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# Development of a robust and sustainable regional demography-based demand management technique

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**ABSTRACT**

This paper presents a robust and sustainable energy management system driven by regional demographic patterns developed using fuzzy logic and mixed integer linear programming (MILP). This method detects and integrates variations in the energy use patterns of urban and rural communities attaining improved efficiency in the management of regional power demand. The detection and integration of the urban and rural energy use patterns were done by combining period partitioning based regional time of use tariff and fuzzy based appliance level renewable resource allocation to develop a function to be optimized using an improved MILP which provides users with the optimum schedule of appliance usage based on their demographic classification. The effectiveness of the proposed method was tested by running MATLAB simulations of different scenarios emulating continuous regional renewable integration planning with urban and rural power consumption profiles generated using LoadProGen. The proposed method's effectiveness is confirmed by the achievement of a reduction upto 31% in the community energy cost as well as significant reduction in the energy costs of each participant over different scenarios compared to the unoptimized base case. The proposed method can be effectively utilized in energy management applications catering to multiregional and mixed demographic communities.



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## 1. INTRODUCTION

A critical aspect of modern energy management systems is grid integration of renewable energy sources in order to utilize the full capacity of prosumers. The main objective is to maximize renewable energy utilization and ensure a reliable and stable electric supply. The major obstacles towards achieving this aim are posed by the intermittent nature of renewable sources and the uncertainty of load demand characteristics at the consumer end. The solution proposed by a work has been to identify the various factors that influence automatic demand response, the effect of real time energy use incentive measures and the utilization of the fast response time of interruptible loads [1]. However, the proposed solutions target a predetermined consumer base. The implementation of a wide area energy management system will have to deal with interruptible loads over different regions that can be demographically divided into urban, semi-urban and rural regions, each consisting of a wide variety of consumers having different energy use priorities. As such, a common incentive may not be appealing to the majority of consumers and thus may result in limited participation in the energy management program. Artificial intelligence (AI) is now seeing a lot of application in the development of energy management systems. The most popular techniques that have seen extensive application in demand side management are the different variations of swarm optimization, fuzzy logic and K-means [2], [3]. Though these methods have been successful in achieving their objectives as described through their validation by better peak to average ratio and user comfort however they fail to address the variation of the load consumption pattern on a regional scale. Regional approaches to demand side management were proposed using the flexibility indices and K-means technique which was further used to determine a discrete user comfort window for appliance scheduling but it did not consider the regional diversity in energy use priority and the availability of renewable sources [4], [5].

The opportunity for developing multi energy hub models and integrated energy management systems have also been sufficiently explored. The proposed solutions seek to provide an optimal solution for the demand supply complexity and increasing energy management efficiency through capturing renewable integrated grid behaviour for different degrees of renewable energy penetration [6]-[11]. The complexity of power system planning is rapidly increasing with the development of smart homes, micro grids and smart distribution systems. Several researchers have proposed different methodologies of energy management to address the uncertain stochastic behaviour of renewable energy sources integrated in these smart power environments and the subsequent stochastic dynamic reconfiguration of smart distribution grids [12], [13]. The increasing applications of smart home technologies has necessitated the development of automatic home energy management systems capable of handling user constraints and develop new strategies for the power flow management of smart building microgrids [14], [15].

The implementation of smart metering has led to the development of non-intrusive load monitoring techniques for better energy management systems to reduce costs and develop better coordination among smart home units [16]. A two-level energy management system has been developed for residential consumers which combine appliance level energy management and global energy management to reduce individual house consumption along with global cost and peak to average ratio [17]. Along with demand side management, development generation side management strategies to address the variations of renewable generation also merits attention to achieve utmost success in proposing a solution [18], [19].

The development of smart microgrids has increased the opportunity of peer to peer energy trading across different microgrids for better load and generation management. The proposed solutions use AI techniques such as fuzzy logic, and incorporates multi agent distribution systems taking into consideration the network and user constraints [20]-[22]. A novel solution for energy scheduling incorporating peer to peer electricity and heat exchange structure, has been proposed by Shi *et al.* [23]. The formation of energy hubs and multi microgrid has increased the intractability of power systems which has prompted researchers to propose novel solutions to solve the computational intractable nature of stochastic energy management of power systems [9], [24]. The advent of smart energy communities has made the development of energy management systems to align the consumer energy demand with the available renewable energy very important. With the increased penetration of different renewable energy sources, energy storage systems, and electric vehicles the complexity of the systems required to manage the scheduling of the load demand and energy storage charging has increased. Several constraints are needed to be considered to ensure optimal operation of these energy communities.

Several research work has been done to incorporate energy storage systems, electric vehicles and different sources of distributed energy in the development of energy management systems [25], [26]. However, even with the multitude of promising research works being conducted, there are still some gaps which can be addressed for increasing the efficiency of the energy management systems further.

The development of an energy management system incorporating demand side and resource allocation management based on per capita energy consumption is yet to be explored. The per capita energy consumption varies with the demography of the region under consideration namely urban, semi urban and rural. The total number of power consumers supplied by any utility can be categorized as urban, semi urban and rural consumers. With the advent of microgrids and energy communities, the demographical aspect of energy management becomes even more important as mixed demographical regions are required to be effectively catered to. The influence of demography on the users' appliance ownership, usage patterns and subsequently on the per capita energy consumption makes it an important aspect to be considered for developing an efficient energy management system. The present solutions also do not consider the effect of preallocation of the available renewable resources towards self and community consumption. The preallocation of resources can play a crucial role in increasing the efficiency of energy management systems as it allows for pre-informed demand response management which can reduce power wastage and supply uncertainty. This can result in a more inclusive energy sharing community which is critical in ensuring affordable, reliable and modern supply to urban, rural and semi urban regions being catered to by the energy management system. Another aspect that is yet to be addressed is the continuous integration planning of renewable resources in both urban and rural regions. With increasing penetration of renewable energy in the primary mix of energy supply it is critical to develop an energy management system which can adjust its parameters with the increasing renewable resource integration to present a long-term sustainable solution to regional energy management.

The proposed method caters to the above problems by developing a mixed integer linear programming (MILP) based regional energy management system which takes into consideration the demographics of a region through a time of use tariff system which can differentiate between urban and rural consumers with an integrated fuzzy module to preallocate the available resources between self and community consumption by considering appliance level usage statistics. The proposed model also caters to the continuous integration planning of renewable resources based on demography which has been verified by exploring multiple scenarios with various combinations of renewable availability and storage capacity. The organization of the rest of the paper is as follows. Section 2 describes the methodology of the proposed energy management system by explaining the formation of the ToU tariff, fuzzy module to determine the resource preallocation and the core MILP model. The results and discussions are present in section 3. The major findings of the paper, implementation areas and future work is summarized in section 4.

## 2. METHOD

The development of an energy management system to cater to urban and rural areas keeping in mind the demographical influence on the energy use priorities requires the implementation of a tariff system which can be used to differentiate between the peak, valley, and flat periods of urban and rural areas. The implementation of this tariff system in the optimization algorithm is critical in effective resource allocation and demand management on a regional basis. A time of day tariff system was developed using the time of use tariff plan provided by the state utility board and the peak, flat, and valley period of power demand partitioning method explained in [27]. The process of the tariff determination using the said method has been shown in Figure 1(a) and is mathematically expressed (1) and (2).

$$min\left\{F\left(P_{fv},P_{pf}\right)=\frac{1}{24}\sum_{\substack{m\in(p,f,v)\\ i\in 24}}(P_i-\overline{P_m})^2\right\} \tag{1}$$

$$\overline{P_m}=\frac{1}{N}\sum_{i\in m}P_i \tag{2}$$

Another important aspect of effective demand response management in a renewable integrated mixed demographic region having both urban and rural components is renewable resource allocation. With efficient management the consumer can be incentivized to fulfill their power requirement at a time instant by drawing power from both grid and the available renewable resource. This consumer may become a prosumer by selling the unused renewable power to the community. However, it is important to determine the maximum share of each participant of the community to ensure maxmum efficiency. A fuzzy logic-based technique was developed end to determine the percentage of hourly demand of all urban and rural consumers which can be supplied from grid or the available renewable energy at an appliance level. This technique benefits not only the consumers having renewable generation but also those who are unable to install any renewable source. The fuzzy rulebase developed to tag the urban and renewable hourly loads as grid or renewable compatible is shown in Table 1.

The process of determining the maximum renewable resource allocation through fuzzy application is explained (3) to (6), where $R_t^T$ is the total renewable energy available at time *t*, $R_{k,t}^C$ denotes community renewable energy available from the $k^{th}$ house at time *t*, $R_t^s$ denotes the renewable energy available from self at time *t*, $S_{j,k,r}$ is the selection coefficient of each appliance of the $j^{th}$ appliance of the $k^{th}$ house of the $r^{th}$ region whose value determines whether the appliance will draw from grid or renewable. A value of 1 denotes renewable source whereas a value of 2 denotes grid source. $rt_{j,k,r}, P_{j,k,r}, L_{t,k,r}^U$, and *TD* are the runtime and power consumption of the $j^{th}$ appliance of the $k^{th}$ house of the $r^{th}$ region, upper limit of renewable resource allocation to the $k^{th}$ house of the $r^{th}$ region at the $t^{th}$ time.

$$R_t^T=\sum_{i=1}^{N}R_{k,t}^C+R_t^s \tag{3}$$

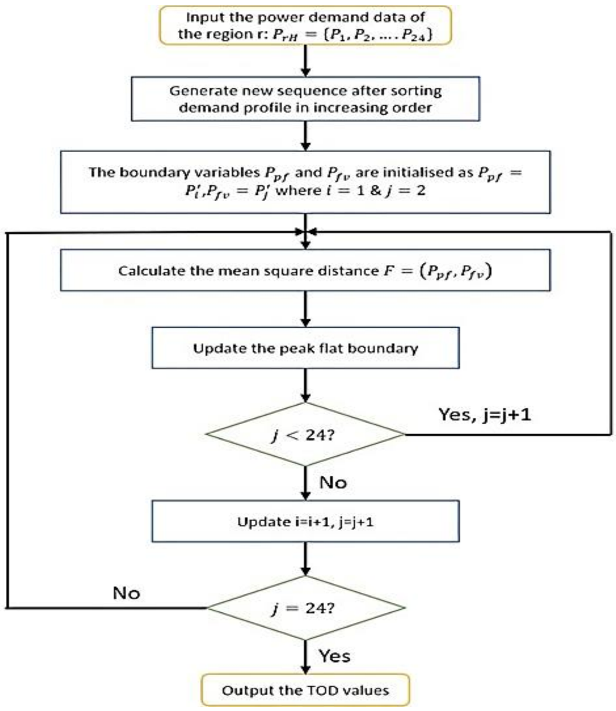
$$S_{j,k,r}=f\left(R_t^T,P_{j,k,r},rt_{j,k,r}\right),\forall S_{j,k,r}\in[1,2] \tag{4}$$

$$rt,P\in f(Urb,Rur) \tag{5}$$

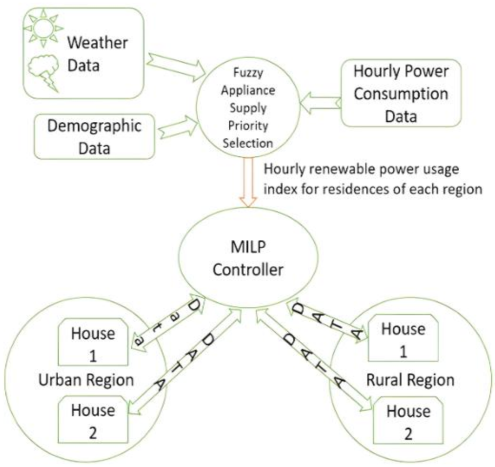
$$L_{t,k,r}^U=\frac{S_{j,k,r}\times P_{j,k,r}}{TD},\forall S_{j,k,r}\in[1] \tag{6}$$

The proposed MILP based predictive control integrates the fuzzy logic module explained above with an intelligent optimizer. The concept underlying the intelligent optimizer for the regional community energy management system (RCEMS) is presented in the Figure 1(b). The intelligent optimizer comprises of a fuzzy logic system and a MILP module. The fuzzy logic module combines the weather parameters and consumer appliance preferences to determine the maximum hourly percentage of loads that can be allocated to each consumer to maximize the benefits of the region catered to by the RCEMS. The output of the fuzzy module is provided as an input to the MILP optimizer along with the following information:

– Information related to electrical consumption and appliance use priority of urban and rural residential units i.e., $P_{t,k,r}$ is consumption of active power in Watts, $R_{t,k,r}$ is consumption of reactive power in Var, and $P_{t,k,r}^{PV}$ is available photovoltaic (PV) power.
– Energy storage availability and storage capacity details, $SoC_{t,k,r}$ is state of charge of the battery bank.
– The appliance switching pattern, regional appliance usage priority, and the fixed or flexible nature of the appliances of house $k$ in region $r$.




(a)




(b)

Figure 1. Flowchart of: (a) TOD tariff development algorithm for urban and rural region power demand and (b) general structure of the work proposed

Table 1. Fuzzy rule base for load source mapping with renewable availability

| | | Appliance power consumption | | | | |
|---|---|---|---|---|---|---|
| Renewable availability | Appliance runtime | Very high | High | Medium | Low | Very low |
| High | Very high | Not likely | Not likely | Not likely | Likely | Likely |
| | High | Not likely | Not likely | Likely | Likely | Very likely |
| | Medium | Not likely | Likely | Likely | Very likely | Very likely |
| | Low | Likely | Likely | Very Likely | Very likely | Very likely |
| | Very low | Likely | Likely | Very Likely | Very likely | Very likely |
| Low | Very high | Not likely | Not likely | Not likely | Not likely | Likely |
| | High | Not likely | Not likely | Not likely | Likely | Likely |
| | Medium | Not likely | Not likely | Likely | Likely | Likely |
| | Low | Not likely | Likely | Likely | Likely | Very likely |
| | Very low | Likely | Likely | Likely | Very likely | Very likely |

The above information was obtained from each house by the aggregator per hour. In case of schedulable appliances that can be automatically controlled, the number of working hours and the time gap between two consecutive working hours of each schedulable appliance for house $k$ of the $r^{th}$ region was provided to the aggregator. The active power consumption is composed of the elements shown in (7).

$$P_{k,t,r} = \sum_{j=1}^{AMC} \upsilon_{k,r,j,t} P_{k,r,j} + \sum_{j=1}^{M\bar{C}} \nu_{k,r,j,t} P_{k,r,j} + \sum_{j=1}^{\bar{M}\bar{C}} \tau_{k,r,j,t} P_{k,r,j} \tag{7}$$

– Appliances whose operation is user defined at a pre-fixed time interval. They are neither monitored nor controlled by the energy management system ($\bar{M}\bar{C}$).
– Appliances with flexible runtime and both controlled and monitored by the energy management system (AMC).
– Appliances monitored by the energy management system but controlled by the user ($M\bar{C}$).
where $t \in [1,2\ldots,24]$, $k \in$ [UH1, UH2, RH1, RH2], $r \in$ [Urb, Rur] and $j \in$ [1, 2, ..., total_appliances]. $\upsilon, \nu, \tau \in [0,1]$ denote the switching states of $\bar{M}\bar{C}$, AMC, and $M\bar{C}$ appliances.

The complexity of forming the problem of community energy management is very high. The proposed RCEMS was able to manage the power consumption of the entire region-based community in order to obtain a solution with the cost of operation minimized to the maximum extent. The complexity of the RCEMS arises from the fact that there are multiple factors to ensure such as the energy balance of each residential unit considered, the energy balance of the demographic regions considered, the balance between the cost reduction and comfort of the users of each region and the energy community as a whole, the state of charge of available energy storage devices, obtaining an economic balance between charging the devices with available renewable or grid energy and the energy balance between the grid and the community under study. The objective function detailed in (8) is solved for each sampling time interval by the proposed appliance specific MILP based optimizer model.

$$minC^{comm} = min \sum_{r=1}^{NR} \sum_{t=1}^{Nt} \sum_{k=1}^{NH} \begin{Bmatrix} P_{t,k,r}^{grid+} \times CG_{t,r}^{+} + P_{t,k,r}^{ren+} \times CR_{t,r}^{+} + P_{t,k,r}^{comm+} \times CC_{t,r}^{+} \\ -P_{t,k,r}^{grid-} \times CG_{t,r}^{-} - P_{t,k,r}^{comm-} \times CC_{t,r}^{-} \end{Bmatrix} \Delta t \tag{8}$$

In (8), the prediction period of 24 hours is denoted by$Nt$, the total number of participating houses from the urban and rural communities are given by $NH$, $NR$ denotes the total number of regional variations considered and the sampling rate of one hour is represented by $\Delta t$. $P_{t,k,r}^{grid+}/P_{t,k,r}^{grid-}$ denotes grid active power (kW) projected to be bought and sold, $P_{t,k,r}^{comm+}/P_{t,k,r}^{comm-}$ is the community active power (kW) projected to be bought and sold, $CG_{t,r}^{+}/CG_{t,r}^{-}$ being the hourly cost of grid active power projected to be bought and sold, $CC_{t,r}^{+}/CC_{t,r}^{-}$ being the hourly cost of regional community active power bought and sold, $P_{t,k,r}^{ren+}$ is the total renewable energy used, $CR_{t,r}^{+}$ being the cost of self-generated renewable energy used by a residential unit, $t \in [1,2,..,Nt]$, $k \in$ [UH1,UH2,RH1,RH2], and $r \in$ [Urb, Rur].

$$0 \leq P_{t,k,r}^{grid+} \leq conn\_load_{k,r} \times S_{t,k,r}^{GB} \tag{9}$$

$$0 \leq P_{t,k,r}^{grid+} \leq conn\_load_{k,r} \times S_{t,k,r}^{GS} \tag{10}$$

The constraints that have been considered are listed from (9) to (21). The grid power bought and sold by a residential unit has to be non-negative and less than the unit's contracted power as ensured by (9) and (10). The variables used to distinguish between the selling or buying mode of a participant from the grid are $\frac{S_{t,k,r}^{GB}}{S_{t,k,r}^{GS}} \in [0,1]$, where 0 means power is being sold and 1 means power is being bought.

$$0 \le P_{t,k,r}^{comm-} \le conn\_load_{k,r} \times S_{t,k,r}^{CS} \tag{11}$$

$$0 \le P_{t,k,r}^{comm+} \le conn\_load_{k,r} \times S_{t,k,r}^{CB} \tag{12}$$

The limits of community power bought and sold by any residential unit is given by (11) and (12) where $\frac{S_{t,k,r}^{CB}}{S_{t,k,r}^{CS}} \in [0,1]$. For these constraints the contracted power is considered to be the connected load $conn\_load_{k,r}$.

$$\sum_{r=1}^{NR} \sum_{k=1}^{NH} P_{k,r}^{comm+} = \sum_{r=1}^{NR} \sum_{k=1}^{NH} \left(1 - L_{k,r}^{U}\right) R_{k,r}^{s} \tag{13}$$

$$app_{S_i^{PV+}} + app_{F_i^{PV+}} + P_{t,k,r}^{grid-} + P_{t,k,r}^{comm-} + P_{t,k,r}^{RB+} = L_{t,k,r}^{U} \tag{14}$$

$$P_{t,k,r}^{GB+} + P\_app_{t,k,r}^{grid+} = P_{t,k,r}^{grid+} + P_{t,k,r}^{comm+} + P_{t,k,r}^{B-} \tag{15}$$

$$S_{t,k,r}^{GB} + S_{t,k,r}^{CS} \le 1 \tag{16}$$

$$S_{t,k,r}^{CB} + S_{t,k,r}^{CS} \le 1 \tag{17}$$

$$S\_app_{t,k,r}^{G} + S\_app_{t,k,r}^{R} + S\_app_{t,k,r}^{comm} \le 1 \tag{18}$$

$$\sum_{t=1}^{Nt} \sum_{i=1}^{n\_app} \left(S\_app_{i,t,k,r}^{G} + S\_app_{i,t,k,r}^{R} + S\_app_{i,t,k,r}^{comm}\right) \times app\_P_{i,k,r} = P_{t,k,r} \tag{19}$$

$$\sum_{t=1}^{Nt} \sum_{i=1}^{n\_app} S\_app_{i,t}^{R} \times app\_P_{i,t} \le P_t^{PV} \tag{20}$$

$$\sum_{r=1}^{NR} \sum_{k=1}^{Nh} \sum_{t=1}^{Nt} \sum_{i=1}^{n\_app} S\_app_{i,t,k,r}^{G} + S\_app_{i,t,k,r}^{R} + S\_app_{i,t,k,r}^{comm} = app\_run_{i,t,k,r} \tag{21}$$

The community power balance is given (13) and the balance of individual unit's allocated renewable energy consumption is implemented (14) where $app_{S_i}^{PV+}$ is the PV power utilized by the i$^{th}$ schedulable appliance, $app_{F_i}^{PV+}$ being the PV power utilized by the i$^{th}$ fixed use appliance. At any time instant, the recharging power drawn by the battery from the PV source or the grid is given by $P_{t,k,r}^{RB+}$ and $P_{t,k,r}^{GB+}$ respectively. $P_{t,k,r}^{B-}$ denotes discharging power drawn from the battery by the residential units and $P_{app}{}_{t,k,r}^{grid+}$ is the total grid power drawn by the combination of fixed and schedulable appliances. The power balance of the appliance power consumptions over the scheduling horizon is given (15). Constraints (16) and (17) restrict the participants from selling the grid or community power bought by them to the community again. Any appliance switched on at a particular time interval is at the liberty to draw power from community, grid or self PV source if available but cannot utilize exploit than one source as implemented (18). The consumer's choice for switching of fixed appliances is adhered to (19). $S_{app}{}_{i,t,k,r}^{G}$, $S_{app}{}_{i,t,k,r}^{R}$, $S_{app}{}_{i,t,k,r}^{comm} \in [0,1]$ denotes the source selection variables for grid, self-renewable and community respectively. $app_{P_{i,k,r}}$ denotes the rated power of the appliance under consideration. The limit of power drawn by the appliances at any instant has to be less than or equal to the available PV power as ensured (20). The daily runtime requirement fulfillment for any appliance is ensured (21). The balance between energy generation and consumption for grid and renewable is delinked and ensured separately (22) and (23). For all these constraints $t \in [1, 2, \ldots, 24]$, $k \in$ [UH1, UH2, RH1, RH2], $r \in$ [Urb, Rur], and $i \in$ [1, 2, ..., total_appliances].

$$\sum_{i=1}^{n\_appS} app\_S_{i,t,k,r}^{PV+} + \sum_{i=1}^{n\_appF} app\_F_i^{PV+} + P_{t,k,r}^{grid-} + P_{t,k,r}^{comm-} + P_{t,k,r}^{RB+} = P_{t,k,r}^{PV} \tag{22}$$

if battery is not available then $P_{t,k,r}^{RB+} = 0$.

$$\sum_{i=1}^{n_{appS}} app_{S_{i,t,k,r}^{grid+}} + \sum_{i=1}^{n_{appF}} app_{F_i^{grid+}} + \sum_{i=1}^{n_{appS}} app_{S_{i,t,k,r}^{comm+}} + \sum_{i=1}^{n_{appF}} app_{F_i^{comm+}} + P_{t,k,r}^{GB+} = P_{t,k,r}^{grid+} + P_{t,k,r}^{comm+} + P_{t,k,r}^{B-} \tag{23}$$

The battery, if available, is allowed to be charged from all three sources as this allows the battery to take advantage of the off-peak grid tariff and also the renewable availability period to get charged allowing the use of the battery during the peak hours.

$$\min \_SOC_k^B \le SoC_k^B \le \max \_SoC_k^B \tag{24}$$

$$SoC_{init,k}^B = SoC_{final,k}^B \tag{25}$$

$$SoC_{k,t}^B = SoC_{k,t-1}^B + \eta_c^b \times ch_t + \eta_{dc}^b \times disch_t \tag{26}$$

$$P_{k,t}^{B+} - P_{k,t-1}^{B+} \le R_u \tag{27}$$

$$P_{k,t-1}^{B-} - P_{k,t}^{B-} \le R_d \tag{28}$$

$$S_c^{BG} + S_c^{BC} + S_c^{BR} \le 1 \tag{29}$$

In (24) specifies that the state of charge $SoC_k^B$ of the storage system of the $k^{th}$ house should lie between the maximum and minimum values given by $max\_SoC_k^B$ and min $\_SoC_k^B$ respectively. $SoC_{init,k}^B$ and $SoC_{final,k}^B$ are the initial and final charging state of the battery banks. $SoC_{k,t}^B$ is the state of charge of the battery bank $B$ of the $k^{th}$ house at time $t$. $\eta_c^b$ and $\eta_{dc}^b$ are the charging and discharging efficiency of the battery bank. The charging and discharging power being drawn by the battery bank at time $t$ is given by the variables $ch_t$ and $disch_t$ respectively $P_{k,t}^{B+}$ and $P_{k,t}^{B-}$ and are the charging and discharging power being drawn by the battery of the $k^{th}$ house at time period $t$. The ramp up and ramp down values for charging and discharging values of the battery are are $R_u$ and $R_d$. $S_c^{BG}$, $S_c^{BC}$, $S_c^{BR}$ are the switching variables of the battery bank for charging from grid, community and renewable sources respectively. In (25) ensures the level of battery bank that needs to be maintained at the end of the period of prediction. The state of charge of the battery at any instant is given (26). The charging and discharging rate cannot be more than the ramp up or ramp down values respectively as ensured (27) and (28). In (29) restricts the battery bank to being charged from only one source at a particular time period.

$$0 \le P_{k,t}^{B+} \le P_{k\_max}^B \times S_{ch} \tag{30}$$

$$0 \le P_{k,t}^{B+} \le P_{k\_max}^B \times (1 - S_{ch}) \tag{31}$$

$$S_{ch} = S_c^{BG} + S_c^{BC} + S_c^{BR} \tag{32}$$

From (30) to (32) ensures that charging or discharging power of the battery banks is non-negative at a particular time. In any household, some appliances have flexible usage times. The operation of this appliances can be shifted to any time period of the day. However, their daily operational quota needs to be maintained. As such, it is practical to include the provision of such flexible and shiftable appliances in the proposed algorithm. The schedulable loads have to follow the following restrictions:

– The appliance must operate for the duration specified by the user denoted by $WM_{r,k,i}$
– It has to remain switched on for a minimum pre-specified period of time $WM_{r,k,i}^{SD}$
– The power demand of the appliance is considered to be constant at its rated power $P_{app_{r,k,i}^{SD}}$

The constraints imposed are expressed in (33) to (36) for $\forall r \in$ [Urb,Rur], $k \in$ [UH1,UH2,RH1,RH2], $t \in$ [1,2,….,24], $i \in$ [1,2…., NS] where UH1=urban house 1, UH2=urban house 2, RH1=rural house 1, RH2=rural house 2, and NS=total number of schedulable appliances.

$$WM_{r,k,i,t}^{on} - WM_{r,k,i,t+x}^{on} \ge TD_{r,k,i}^{WM} \tag{33}$$

$$WM_{r,k,i,t}^{SD} = P_{WM}^{SD} \times WM_{r,k,i,t}^{ON} \tag{34}$$

$$\sum_{i=1}^{NS}\left(v_{t,i}^{G}+v_{t,i}^{R}\right)\leq 1 \tag{35}$$

$$v_{t,i}^{on}+v_{t,i}^{off}\leq 1 \tag{36}$$

$$\sum_{t=1}^{NT}WM_{r,k,i,t}^{ON}=rt_{i,k,r} \tag{37}$$

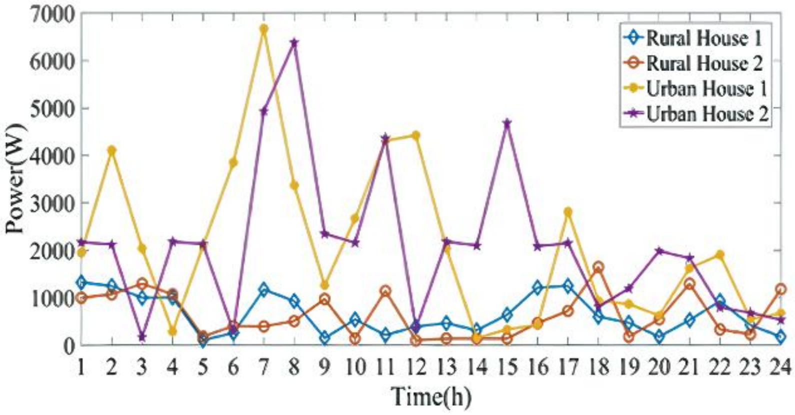
$v_{t,i}^{on}$ and $v_{t,i}^{off}$ are the switch on and switch off status of the appliance. $TD_{r,k,i}^{WM}$ is the time delay between successive switching on time of the appliance. The condition of the appliance remaining switched on for the prespecified number of consecutive hours is ensured by the constraint in (33). In (34) ensures that the power consumption $P_{WM}^{SD}$ of the appliance is constant and equal to its rating during the periods of switched on time of the appliance $WM_{r,k,i,t}^{ON}$. The shift able appliance switched on at a particular time can draw power either from the grid or renewable source as ensured (35). The startup and shut down time of a schedulable appliance cannot be at the same time instant as ensured (36) whereas the adherence to total daily runtime of the appliance is met (37).

## 3. RESULTS AND DISCUSSION

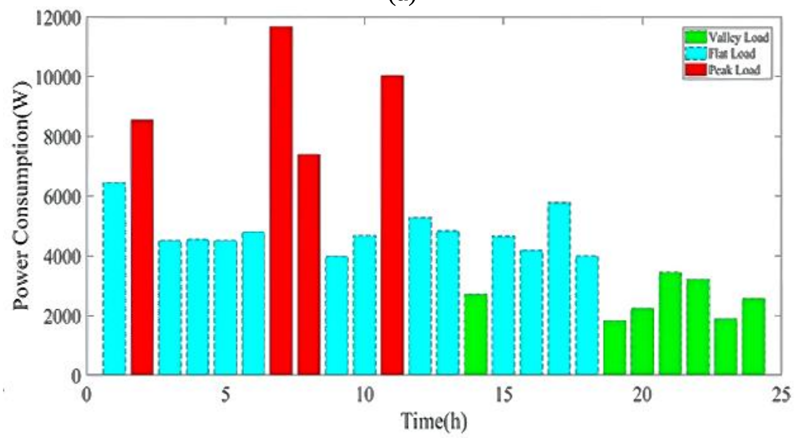
The simulations are performed on energy profiles of two urban and two rural houses together forming an energy community. These load profiles were simulated using LoadProGen simulator [28] in MATLAB 2021a®. The parameters of urban and rural power consumption preferences, appliance ownership and appliance usage time for simulating these load profiles were obtained from surveys conducted on residential houses of rural and urban areas [29], [30] and are shown in Table 2 where R denotes rural house and U denotes urban house. The unoptimised power consumption of the two urban and two rural houses forming the energy community simulated for the prediction horizon of 24 hours are shown in Figure 2(a). Figure 2(b) shows the peak, flat, and valley hours obtained by applying the period partitioning model to the community energy consumption formed by adding the consumption of the four houses together. It shows a few peak hours in the morning while the valley hours are seen near the evening. The concentration of peak and flat hours during the daytime can be explained by the running of the space cooling appliances during the daytime. As these appliances consume a large amount of power they increase the community energy consumption values by a significant amount. The time horizon for performing the simulations is considered as 24 hours. The simulations are performed using MILP based community optimization. The upper and lower limits of the renewable power made available toeach house of the community per hour is obtained by using the fuzzy inference method explained in section.

Table 2. Appliance ownership and usage details for urban and rural consumers

| Appliance name | Rated power (W) | Number | | Functioning cycle (hours) | | Functioning duration (hours) | | Functioning window | |
|---|---|---|---|---|---|---|---|---|---|
| | | R | U | R | U | R | U | R | U |
| TV | 127 | 1 | 2 | 1 | 1 | 5 | 6 | 11-22 | 18-24 |
| Music system | 100 | - | 2 | - | 1 | - | 6 | - | 24 |
| Refrigerator | 150 | 1 | 1 | 1 | 1 | 11 | 24 | 24 | 24 |
| Computer | 250 | - | 2 | - | 1 | - | 3 | - | 10-12<br>18-22 |
| Geyser | 2000 | - | 2 | - | 1 | - | 1 | - | 6-9 |
| Washing machine | 400 | 1 | 1 | 1 | 1 | 1 | 2 | 8-16 | 10-15 |
| Water pump | 750 | 1 | 1 | 1 | 1 | 2 | 2 | 24 | 24 |
| Iron | 1100 | - | 1 | - | 1 | - | 1 | - | 24 |
| Ceiling fan | 40 | 1 | 3 | 1 | 1 | 5 | 8 | 24 | 24 |
| AC | 1800 | 1 | 2 | 1 | 1 | 5 | 8 | 1-7<br>12-15<br>18-24 | 1-6<br>12-16<br>22-24 |
| Table fan | 70 | - | 1 | - | 1 | - | 4 | - | 24 |
| Incandescent lamp/CFL/LED | 97/12/8 | 2 | 3 | 1 | 1 | 9 | 8 | 5-8<br>18-24 | 24 |
| LED tubes | 20 | - | 3 | - | 1 | - | 4 | 5-8<br>18-24 | 18-24 |
| OTG/microwave | 1000 | 1 | 1 | 1 | 1 | 1 | 2 | 5-11<br>16-18 | 8-10<br>21-24 |
| Cooler | 224 | 1 | - | 1 | - | 3 | - | 24 | - |




(a)




(b)

Figure 2. The simulated outputs of: (a) power consumption of the urban and rural houses and (b) the peak, flat, and valley periods of the community obtained using the period partitioning model

Time of day prices of energy has been used for optimization and the day ahead forecasted values of the renewable power availability of each house is obtained by using artificial neural network (ANN). The control signals for battery banks and flexible loads for both the urban and rural residential units are generated based on the optimized cost function. The simulations are presented for a single season i.e., summer, but with two distinct regional power consumption characteristics and a community TOD tariff system to capture the effect of the regional power usage variation on the operation of AI controlled energy community. This study is crucial for developing a smart energy management system for application to areas encompassing regions having different demographic patterns. The residential units use a time of use tariff for purchasing energy from the grid. The purchasing and selling prices for the interactions with grid are shown in Table 3 and that of the community is shown in Table 4. This helps in observing the performance of the system under an organized dynamic tariff system. The fuzzy module output $L^{U}_{t,k,r}$ has been considered as the upper boundary value of total PV power available to a participant household for self utilization for each time period. The rated capacity of the battery considered for one urban household has been fixed at 10 kW which is sufficient to supply the entire connected load of the household. The limit of charging and discharging power is considered to be 5 kW whereas the ramping power is considered to be 2 kW for both charging and discharging. The efficiency of charging and discharging is considered to be 95%. The number of schedulable appliances considered are $app_{S_U} \in$ [washing machine, electric iron, and water pump] and $app_{S_R} \in$ [washing machine and water pump] where $app_{S_U}$ denotes the urban schedulable appliances and $app_{S_R}$ denotes the rural schedulable appliances. The restrictions imposed on these appliances are as given in (33) to (37). The total runtime value that needs to satisfied for each appliance and their rated power is as given in the columns functioning duration and rated power respectively in Table 2.

Table 3. Purchase and sale price of the interaction between home and grid

| Price in INR/KWh | | | |
|---|---|---|---|
| Period of demand | Medium | High | Low |
| Purchase from grid utility | 7.97 | 9.51 | 6.81 |
| Sell to grid by prosumer | 2.4 | 2.85 | 2.04 |

Table 4. Purchase and sale price of the interaction between home and community

| Price in INR/KWh | | | |
|---|---|---|---|
| Period of demand | Medium | High | Low |
| Self renewable buy | 3.99 | 4.78 | 3.405 |
| Community buy/sell by prosumer | 3.2 | 3.8 | 2.724 |

The houses are equipped with solar power output with peak value equivalent to 30% of their connected load. The forecasted PV power output of the four homes of the community are provided for the prediction horizon of 24 hours in Figure 3. The implementation is done in MATLAB 2021a and the optimization problem was solved with Gurobi using MATLAB-Gurobi interface. Nine scenarios are considered for performing the simulations as shown in Table 5. These nine scenarios are chosen due to their relation with the need to assess the operational gains of continuous regional renewable integration in an interregional energy community over a non-energy community operation with varying degree of renewable energy production by each household and/or the presence of controlled energy storage capacity and appliances.

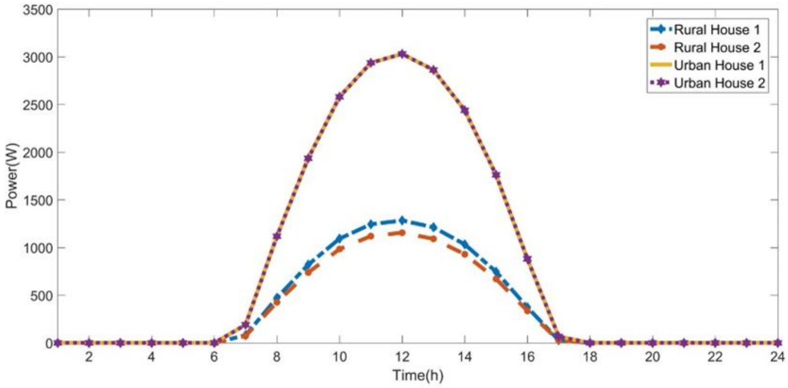



Figure 3. Forecasted PV power generation for the urban and rural regions

An important point to note is that one of the contributions of this paper is to minimize the energy cost of the community as a whole with less importance to the cost of individual members. The ideal value of the energy purchased and sold between the entities involved in the optimization at each time period is determined by the program with focus on the minimization of community energy costs. The cost of operation for all scenarios is shown in Table 5. Here U1 denotes UH 1, U2 denotes UH 2, R1 denotes rural house 1 and R2 denotes rural house 2. It is observable from the table that there is an operational cost reduction in all other scenarios compared to the initial scenario 0 where the power consumption of individual houses were optimized without any community formation. The selling price to the community is considered to be more than the selling price to the grid, both of which are less than the power purchased from the grid. This distinction was done to ensure that the available renewable energy is first utilized by the households themselves with certain constraints. For homes having low energy consumption, specifically being the homes of the rural region, the unallocated power is sold to the community first and then to the grid. The power purchased (positive) and sold (negative) by the four urban and rural households to the community is shown in Figures 4(a) to (d) and the power purchased from the grid by the community for all the nine scenarios is shown in Figure 5. The cost comparison for all the houses along with the community is shown in Figure 6. Figures 4(a) to (d) shows the power buying and selling pattern of the individuals which corresponds to the power consumption pattern which is reflected through the community and grid energy buying and selling prices. Figure 5 shows that a significnt reduction grid demand has been achieved both in the terms of peak demand periods and average demand. The peak demand period of the grid has been replaced by a new renewable demand peak during the solar availability hours thus representing the effectiveness of this method. The results shown in Figure 6 indicate that there might be slight increase in the cost of individual houses in some scenarios. This results from the fact that the RCEMS developed is focussed towards decreasing the cost of the regional community as a whole and not individual houses. The increase in energy cost can also be attributed to the appliance usage choices made by the users. However, this slight increase in energy cost in some days might be offset by larger decrease in some other day depending upon the appliance usage preferences of the user. It can also be observed from Table 6 that cost variation of urban users is more than that of the rural users when all the scenarios are considered. This can be attributed to the fact that appliance level classification for usage of renewable energy has been done in this work. Thus, high energy users with higher appliance ownership variation, more number of shiftable appliances and higher PV generation will be able to benefit more from the scheme when compared with low energy use households. With increasing energy use in urban areas this advantage can incentivize the urban households to form communities with low energy use rural households thus benefiting both the parties.

Table 5. List of scenarios simulated for continuous regional renewable integration

| Scenario # | Resource availability | | |
|---|---|---|---|
| | PV power | Battery energy storage system | Demand side management |
| 0 | None | None | Individual |
| 1 | RH 1 | None | Community |
| 2 | UH 1 | None | Community |
| 3 | UH 1, RH 1 | None | Community |
| 4 | UH 1, UH 2 | None | Community |
| 5 | UH 2, RH 1 | None | Community |
| 6 | UH 1, UH 2, RH 1 | None | Community |
| 7 | UH 1, UH 2, RH 1, RH 2 (50%) | None | Community |
| 8 | UH 1, UH 2, RH 1, RH 2 (90%) | None | Community |
| 9 | UH 1, UH 2, RH 1, RH 2 (90%) | UH 1 | Community |

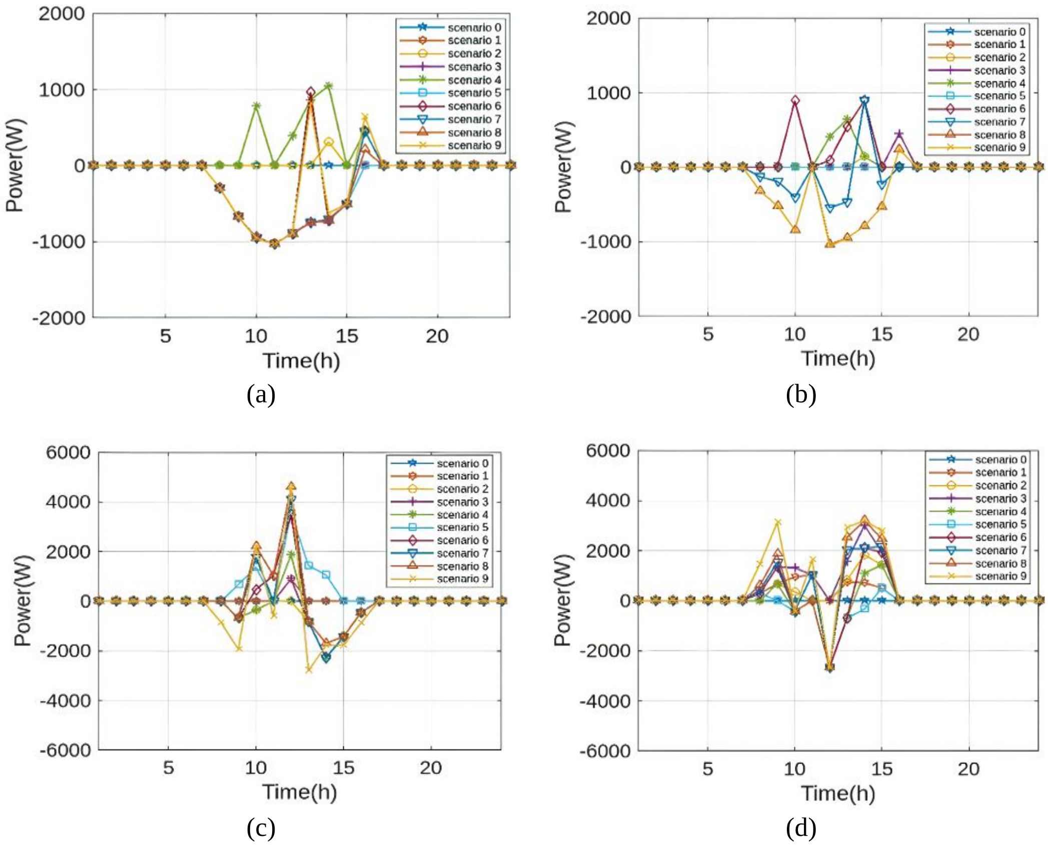



Figure 4. Buying (positive) and selling (negative) power from and to the community by: (a) rural home 1, (b) rural home 2, (c) urban home 1, and (d) urban home 2

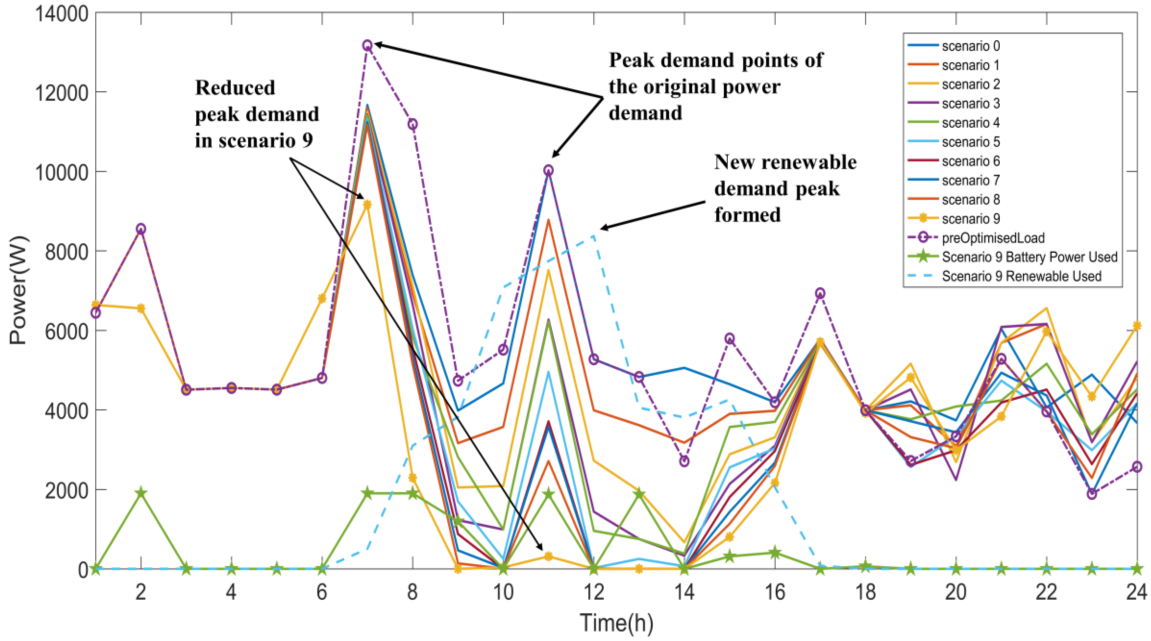



Figure 5. Total power bought from the grid by the community for all the scenarios

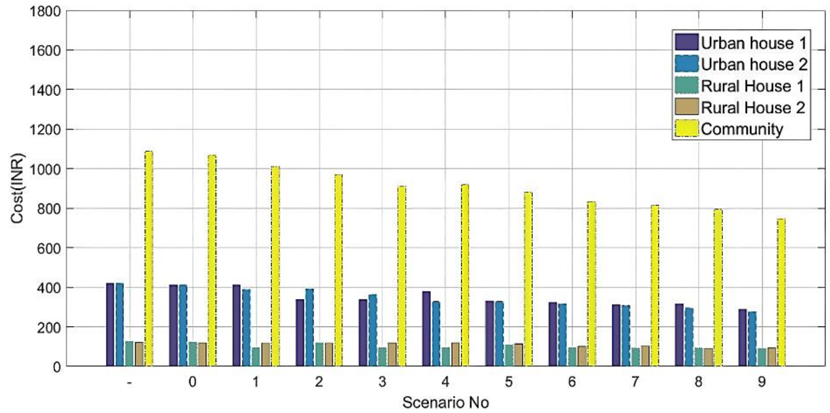



Figure 6. Cost comparison of the participating households and the community for all the scenarios

Table 6. Home and community costs obtained by the proposed method

| # Scenario | U1 | U2 | R1 | R2 | Community cost | Percentage reduction in community cost |
|---|---|---|---|---|---|---|
| Experimental case | 419.23 | 420.29 | 125.86 | 122.29 | 1087.67 | - |
| Scenario 0 | 412.84 | 413.21 | 122.91 | 119.88 | 1068.84 | 1.73 |
| Scenario 1 | 410.78 | 388.99 | 93.74 | 117.66 | 1011.16 | 7.03 |
| Scenario 2 | 339.68 | 392.16 | 119.59 | 116.98 | 968.41 | 10.96 |
| Scenario 3 | 335.41 | 363.39 | 93.74 | 118.20 | 910.74 | 16.27 |
| Scenario 4 | 378.72 | 327.91 | 93.74 | 119.23 | 919.60 | 15.45 |
| Scenario 5 | 329.65 | 328.44 | 108.67 | 114.30 | 881.06 | 19.00 |
| Scenario 6 | 323.96 | 316.40 | 93.75 | 99.87 | 833.98 | 23.32 |
| Scenario 7 | 311.81 | 308.00 | 91.58 | 102.48 | 813.87 | 25.17 |
| Scenario 8 | 314.45 | 294.31 | 92.74 | 91.50 | 793.00 | 27.09 |
| Scenario 9 | 289.28 | 276.36 | 90.15 | 92.30 | 748.09 | 31.22 |

It is to be noted that the households only buy energy from the community during the daytime when solar energy is available. This restricted the cost reduction operation during the solar hours only. The introduction of energy storage in the community can further decrease the cost by allowing the households to store the available solar energy bought from the community and using it in the non solar hours as demonstrated in scenario 9 where a battery bank was introduced in urban house no 1.

## 4. CONCLUSION

This paper provides the formation of a regional energy management system for application to multiregional and mixed demographics energy communities. The proposed energy management system addresses the regional diversity in per capita energy consumption by catering to the specific energy consumption features of urban and rural power consumers. The proposed regional energy management system addresses the regional diversity in per capita energy consumption by catering to the specific energy consumption features of urban and rural power consumers. It incorporates the demography influenced differences in power consumption patterns through a demography oriented ToU tariff system and a fuzzy logic decision module to control the preallocation of available renewable resources to the different consumers based on their demographical categorization. The problem is formulated in the form of MILP incorporating the regional power use restrictions to obtain a more realistic technical and economical solution. The hourly renewable energy allocation limit to each urban and rural house is obtained by using the fuzzy logic inference system. The system is tested on the energy profiles of two urban and two rural households simulated using LoadProGen in MATLAB 2021a. The results show that the implementation of the system always provides operational savings compared to the conventional systems. The results clearly show the relevance of forming a multiregional energy community as it reduces both the load on the grid and the energy cost of the houses as well as the community. The relevance of energy prices from different sources is also very significant as they can directly affect the amount of power being traded amongst the individual houses, community and grid. The results also show that incremental integration of the renewable sources and storage devices in the urban and rural region energy communities can give the best possible results as it can increase the flexibility of appliance usage outside the renewable availability hours also. Future work will be done to extend the proposed methodology to incorporate the commercial and industrial consumers of the urban and rural regions along with all the different consumer categories for the semi urban regions. The development of the required hardware will then be done to implement the proposed solution in utility sectors.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## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Arindam Kumar Sil | | ✓ | | | | ✓ | ✓ | ✓ | | ✓ | | ✓ | | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study. The data used is given in Table 2, the simulation softwares used is given in the results and discussion section. The source of the data is given in references as cited in the text.

## REFERENCES


[1] H. Huang *et al.*, "Research on Interruptible Load participating in electricity and reserve joint market," *E3S Web of Conferences*, vol. 257, p. 01045, May 2021, doi: 10.1051/e3sconf/202125701045.

[2] R. Khalid, N. Javaid, M. H. Rahim, S. Aslam, and A. Sher, "Fuzzy energy management controller and scheduler for smart homes," *Sustainable Computing: Informatics and Systems*, vol. 21, pp. 103–118, Mar. 2019, doi: 10.1016/j.suscom.2018.11.010.

[3] P. Ramu, S. Gangatharan, S. Rangasamy, and L. Mihet-Popa, “Categorization of Loads in Educational Institutions to Effectively Manage Peak Demand and Minimize Energy Cost Using an Intelligent Load Management Technique,” *Sustainability*, vol. 15, no. 16, p. 12209, Aug. 2023, doi: 10.3390/su151612209.
[4] G. Yao, Y. Zhang, T. Zhang, Q. Ma, and J. Chen, “Adaptive Grid Partitioning Considering Power Supply and Load Distribution,” *IEEE Access*, vol. 10, pp. 111066–111076, 2022, doi: 10.1109/ACCESS.2022.3208886.
[5] G. K. Chellamani and P. V. Chandramani, “An Optimized Methodical Energy Management System for Residential Consumers Considering Price-Driven Demand Response Using Satin Bowerbird Optimization,” *Journal of Electrical Engineering & Technology*, vol. 15, no. 2, pp. 955–967, Mar. 2020, doi: 10.1007/s42835-019-00338-z.
[6] M. M. Alam, M. Shahjalal, M. M. Islam, M. K. Hasan, M. F. Ahmed, and Y. M. Jang, “Power Flow Management With Demand Response Profiles Based on User-Defined Area, Load, and Phase Classification,” *IEEE Access*, vol. 8, pp. 218813–218827, 2020, doi: 10.1109/ACCESS.2020.3041841.
[7] T. Räsänen, D. Voukantsis, H. Niska, K. Karatzas, and M. Kolehmainen, “Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data,” *Applied Energy*, vol. 87, no. 11, pp. 3538–3545, Nov. 2010, doi: 10.1016/j.apenergy.2010.05.015.
[8] H. Yang, M. Li, Z. Jiang, and P. Zhang, “Multi-Time Scale Optimal Scheduling of Regional Integrated Energy Systems Considering Integrated Demand Response,” *IEEE Access*, vol. 8, pp. 5080–5090, 2020, doi: 10.1109/ACCESS.2019.2963463.
[9] S. A. Mansouri, E. Nematbakhsh, A. Ahmarinejad, A. R. Jordehi, M. S. Javadi, and S. A. A. Matin, “A Multi-objective dynamic framework for design of energy hub by considering energy storage system, power-to-gas technology and integrated demand response program,” *Journal of Energy Storage*, vol. 50, p. 104206, Jun. 2022, doi: 10.1016/j.est.2022.104206.
[10] D. V. Pombo, H. T. Nguyen, L. Chebbo, and D. A. Sorensen, “A Multipurpose Reference System Based on the Hybrid Power Grid of Cape Verde,” *IEEE Transactions on Smart Grid*, vol. 13, no. 6, pp. 4562–4571, Nov. 2022, doi: 10.1109/TSG.2022.3185314.
[11] C. Cruz, M. Tostado-Véliz, E. Palomar, and I. Bravo, “Pattern-driven behaviour for demand-side management: An analysis of appliance use,” *Energy and Buildings*, vol. 308, p. 113988, Apr. 2024, doi: 10.1016/j.enbuild.2024.113988.
[12] K. Bhagat, C. Dai, S. Ye, M. Z. Bhayo, B. A. Kalwar, and M. A. Mari, “Stochastic Energy Management Strategy of Smart Building Microgrid with Electric Vehicles and Wind-Solar Complementary Power Generation System,” *Journal of Electrical Engineering & Technology*, vol. 18, no. 1, pp. 147–166, Jan. 2023, doi: 10.1007/s42835-022-01193-1.
[13] M. Hematian, M. Vahedi, M. Samiei Moghaddam, N. Salehi, and A. Azarfar, “Stochastic Dynamic Reconfiguration in Smart Distribution System Considering Demand-Side Management, Energy Storage System, Renewable and Fossil Resources and Electric Vehicle,” *Journal of Electrical Engineering & Technology*, vol. 18, no. 5, pp. 3429–3441, Sep. 2023, doi: 10.1007/s42835-023-01427-w.
[14] D. Setlhaolo and X. Xia, “Optimal Scheduling of Household Appliances Incorporating Appliance Coordination,” *Energy Procedia*, vol. 61, pp. 198–202, 2014, doi: 10.1016/j.egypro.2014.11.1062.
[15] P. Dimitroulis and M. Alamaniotis, “Multimodal energy management system for residential building prosumers utilizing various lifestyles,” *Electric Power Systems Research*, vol. 213, p. 108732, Dec. 2022, doi: 10.1016/j.epsr.2022.108732.
[16] H. Cimen, N. Cetinkaya, J. C. Vasquez, and J. M. Guerrero, “A Microgrid Energy Management System Based on Non-Intrusive Load Monitoring via Multitask Learning,” *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 977–987, Mar. 2021, doi: 10.1109/TSG.2020.3027491.
[17] R. Naji El Idrissi, M. Ouassaid, and M. Maaroufi, “Game Theory Approach for Energy Consumption Scheduling of a Community of Smart Grids,” *Journal of Electrical Engineering & Technology*, vol. 18, no. 4, pp. 2695–2708, Jul. 2023, doi: 10.1007/s42835-023-01379-1.
[18] Z.-P. Yuan, P. Li, Z.-L. Li, and J. Xia, “Data-Driven Risk-Adjusted Robust Energy Management for Microgrids Integrating Demand Response Aggregator and Renewable Energies,” *IEEE Transactions on Smart Grid*, vol. 14, no. 1, pp. 365–377, Jan. 2023, doi: 10.1109/TSG.2022.3193226.
[19] S. Dixit, P. Singh, J. Ogale, P. Bansal, and Y. Sawle, “Energy Management in Microgrids with Renewable Energy Sources and Demand Response,” *Computers and Electrical Engineering*, vol. 110, p. 108848, Sep. 2023, doi: 10.1016/j.compeleceng.2023.108848.
[20] M. Afzal, Q. Huang, W. Amin, K. Umer, A. Raza, and M. Naeem, “Blockchain Enabled Distributed Demand Side Management in Community Energy System With Smart Homes,” *IEEE Access*, vol. 8, pp. 37428–37439, 2020, doi: 10.1109/ACCESS.2020.2975233.
[21] K. Thirugnanam, M. S. El Moursi, V. Khadkikar, H. H. Zeineldin, and M. Al Hosani, “Energy Management of Grid Interconnected Multi-Microgrids Based on P2P Energy Exchange: A Data Driven Approach,” *IEEE Transactions on Power Systems*, vol. 36, no. 2, pp. 1546–1562, Mar. 2021, doi: 10.1109/TPWRS.2020.3025113.
[22] M. Tofighi-Milani, S. Fattaheian-Dehkordi, M. Fotuhi-Firuzabad, and M. Lehtonen, “Decentralized Active Power Management in Multi-Agent Distribution Systems Considering Congestion Issue,” *IEEE Transactions on Smart Grid*, vol. 13, no. 5, pp. 3582–3593, Sep. 2022, doi: 10.1109/TSG.2022.3172757.
[23] M. Shi, H. Wang, P. Xie, C. Lyu, L. Jian, and Y. Jia, “Distributed Energy Scheduling for Integrated Energy System Clusters With Peer-to-Peer Energy Transaction,” *IEEE Transactions on Smart Grid*, vol. 14, no. 1, pp. 142–156, Jan. 2023, doi: 10.1109/TSG.2022.3197435.
[24] Y. Zhuo *et al.*, “RSM-Based Approximate Dynamic Programming for Stochastic Energy Management of Power Systems,” *IEEE Transactions on Power Systems*, vol. 38, no. 6, pp. 5392–5405, Nov. 2023, doi: 10.1109/TPWRS.2022.3227345.
[25] G. Eragamreddy and S. Gopiya Naik, “Power management system for a hybrid energy storage electric vehicle using fuzzy logic controller,” *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 3, pp. 1443–1452, Jun. 2024, doi: 10.11591/eei.v13i3.6608.
[26] Y. Shklyarskiy, I. Andreeva, T. Sutikno, and M. H. Jopri, “Energy management in hybrid complexes based on wind generation and hydrogen storage,” *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 3, pp. 1483–1494, Jun. 2024, doi: 10.11591/eei.v13i3.6757.
[27] H. Yang, L. Wang, and Y. Ma, “Optimal Time of Use Electricity Pricing Model and Its Application to Electrical Distribution System,” *IEEE Access*, vol. 7, pp. 123558–123568, 2019, doi: 10.1109/ACCESS.2019.2938415.
[28] S. Mandelli, C. Brivio, M. Moncecchi, F. Riva, G. Bonamini, and M. Merlo, “Novel LoadProGen procedure for micro-grid design in emerging country scenarios: application to energy storage sizing,” *Energy Procedia*, vol. 135, pp. 367–378, Oct. 2017, doi: 10.1016/j.egypro.2017.09.528.
[29] A. Chunekar, S. Varshney, and D. Shantanu, “Residential Electricity Consumption in India: What do we know?,” 2016. [Online]. Available: https://energy.prayaspune.org/our-work/research-report/residential-electricity-consumption-in-india-what-do-we-

know#:~:text=The residential electricity consumption (REC,household incomes%2C and technology development. (Accessed 25th March 2024).
[30] S. Agrawal, N. Bali, and J. Urpelainen, "Rural Electrification in India: Customer behaviour and demand," The Rockefellerf Fundatio,n 2019, [Online]. Available: https://www.rockefellerfoundation.org/reports/rural-electrification-india-customer-behaviour-demand/. (Accessed 25th March 2024).

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