,i}$$
$$2)\ LD_{prv} \leq DTL_{home,i,k} \quad \forall i = 1,\ldots,N \quad \forall k = 1,\ldots,K$$

The demand restraining limit ($DTL_{home,i,k}$) of a home $k \in K$ associated with transformer $i \in N$ in a time interval j can be calculated as follows:

$$DTL_{home,i,k} = C_{R\_L} + R_{j,ac} + R_{j,wh} + R_{j,cd} + R_{j,ev} \quad (36)$$

where "C_{R_L}" is the power required (kW) by critical loads.

To analyze the effectiveness of the designed architecture, a case study is performed in the next section.

V. CASE STUDY

In this section, a node of a distribution feeder of load 300kW consisting of 9 single-phase transformers of ABB has been simulated. Six of the transformers are of rating 37.5kVA, and each one is serving 5 homes, whereas 3 transformers are of rating 25kVA and each one is serving 3 homes.

For appliances' rated power, RELOAD database is used [48]. Table 1 summarizes the important parameters and attributes of the consumers.

TABLE 1. Parameters of the consumers under study.

Attributes	Values	Unit
Area of homes	850+225 basement	square ft
$S_{Ceiling}$, S_{Window}, S_{Wall}	35, 4, 13	$ft^2.^\circ F$(Btu/h)
Number of persons	3-5	person
Temperature setting of HVAC	(74-79)±2	$^\circ F$
Ambient temperature	New York average temperature for January	$^\circ F$
Temperature setting of WH	(118-127)± 3.5	$^\circ F$
Tank capacity of WH	52	gallons
R-value of WH	14.57± 2	$ft^2.^\circ F$ (Btu/h)
Consumption of hot water	Real data from NAHBRC [49]	gallons/min
Clothes dryer starting time	19:15-21:30	-
Clothes dryer stop time	00:00-01:30	-
Operating duration of CD	1 hour to finish the job	-
Plugged-in time of EVs	Assesses by Gaussian random distribution	-
Departure time of EVs	06:30-07:30	-
Appliances' priority	HVAC >WH >CD >EV	-

The starting time of simulation for this study has been considered 17:00 as majority of the EVs start approaching home after 17:00. New York's average temperature for January has been considered to perform the simulation of the modeled infrastructure. The time interval of 15 minutes has been considered in this study. The arrival time of electric vehicles have been generated by using Gaussian random distribution, and Monte-Carlo simulations are performed to fetch initial important parameters such as initial temperature of hot water, initial room temperature, convenience level settings of smart household loads, plug-in time of CD etc.

Table 2 indicates the smart appliances' priority order along-with their convenience level settings. In this study, the electric vehicles of Chevrolet [50] and Nissan Leaf [51] have been modeled and their specifications are provided in Table 3.

TABLE 2. Priority list and convenience setting of smart appliances.

Smart Appliances	Priority Order	Convenience level setting
HVAC	1	Set point of room temperature (65-71)$^\circ F$
WH	2	Set point of hot water temperature (105-113)$^\circ F$
CD	3	00:00-01:30
EV	4	06:30-07:30

TABLE 3. Specifications of EVs.

Type	Charger rating	Battery size	Driving range	Energy available
Chevrolet	6.6 kW	60 kWh	238 miles	47 kWh
Nissan Leaf	3.3 kW	24 kWh	100 miles	19.2 kWh

A. VALIDATION AND COMPARISON

The effectiveness of the designed EDR infrastructure has been assessed by evaluating the performance of proposed EDR strategy against simple fair distribution approach during contingency condition, whereas the results of the proposed technique have also been compared with that of another decentralized technique, which uses water-filling algorithm [52], [53] to control smart appliances, for the simulation time of 17:00 to 08:00 at a transformer level.

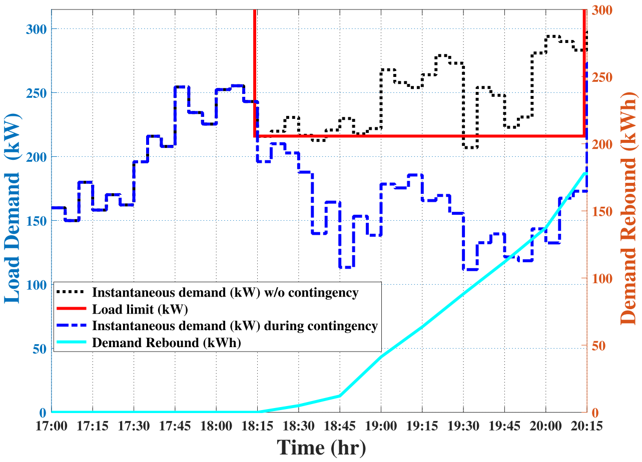
In simple fair distribution, FA allocates the demand limit ($L_{TR,i}$) to the associated transformers during contingency condition and then TA allocates the demand restraining limit ($DTL_{home,i,k}$) to the associated homes by fair distribution, i.e. by dividing the assigned power to the total number of homes. Fig. 5a shows the simulation results at the feeder node level with simple fair distribution and Fig. 5b shows the simulation results at the distribution feeder node level with the proposed EDR infrastructure. After receiving the EDR event signal from grid operator with load limit (L_{GO}) of 216 kW for 18:15 to 20:15, FA immediately assigns the demand limit ($L_{TR,i}$) to each transformer based on (3). The demand limit assigned to 37.5 kVA transformer is 27 kVA and for 25 kVA transformer is 18 kVA. According to Fig. 5a and Fig. 5b, the total instantaneous power demand (kW) is retained below the load limit assigned to feeder node during EDR event, for both techniques. The assessed demand rebound at the feeder node ($DRBI_{FN}$) for the simple fair distribution technique is 177.78 kWh as shown in Fig. 5a, where $DRBI_{FN}$ is mathematically expressed as follows:

$$DRBI_{FN} = \int_{t_{EN_{start}}}^{t_{EN_{end}}} (D_{FN,hist} - D_{FN,act})dt \tag{37}$$

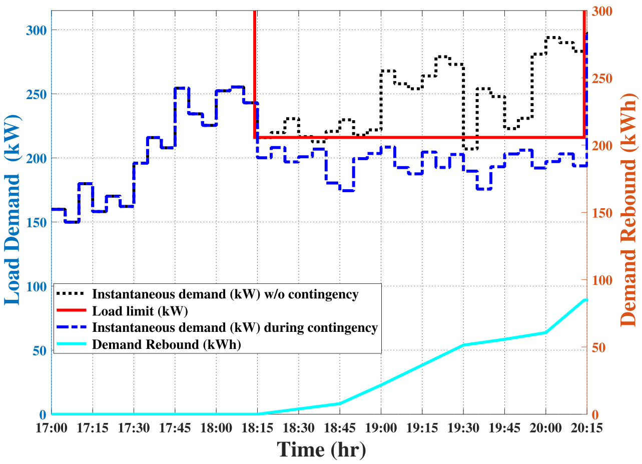
where "$D_{FN,hist}$" is the historical load profile at the feeder node without EDR event and "$D_{FN,act}$" is the actual load profile at the feeder node during EDR event. The smaller the $DRBI_{FN}$, the lower will be the impacts of demand rebound.

The demand rebound of 177.78 kWh for the simple fair distribution technique can be illustrated as equivalent to a 177.78 kW increase in load demand for 1 hour due to load compensation of deferred smart household appliances. This can cause an undesired overloading of the distribution network as well as under-voltage issue as the impacts of demand rebound following an EDR event. The assessed demand rebound at the feeder node for proposed EDR strategy is 84.86 kWh as shown in Fig. 5b. This can be considered as a 84.86 kW increase in load demand for 1 hour due to load compensation of smart household appliances that have been deferred.

Considering performance evaluation of the FA, TAs and HLAs, the proposed EDR infrastructure considerably reduces the demand rebound index as compared to the simple fair distribution approach. According to Table 4, the assessed $DRBI_{FN}$ of 84.86 kWh with the proposed EDR technique representing approximately 53% reduction compared to the 177.78 kWh $DRBI_{FN}$ with the simple fair distribution approach. The lesser the demand rebound index, the lesser



(a) For simple fair distribution



(b) For proposed EDR strategy

FIGURE 5. Simulation results at feeder node during contingency condition.

TABLE 4. Comparison of demand rebound (kWh).

Parameter	With water-filling algorithm	With proposed EDR strategy	%age reduction
Demand rebound	177.78 kWh	84.86 kWh	53%

the chance that an undesired overloading of the distribution network occurs following an EDR event.

In order to evaluate the effectiveness of the proposed infrastructure, a comparison is drawn against another decentralized approach which uses water-filling algorithm [52], [53] to control the smart household appliances. A simulation is performed at a transformer (37.5 kVA) level serving 5 homes. The duration of the simulation is 16 hours from 17:00 to 08:00 with time step of 15 minutes. The simulation time duration is considered according to arrival and departure time of EVs, as majority of the EVs depart home before 08:00 and arrive home after 17:00.

Fig. 6 represents the load profile of transformer with and without EVs which shows a rise in load demand after EVs start arriving homes. Fig. 7 shows the load profile of transformer by restraining the peak demand using water-filling algorithm during overload condition. The demand restrain-

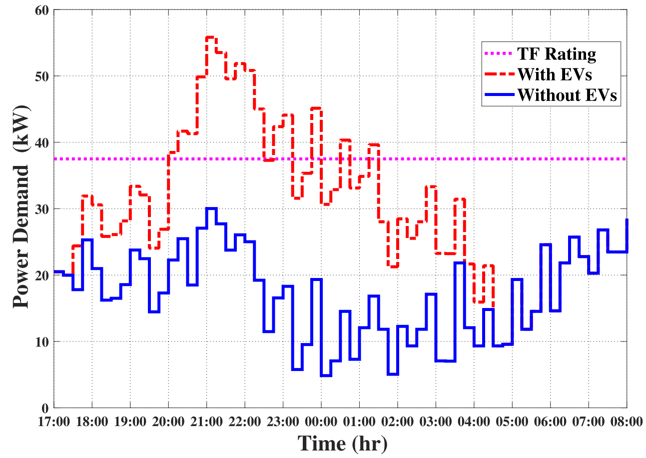


FIGURE 6. Transformer load profile with and without EVs.

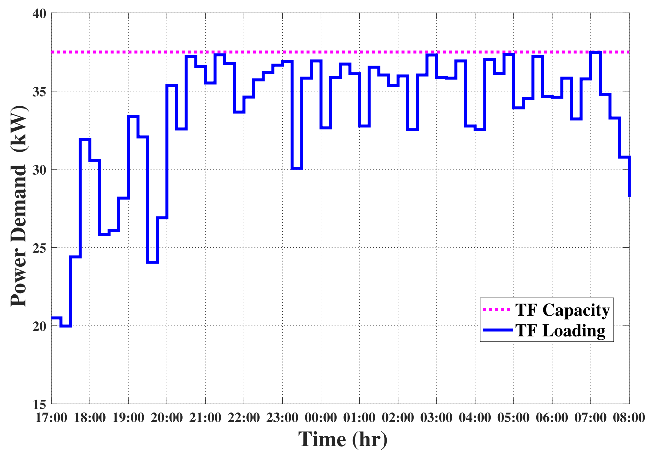


FIGURE 7. Load profile of transformer with water-filling algorithm.

ing limit ($DTL_{home,WF}$) is allocated by using water-filling algorithm to each associated home. The load profile (kW) of each home considering $DTL_{home,WF}$ as a demand limit during overload condition is outlined in Fig. 9(a)-13(a). Where, "LD1-5" are the instantaneous load demands of the five associated homes. The results show that the load (kW) of all the associated homes has been retained below the allocated $DTL_{home,WF}$ and the transformer load does not exceed its rated capacity. For each smart household load of the associated consumers, the deviation of simulated results against an appliance convenience level setting has been illustrated in Table 5. The simulation results of the proposed infrastructure have been shown in Fig. 9(b)-13(b) for the associated homes and in Fig. 8 for the distribution transformer, whereas the deviation of the simulated results against an appliance convenience level setting is summarized in Table 6 for each customer.

B. DISCUSSION

In this section, the effectiveness of the proposed technique has been assessed by evaluating the load profile of each home represented in Fig. 9(b)-13(b) for entire simulation duration with the load profile of homes obtained by using water-filling algorithm in Fig. 9(a)-13(a).

TABLE 5. Simulation results of water-filling algorithm.

Parameter	Customer 1		Customer 2		Customer 3		Customer 4		Customer 5	
	Conve. Setting	Actual Result	Conve. Setting	Actual Result	Conve. Setting	Actual Result	Conve. Setting	Actual Result	Conve. Setting	Actual Result
HVAC	$71°F$	$68.84°F$	$65°F$	$68.23°F$	$69.2°F$	$65.41°F$	$71°F$	$72.24°F$	$70.1°F$	$66.83°F$
WH	$113°F$	$108.8°F$	$105°F$	$106.2°F$	$109.4°F$	$108.7°F$	$110°F$	$112.4°F$	$107°F$	$101.5°F$
CD	12:00 am	10:30 pm	12:30 am	12:00 am	01:00 am	12:15 am	01:30 am	12:00 am	01:15 am	11:30 pm
EV	07:00 am	07:30 am	06:30 am	05:30 am	07:15 am	07:45 am	07:30 am	06:45 am	07:00 am	07:15 am

TABLE 6. Simulation results of proposed strategy.

Parameter	Customer 1		Customer 2		Customer 3		Customer 4		Customer 5	
	Conve. Setting	Actual Result	Conve. Setting	Actual Result	Conve. Setting	Actual Result	Conve. Setting	Actual Result	Conve. Setting	Actual Result
HVAC	$71°F$	$71.08°F$	$65°F$	$68.24°F$	$69.2°F$	$68.97°F$	$71°F$	$72.41°F$	$70.1°F$	$68.13°F$
WH	$113°F$	$120.3°F$	$105°F$	$121.7°F$	$109.4°F$	$114.9°F$	$110°F$	$115.9°F$	$107°F$	$113.2°F$
CD	12:00 am	08:30 pm	12:30 am	09:15 am	01:00 am	10:30 pm	01:30 am	10:15 pm	01:15 am	10:30 pm
EV	07:00 am	05:00 am	06:30 am	01:30 am	07:15 am	05:15 am	07:30 am	06:00 am	07:00 am	06:45 am

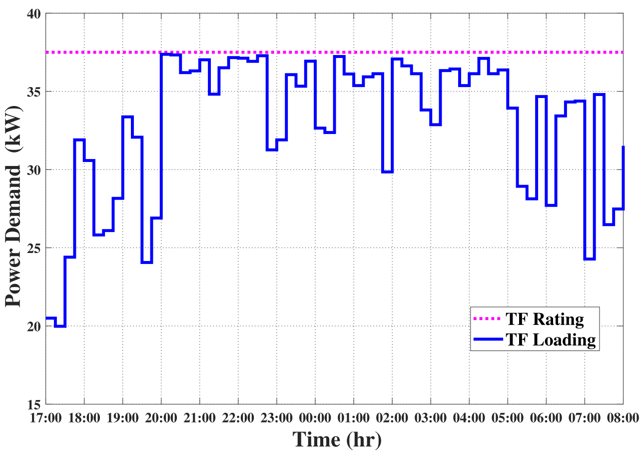


FIGURE 8. Load profile of transformer with the proposed infrastructure.

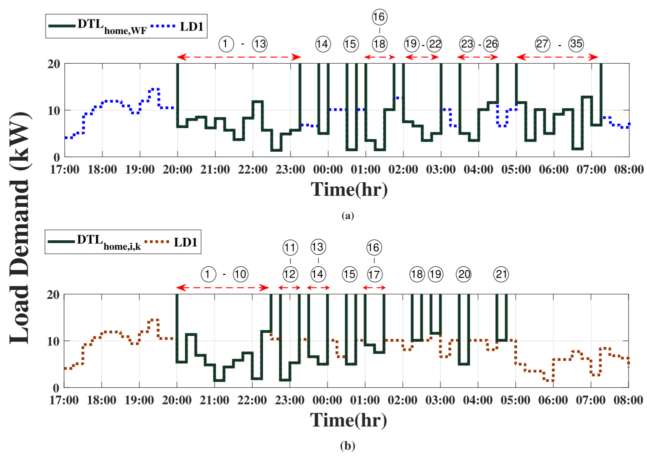


FIGURE 9. Instantaneous load of customer 1. (a) For water-filling algorithm, (b) For proposed EDR strategy.

Table 5 represents the difference between appliances' parameters and their convenience level settings using water-filling algorithm. An appliance convenience level setting has been exhibited in "Conve. Setting" column. The "Actual Result" column illustrates the job finish time for EV and CD, whereas it exhibits the lowest temperature ($°F$) measured throughout the simulation duration for WH and HVAC. The results manifested in Table 6 represent substantial improvements using the proposed approach in comparison to water-filling algorithm based approach with almost zero adverse effect on the customers' comfort. However, the proposed technique is more beneficial in mitigating the demand rebound impacts and it can be observed by comparing Fig. 9(a)-13(a) and Fig. 9(b)-13(b). The demand rebound events by using water-filling algorithm based approach are 35 during the entire simulation duration as shown in Fig. 9(a)-13(a) by the assignment of $DTL_{home,WF}$, whereas the demand rebound events are reduced to 21 by using the proposed technique and it is shown in Fig. 9(b)-13(b) by the assignment of $DTL_{home,i,k}$. The lesser the demand rebound events implies that whenever the power demand at the transformer exceeds beyond its rated capacity, the proposed approach efficiently and optimally allocates the demand restraining limit to each customer ($DTL_{home,i,k}$) in such a way that the demand rebound due to the load compensation of deferred smart household appliances is reduced in the future, following an overloading event. Therefore it reduces the congestion at distribution transformer and consequently of the entire distribution network. The congestion at transformer is measured as transformer congestion index (TCI) as follows:

$$TCI = \frac{\Psi_{cr}^{\mathbb{T}}}{\Psi_{si}^{\mathbb{T}}} \tag{38}$$

where "$\Psi_{cr}^{\mathbb{T}}$" represents the total time for which the required demand at transformer exceeded beyond its rated capacity

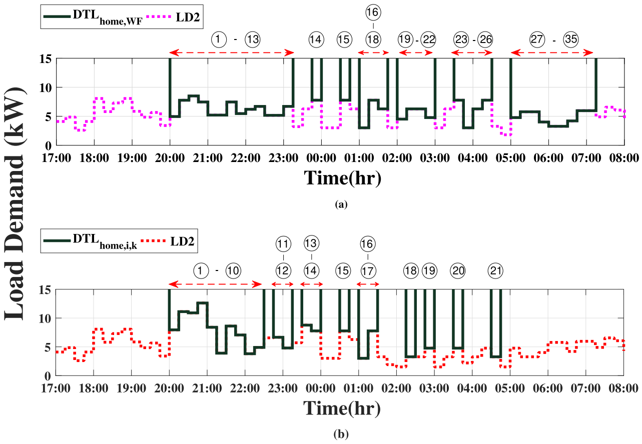


FIGURE 10. Instantaneous load of customer 2. (a) For water-filling algorithm, (b) For proposed EDR strategy.

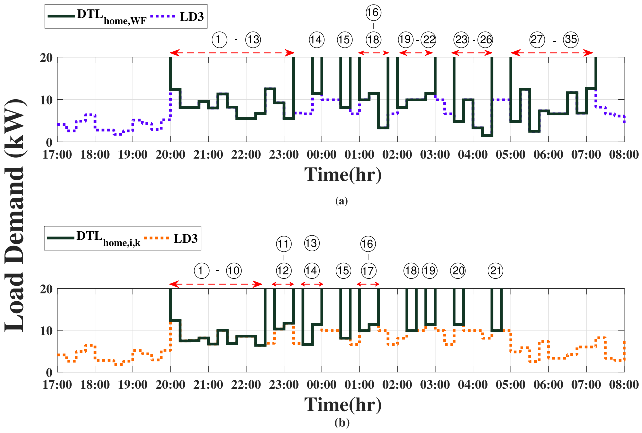


FIGURE 11. Instantaneous load of customer 3. (a) For water-filling algorithm, (b) For proposed EDR strategy.

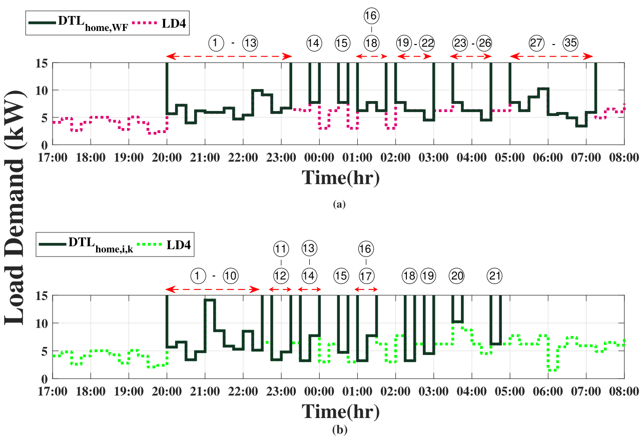


FIGURE 12. Instantaneous load of customer 4. (a) For water-filling algorithm, (b) For proposed EDR strategy.

while retaining the transformer loading below its rating, and "$\Psi_{si}^{\mathbb{T}}$" represents the total simulation time.

The TCI index for water-filling algorithm and the proposed EDR strategy to manage smart loads is outlined in Table 7.

There is a 40% reduction in transformer congestion index while using the proposed approach for allocation of demand

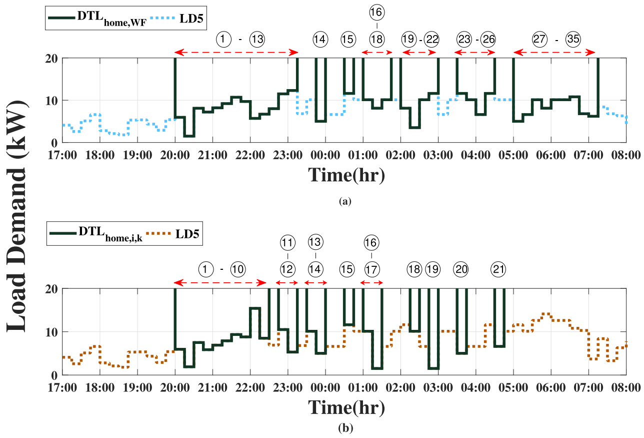


FIGURE 13. Instantaneous load of customer 5. (a) For water-filling algorithm, (b) For proposed EDR strategy.

TABLE 7. Comparison of transformer congestion index.

Parameter	For water-filling algorithm	For proposed EDR strategy	%age reduction
TCI	0.574	0.344	40 %

restraining limit compared to water-filling algorithm based approach and consequently, we can accommodate more EV load in a distribution network without upgrading it and can avoid the unnecessary overloading of the power system. Furthermore, the reduction in demand rebound events shows that during the overload condition, the proposed strategy optimally assigns the demand restraining limit such that the rise in load demand after an EDR event is reduced. This shows that the proposed strategy is more efficient and effective in mitigating the demand rebound impacts and optimally allocates the available capacity.

It can be inferred from the simulation results that even though water-filling algorithm performs well in utilizing the available resources at their best but still it lacks the efficient and effective allocation of the resources and the proposed technique outperforms it in terms of distribution network congestion and accommodation of load.

VI. CONCLUSION

This paper presented a decentralized approach over system-wide span for distribution feeder load management (DFLM) using autonomous decision making entities. The developed approach not only relieves the system stress, but also ensures customer satisfaction by optimal allocation of demand restraining limit in order to mitigate the demand rebound effects. The designed strategy controls the smart household appliances to achieve the objectives of FA, TAs and HLAs, and the performance of the developed approach is analyzed by comparing the results with that of the water-filling algorithm based approach and simple fair distribution approach. Furthermore, in order to evaluate the performance of the proposed approach, consumers' convenience, demand rebound and transformer congestion indices are developed and calculated. These indices can be used by the electric utilities to measure the efficiency and effectiveness of the demand response programs and to estimate the accommodation of EV fleet in a distribution network. The developed infrastructure satisfied the concerns of both utility and consumers. However, from utility perspective, the results of the developed approach showcased that the designed methodology is more efficient and effective compared to the simple fair distribution and water-filling algorithm based approaches in mitigating the demand rebound impacts after an EDR event. The comparison of the simulation results inferred that the subsequent demand response potential is reduced by 53% and the congestion at transformer is reduced 40% by employing the designed methodology while maintaining the consumers' comfort.

In future work, the proposed infrastructure can be scaled-up by including multiple nodes of a distribution network to consider more distribution transformers in order to involve more customers and smart appliances. However, the consumers' comfort will be negatively influenced with higher penetrations of EVs. At that stage, the grid operators cannot exclusively rely on DR approaches to cope with the load demand, and other resources e.g. network upgrade and distributed generation may be exploited.

REFERENCES

[1] *Renewables 2016 Global Status Report*. Accessed: Aug. 28, 2020. [Online]. Available: http://ren21.net/wp-content/uploads/2016/06/GSR_2016_Full_Report.pdf

[2] *Renewables Electricity Futures Study*. Accessed: Aug. 21, 2020. [Online]. Available: https://www.nrel.gov/docs/fy13osti/52409-ES.pdf

[3] *Integrating Renewable Electricity on the Grid*. Accessed: Aug. 18, 2020. [Online]. Available: https://www.aps.org/policy/reports/popa-reports/integrating.cfm

[4] *IEEE Guide for Smart Grid Interoperability of Energy Technology and Information Technology Operation With the Electric Power System (EPS), End-Use Applications, and Loads*, IEEE Standard 2030TM, 2016.

[5] *By 2022, 35 Million Electric Vehicles Will Hit the Roads*. Accessed: Aug. 23, 2020. [Online]. Available: http://ht.ly/2CM0d2

[6] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 371–380, Feb. 2010.

[7] K. J. Dyke, N. Schofield, and M. Barnes, "The impact of transport electrification on electrical networks," *IEEE Trans. Ind. Electron.*, vol. 57, no. 12, pp. 3917–3926, Dec. 2010.

[8] L. P. Fernández, T. G. S. Roman, R. Cossent, C. M. Domingo, and P. Frías, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 206–213, Feb. 2011.

[9] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, "Integration of electric vehicles in the electric power system," *Proc. IEEE*, vol. 99, no. 1, pp. 168–183, Jan. 2011.

[10] Y. Wang, I. R. Pordanjani, and W. Xu, "An event-driven demand response scheme for power system security enhancement," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 23–29, Mar. 2011.

[11] D.-M. Kim and J.-O. Kim, "Design of emergency demand response program using analytic hierarchy process," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 635–644, Jun. 2012.

[12] M. M. Sahebi, E. A. Duki, M. Kia, A. Soroudi, and M. Ehsan, "Simultanous emergency demand response programming and unit commitment programming in comparison with interruptible load contracts," *IET Generat. Transmiss. Distrib.*, vol. 6, no. 7, pp. 605–611, Jul. 2012.

[13] F. Yang, X. Feng, and Z. Li, "Advanced microgrid energy management system for future sustainable and resilient power grid," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 7251–7260, Nov. 2019.

[14] S. Sun, J. Fu, L. Wei, and A. Li, "Multi-objective optimal dispatching for a grid-connected micro-grid considering wind power forecasting probability," *IEEE Access*, vol. 8, pp. 46981–46997, 2020.

[15] C. Gouveia, J. Moreira, C. L. Moreira, and J. A. P. Lopes, "Coordinating storage and demand response for microgrid emergency operation," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1898–1908, Dec. 2013.

[16] Y. Li, B. L. Ng, M. Trayer, and L. Liu, "Automated residential demand response: Algorithmic implications of pricing models," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1712–1721, Dec. 2012.

[17] J. H. Yoon, R. Baldick, and A. Novoselac, "Dynamic demand response controller based on real-time retail price for residential buildings," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 121–129, Jan. 2014.

[18] M. B. Rasheed, M. A. Qureshi, N. Javaid, and T. Alquthami, "Dynamic pricing mechanism with the integration of renewable energy source in smart grid," *IEEE Access*, vol. 8, pp. 16876–16892, 2020.

[19] C. Vivekananthan, Y. Mishra, G. Ledwich, and F. Li, "Demand response for residential appliances via customer reward scheme," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 809–820, Mar. 2014.

[20] E. S. Parizy, H. R. Bahrami, and K. A. Loparo, "A decentralized three-level optimization scheme for optimal planning of a prosumer nano-grid," *IEEE Trans. Power Syst.*, vol. 35, no. 5, pp. 3421–3432, Sep. 2020.

[21] C. Li, X. Yu, W. Yu, G. Chen, and J. Wang, "Efficient computation for sparse load shifting in demand side management," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 250–261, Jan. 2017.

[22] A. Khalid, N. Javaid, M. Guizani, M. Alhussein, K. Aurangzeb, and M. Ilahi, "Towards dynamic coordination among home appliances using multi-objective energy optimization for demand side management in smart buildings," *IEEE Access*, vol. 6, pp. 19509–19529, 2018.

[23] B. Wang, Y. Li, W. Ming, and S. Wang, "Deep reinforcement learning method for demand response management of interruptible load," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3146–3155, Jul. 2020.

[24] F. Luo, W. Kong, G. Ranzi, and Z. Y. Dong, "Optimal home energy management system with demand charge tariff and appliance operational dependencies," *IEEE Trans. Smart Grid*, vol. 11, no. 1, pp. 4–14, Jan. 2020.

[25] X. Xu, Y. Jia, Y. Xu, Z. Xu, S. Chai, and C. S. Lai, "A multi-agent reinforcement learning-based data-driven method for home energy management," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3201–3211, Jul. 2020.

[26] S. Zheng, Y. Sun, B. Li, B. Qi, K. Shi, Y. Li, and X. Tu, "Incentive-based integrated demand response for multiple energy carriers considering behavioral coupling effect of consumers," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3231–3245, Jul. 2020.

[27] M. H. K. Tushar, A. W. Zeineddine, and C. Assi, "Demand-side management by regulating charging and discharging of the EV, ESS, and utilizing renewable energy," *IEEE Trans. Ind. Informat.*, vol. 14, no. 1, pp. 117–126, Jan. 2018.

[28] J. Jo and J. Park, "Demand-side management with shared energy storage system in smart grid," *IEEE Trans. Smart Grid*, vol. 11, no. 5, pp. 4466–4476, Sep. 2020.

[29] D. Li, W.-Y. Chiu, H. Sun, and H. V. Poor, "Multiobjective optimization for demand side management program in smart grid," *IEEE Trans. Ind. Informat.*, vol. 14, no. 4, pp. 1482–1490, Apr. 2018.

[30] E. Saeidpour Parizy, S. Choi, and H. R. Bahrami, "Grid-specific co-optimization of incentive for generation planning in power systems with renewable energy sources," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 947–957, Apr. 2020.

[31] M. M. Rahman, A. Arefi, G. M. Shafiullah, and S. Hettiwatte, "A new approach to voltage management in unbalanced low voltage networks using demand response and OLTC considering consumer preference," *Int. J. Electr. Power Energy Syst.*, vol. 99, pp. 11–27, Jul. 2018.

[32] A. Ehsan and Q. Yang, "Active distribution system reinforcement planning with EV charging stations—Part I: Uncertainty modeling and problem formulation," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 970–978, Apr. 2020.

[33] A. Ehsan and Q. Yang, "Active distribution system reinforcement planning with EV charging stations–Part II: Numerical results," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 979–987, Apr. 2020.

[34] M. B. Rasheed, M. Awais, T. Alquthami, and I. Khan, "An optimal scheduling and distributed pricing mechanism for multi-region electric vehicle charging in smart grid," *IEEE Access*, vol. 8, pp. 40298–40312, 2020.

[35] E. Sortomme, M. M. Hindi, S. D. J. MacPherson, and S. S. Venkata, "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 198–205, Mar. 2011.

[36] H. Liu, P. Zeng, J. Guo, H. Wu, and S. Ge, "An optimization strategy of controlled electric vehicle charging considering demand side response and regional wind and photovoltaic," *J. Mod. Power Syst. Clean Energy*, vol. 3, no. 2, pp. 232–239, Jun. 2015.
[37] O. Fallah-Mehrjardi, M. H. Yaghmaee, and A. Leon-Garcia, "Charge scheduling of electric vehicles in smart parking-lot under future demands uncertainty," *IEEE Trans. Smart Grid*, vol. 11, no. 6, pp. 4949–4959, Nov. 2020.
[38] A. Ghavami, K. Kar, and A. Gupta, "Decentralized charging of plug-in electric vehicles with distribution feeder overload control," *IEEE Trans. Autom. Control*, vol. 61, no. 11, pp. 3527–3532, Nov. 2016.
[39] A. Ghazanfari, M. Hamzeh, and Y. Abdel-Rady I. Mohamed, "A resilient plug-and-play decentralized control for DC parking lots," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1930–1942, May 2018.
[40] M. Liu, P. K. Phanivong, Y. Shi, and D. S. Callaway, "Decentralized charging control of electric vehicles in residential distribution networks," *IEEE Trans. Control Syst. Technol.*, vol. 27, no. 1, pp. 266–281, Jan. 2019.
[41] H. Xing, M. Fu, Z. Lin, and Y. Mou, "Decentralized optimal scheduling for charging and discharging of plug-in electric vehicles in smart grids," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 4118–4127, Sep. 2016.
[42] Y. Wan, J. Qin, F. Li, X. Yu, and Y. Kang, "Game theoretic-based distributed charging strategy for PEVs in a smart charging station," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 538–547, Jan. 2021.
[43] S. U. Khan, K. K. Mehmood, Z. M. Haider, M. K. Rafique, M. O. Khan, and C.-H. Kim, "Coordination of multiple electric vehicle aggregators for peak shaving and valley filling in distribution feeders," *Energies*, vol. 14, no. 2, p. 352, Jan. 2021.
[44] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "Optimal residential load management in smart grids: A decentralized framework," *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 1836–1845, Jul. 2016.
[45] S. Shao, M. Pipattanasomporn, and S. Rahman, "Development of physical-based demand response-enabled residential load models," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 607–614, May 2013.
[46] J. Taylor, A. Maitra, M. Alexander, D. Brooks, and M. Duvall, "Evaluations of plug-in electric vehicle distribution system impacts," in *Proc. IEEE PES Gen. Meeting*, Jul. 2010, pp. 1–6.
[47] *National Household Travel Survey*. Accessed: Sep. 17, 2020. [Online]. Available: https://nhts.ornl.gov/2001/usersguide/UsersGuide.pdf
[48] *Reload Database Documentation and Evaluation and Use in NEMS*. Accessed: Sep. 16, 2020. [Online]. Available: http://industrycortex.com/datasheets/pro_le/1251033309
[49] *Domestic Hot Water Heater System Modeling for the Design of Energy Efficient Systems*. Accessed: Sep. 20, 2020. [Online]. Available: http://allianceforwateref_ciency.org/WorkArea/linkit.aspx-?ItemID=2256
[50] *Chevrolet All-Electric EV*. Accessed: Sep. 18, 2020. [Online]. Available: http://chevrolet.com/bolt-ev-electric-vehicle.html
[51] *Nissan Leaf Features + Specifications*. Accessed: Sep. 13, 2020. [Online]. Available: https://nissanusa.com/electric-cars/leaf/versions-specs/
[52] P. He, M. Li, L. Zhao, B. Venkatesh, and H. Li, "Water-filling exact solutions for load balancing of smart power grid systems," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1397–1407, Mar. 2018.
[53] Z. M. Haider, K. K. Mehmood, M. K. Rafique, S. U. Khan, S.-J. Lee, and C.-H. Kim, "Water-filling algorithm based approach for management of responsive residential loads," *J. Mod. Power Syst. Clean Energy*, vol. 6, no. 1, pp. 118–131, Jan. 2018.

ZUNAIB MAQSOOD HAIDER received the B.Sc. degree in electrical engineering from Bahaudding Zakariya University, Multan, Pakistan, in 2010, and the M.Sc. and Ph.D. degrees in electrical engineering from Sungkyunkwan University, South Korea, in 2015 and 2019, respectively. He is currently working as an Assistant Professor with the Department of Electrical Engineering, The Islamia University, Bahawalpur, Pakistan. His research interests include demand response techniques, smart grids, integration of electric vehicles and distribution system planning, and optimization techniques.

KHAWAJA KHALID MEHMOOD received the B.Sc. degree in electrical engineering from the Mirpur University of Science and Technology, Mirpur, Pakistan, in 2012, and the M.Sc. and Ph.D. degrees in electrical engineering from Sungkyunkwan University, South Korea, in 2015 and 2019, respectively. He is currently working as an Assistant Professor with the Department of Electrical Engineering, The University of AJ&K, Muzaffarabad, Azad Kashmir, Pakistan. His research interests include planning and operations of distribution systems, electric vehicles, and electrical energy storage systems.

SAAD ULLAH KHAN received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Taxila, Pakistan, in 2012, and the M.Sc. and Ph.D. degrees in electrical engineering from Sungkyunkwan University, South Korea, in 2015 and 2019, respectively. He is currently working as an Assistant Professor with the Department of Electrical and Computer Engineering, Air University, Islamabad, Pakistan. His research interests include power system operation, active distribution systems, energy management, and electric vehicles.

MUHAMMAD OMER KHAN received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Peshawar, Pakistan, in 2008, and the M.Sc. and Ph.D. degrees in electrical engineering from Sungkyunkwan University, South Korea, in 2015 and 2019, respectively. He is currently working as an Assistant Professor with the Department of Electrical Engineering and Technology, Riphah International University, Faisalabad, Pakistan. His research interests include hybrid AC/DC distribution network, multi-terminal DC transmission and distribution networks and renewable energy resources.

ABDUL WADOOD received the B.S. degree in electronic engineering from the University of Engineering and Technology Peshawar, Pakistan, in 2012, and the master's degree in electrical engineering from the Sarhad University of Science and Information Technology, Peshawar, Pakistan, in 2015, and the Ph.D. degree from the Department of Electrical Engineering, Yeungnam University, Gyeongbuk, South Korea, in 2019. He is currently an Assistant Professor and the Head of the Department of Electrical Engineering, Air University, Islamabad, Kamra Campus, Pakistan. His research interests include power system relaying, power system protection, energy management system, renewable energy, evolutionary, and metaheuristic algorithms.

SANG-BONG RHEE received the B.S., M.S., and Ph.D. degrees from Hanyang University, South Korea, in 1994, 1999, and 2004, respectively. He was a Research Professor with the School of Electrical and Computer Engineering, Sungkyunkwan University, South Korea. He is currently a Professor with the Department of Electrical Engineering, Yeungnam University, Gyeongbuk, South Korea. His research interests include distribution system control and operation, and artificial intelligence applications to power system protection.