Peak Demand Management in a Smart Community using Coordination Algorithms

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Abstract

In this paper, we propose peak demand management techniques for a smart community using different types of coordination mechanisms for coordination of multiple house agents working in the same environment. These algorithms use centralized model, decentralized model, hybrid model and Pareto resource allocation model for resource allocation. We modeled user comfort for the appliance based on user preference, the power reduction capability and the important activities that run around the house associated with that appliance. Moreover we compare these algorithms with respect to their peak reduction capability, overall comfort of the community, simplicity of the algorithm and community involvement and finally able to find the best performing algorithm among them. Our simulation results show that the proposed coordination algorithms can effectively reduce peak demand while maintaining user comfort. We confirm that using our proposed algorithms, the demand for electricity of a smart community can be managed intelligently and sustainably.

Keywords: *Peak demand management, algorithm, coordination, community agent, centralized, decentralized, Diversity factor, Election rule, balancing responsible agent, Pareto efficiency, Nash negotiation*

1. Introduction

1.1. Importance of Peak Demand Management in Residential Sector

The emission of greenhouse gases when electricity is generated started to have significant impacts on the climate change. This is emerging as one of the major global challenges and researchers all over the world are working towards sustainability and climate change challenges.

Houses and buildings consume over 30% of all energy and 50% of the electricity. Electricity peak demand is also expected to increase nearly by 30% in the coming decade mostly driven by increased use of Air conditioners and other high energy appliances in new and existing homes and buildings. According to a research commissioned for the power of choice Air-conditioners are forecast to be the sixth largest energy consuming appliances by 2020 in terms of total annual demand [1]. They are likely to have a higher impact on peak demand relative to many other high energy appliances due to the observed relationship between temperature and peak demand. Televisions are forecast to generate the greatest amount of total demand by 2020 of all household appliances, followed by water heating, lighting and refrigerators. These appliances are the main reasons for residential peak demand growth and therefore it is essential to find a systematic approach to managing energy efficiency and the cost of electricity in residential sector.

Recently many researchers focus on the smart home which can enable the residents with monitoring, control of the smart home appliances and ensuring security from remote. In this work we try to develop a smart community by grouping a number of houses which will be able to create a reliable and sustainable energy future by effectively managing energy consumption during peak demand. In this paper we assume a smart community as a suburb which consists of a number of smart homes where each smart home is incorporated with a home agent which is capable of monitoring, controlling the operation (states) of all house hold appliances according to user preferences using a policy based framework which we proposed in our paper [2].

1.2. Benefits of Smart Community

By properly incorporating a suitable energy management framework for a smart community, we can have a number of benefits in terms of long term health and prosperity of the community [3].

- Cost of electricity will be consistently lower than the neighboring communities
- The quality of air with reduced greenhouse gas emissions will be better.
- The community residents are satisfied by knowing that these advantages are received with minimum impact on the earth.
- The consumers will have reliable power supply.
- Electricity prices will not be subjected to market volatility.

On the other side the suppliers of electricity also benefit from smart community such as greater understanding of customer end energy requirements and reduced carbon tax.

Contribution of this paper is summarized as follows: *i)* Proposing different types of peak reduction algorithms for community energy management; *ii)* Obtaining comfort model and community involvement for the community with each peak reduction algorithm; *iii)* Performing qualitative and quantitative analysis of all the algorithms in terms of community comfort, simplicity of algorithm and community involvement.

The structure of the paper is as follows: Section 3 explains briefly about energy consumption management of smart home using policy based framework with user comfort model, Section 4 explains the significance of diversity factor for power management, Section 5 shows the smart community management architecture, Sections 6, 7, 8 and 9 describes different peak reduction algorithms and in Sections 10 and 11 we present simulation results, performance analysis of our algorithms and finally we conclude.

2. Related Work

In [4] the authors proposed a policy based framework which allows intelligent and flexible power consumption management of smart home appliances in a smart home so that the peak demand is managed efficiently with minimum inconvenience to the users. The house agent is a program with a set of policy rules for the smart home appliances. The house agent which is embedded in a smart home keeps comparing the actual power consumption of the house and the notional available power to that house. If there is a discrepancy it controls the states of appliances appropriately and maintains the power consumption of the smart house less than the available power. In [5] the authors modeled individual consumers, consumer resources, utility companies and production companies as autonomous agents and they interact with each other using a negotiation protocol. They proposed three different types of negotiation such as offer method, the request for bids method and the announce rewards table method. Throughout the paper they explained the reward table approach which is a combination of first two methods. The idea is utility agent will have a reward table which have possible cut down values associated with the reward and communicate this with the consumers. Then the customer agent can decide to cut down some power consumption for that award or not. After receiving the responses from consumers utility company agent will update the reward table based on the aggregated information. This will continue until the stability of the power system is reached.

In [6] the authors contributed their work in identifying the elasticity property of appliances that enables the reduction of the power with a quantifiable impact on the appliance operation, providing a taxonomy of ten common household appliances with respect to their elasticity, collecting and comparing a comprehensive data sheet on all the appliances, penetration rate and load profiles and their usage patterns and finally validating their simulations using probabilistic computations. In [7] the authors proposed an organizational model called garbage can model (GCM). They extended the concept of original GCM by introducing autonomous agents in to it to get the benefits of both methods and eliminating the disadvantages of original GCM. In this model the resources are allocated to each agent not only by agents own efforts but also with the help of problem solving status of other agents. In [8] the authors proposed principled negotiation for AAS (Aircraft/Airspace system) which allows coordination of agents with different interests allowing distributed optimization. In [9] the authors developed peak reduction methods for a group of 30 households which are load shifting, load delaying and optimizing the on off switching of the intermittent loads such as refrigerator and toilet washer. In this they have not considered the coordination of houses for maximum comfort.

In [12] the authors present *Span*, a power saving technique for multi hop ad hoc wireless networks which will reduce energy consumption while maintaining the connectivity and capacity of the network. Instead of all the nodes to participate in data transfer only few nodes will be awake as coordinators and participate in the forwarding backbone topology. The authors used an election rule to choose the coordinators in which a node with larger E_r/E_m (E_r is the amount of energy at a node and E_m is the maximum energy available at the same node) is more likely to volunteer to become a coordinator. In [10] the authors proposed a model based on information fusion and multi agent control system to manage indoor energy and comfort for smart buildings developed a control system to maximize comfort with minimum energy consumption. They proposed two different comfort models for the users. They controlled thermal comfort, visual comfort and air quality using three local controller agents and used particle swarm optimization to optimize two parameters of their model named set points and OWA weights so that comfort index can be maximized with minimum energy consumption. In [13] the authors tried to develop a smart grid city simulator based on software agents which consists of houses, house hold appliances, vehicles and power stations. In this the appliances are modeled based on continuous cyclic behavior which is not realistic. In this paper we consider a large number of households as a community and propose different kinds of peak load reduction algorithms by properly coordinating the house agents (house) to maximize the user comfort level, using different coordination structure such as centralized, decentralized and negotiation.

3. Policy based Smart Home Architecture

In our previous work we proposed a policy based smart home for peak power consumption management. when there is a peak demand a house agent which is embedded in a smart home will be able to monitor and control various states of appliances based on the electrical energy available and user preferences on the appliances so that the comfort level of the user is not very much affected. In the smart home all house hold appliances will be connected together and controlled by a home gateway which also can connect other user devices through internet [11].

3.1. State based Model of a House Hold Appliance

In our previous work [2], appliances are modeled using state diagrams having the idea that all the appliances go through various states during their operation. Each state of an appliance will describe what state it holds, how much power it consumes, duration of the state, from where it transited into the present state and the future state it is going to occupy and the time. A complex device can have any number of states and when we can identify more states the model will become more precise.

3.2. Policy based Framework

Smart homes use a range of appliances which are connected together in a home network for the purpose of monitoring and controlling them from remote and these appliances are called intelligent appliances. They communicate with the house agent through Zigbee network. The house agent will have a set of policy rules for the appliances which also lets users to edit and add any new policy rule according to their convenience thus offering greater flexibility to the framework. Every instant all the appliances will send information about their state and power consumption. The house agent calculates the total consumption and compares with the available power. When there is a discrepancy the house agent executes appropriate rules to change the states of appliances so that the total power consumption is less than the available power with minimum inconvenience to the user.

3.3. Policy for a House Agent

Table 1. Policy Rules for the House Agent

Rules for House Agent t =sampling time starts at 0 and incremented by 0.1; ***R1****: t ≥ ontimegrade3appliance →* *Turn off other grade3 appliances* // only one grade3 appliance will be allowed to operate at any time. ***R2****: t = ontimegrade1 appliance →* turn on grade1 appliance; ***R3****: t = ontimeironbox & t = AC time →* *turn off Iron box;* //to prevent power consumption to go high when A/C is ON, the iron box is turned off ***R4****: ontimeTV = ontimeNintendo →* *turn off TV and turn on Nintendo;* //TV and Nintendo are not operated together. ***R5****: ontimeNintendo <15 →* *turn off Nintendo;* //Nintendo is not allowed before school hours. ***R6****: total power >available power →* *turn off Music;* //if total power exceeds available power music is turned off.	***R7****: t=ontimeTV=ontimemusic* *& power>available power → turn off music;* //if lights are on during the day and if actual power exceeds //available power then lights will be turned off. ***R8****: t = ontimelights & 10≤t≤16* *& power >available power → turn off lights.* ***R9****: if t>10 &t<16 turn on fridge for 5 sampling periods and turn off for 5 sampling periods.* ***R10****: If t >10 & t <16 & t =RonAC then Turn on AC for 5 sampling periods and turn off for 5 sampling periods.* *//AC and Fridge are turned on alternately during AC hours so that only one consuming energy at a time* **R11***: if t<10 &t>16 turn on fridge for 10 sampling periods and turn off for 5 sampling periods.* //Outside AC time fridge will work normally. ***R12****: If t <10 or t>16 & if power>available power →* *turn off AC.* //Outside AC time if A/C is on and if power //exceeds the available power then A/C will be switched off. **R13**: if t ≥ Ontimegrade3 appliance & power>available power *→Pause grade 3 appliances for 5 sampling periods and then resume. Change the states of grade 3 appliance for time being so that it doesn't consume power for a while.*

Each house agent will have a set of policy rules on which the user can operate his appliances during peak demand period. Policy rules are developed based on states of the appliances, process on which the appliance is involved and the history of the usage of the appliances. The policy may look like Table 1.

3.4. User Comfort Model

When the operation of appliances is controlled by the house agent depending on the energy availability, the comfort level of the resident may get affected. In order to develop user comfort model for an appliance, we first used some parameters to identify the significance of the appliance to the user such as priority, power reduction capability and the intended time of operation for a particular activity to happen associated with that device. We also considered the fact that user preference on appliances and the change in power consumption of appliances change from time to time. Power consumption is not always equal to the rating of the appliance and it depends on the state it goes through during its operation. Hence a state model of the appliances is employed when formulating the comfort model precisely as shown below.

Device [Name, Priority, Power reduction capability]
Priority (Pr(t)) is assumed to be varied from 1 to 0 every hour; Power reduction capability (Pd(t))is also ranging from 1 to 0

Pr(t) = 1,0.9,0.8,0.7,0.6,0.5,0.4,0.3,0.2,0.1,0 (high to low)
Pd(t) = 1,0.9,0.8,0.7,0.6,0.5,0.4,0.3,0.2,0.1,0 (high to low)

Power rating of all the appliances is normalized against the maximum rating of the appliance in a home.

Let us assume that Air conditioner is on by a resident. Now if a policy rule turns off this device due to peak demand at any time t, then discomfort ($D_{pr}(t)$) of the user due to this device with respect to priority will be.

$$D_{pr}(t) \quad \alpha \quad Pr_{AC}(t)$$

If priority of AC during summer time is 1 and if turned off by a policy rule then the discomfort will be maximum.

Then discomfort due to this device with respect to its power reduction capability may be obtained as follows. Let the power rating of AC is 1 (max) then discomfort ($D_{pd}(t)$) with respect to this parameter will be minimum.

$$D_{pd}(t) \quad \alpha \quad 1- Pd_{AC}(t)$$

Overall discomfort is the average of this two

$$\text{Discomfort}(t) = (D_{pr}(t) + D_{pd}(t))/2$$

And for AC in this case discomfort is 0.5.

Comfort of the consumer due to this appliance when turned off by a policy rule [10] will be

$$\text{Comfort}(t) = 1\text{-Discomfort}(t) = 1- (D_{pr}(t) + D_{pd}(t))/2$$

If a number of appliances is operating simultaneously only few policy rules may operate on some appliances according to the conditions for policy rules to be executed on appliances (user preferences).

Then the comfort of the user at any time is expressed as

$$Comfort\,(t) = \frac{N(t) - \sum_{j=1}^{R} Discomfort_j\,(t)}{N(t)}$$

Where
N (t) = No of appliances operating at any instant t
R = No of rules executed at that instant

4. Diversity Factor and Peak to Average Ratio

Diversity factor is the probability that an appliance will come on at the time of the system's peak load. Since the consumers in each house and the appliances are diverse in nature sum of their individual peaks may not contribute to the community peak power. This diversity factor plays an important role in calculating the overall cost per unit generated. Greater the diversity factor lesser is the cost of generation of power. With the given number of consumers the higher the diversity factor of their loads, the lesser will the capacity of the plant that results in reduced capital investment. The suppliers always try to improve the diversity factor by motivating the consumers to use the electrical energy during off peak periods.

It is the ratio of the sum of the individual non-coincident maximum demands of various subdivisions of the system to the maximum demand of the complete system. The diversity factor is always greater than 1. We calculated diversity factor for various community size starting from 1. For this purpose we randomized the on time and duration of operation of appliances around the peak period so that our model looks similar to the real time demand curve.

$$Diversity\ factor = \frac{sum\ of\ individual\ maximum\ demands}{Maximum\ demand\ on\ Power\ station}$$

Diversity factor is plotted against community size and for various randomness of operation of appliances as shown in in Figure 1. For this we assumed that there are 14 appliances in each house and operated once at any time during the day. The figure clearly shows that as the community size increases diversity factor increases with complete randomization of appliances. But in daily operation the user may tend to operate the appliances in the morning and evening before he goes to work and after coming back from work. So in order to mimic the real time demand curve we assumed that the appliances are turned on during the peak period and then plotted the diversity factor as a function of community size.

The figure indicates that as the community size increases the diversity factor increases but not as much as it does with complete randomization, it then saturates after 1.97 for community size greater than 1500(because of the uniform distribution of random numbers after 1500).The saturation point and the value mainly depends on the number of appliances, rating of appliances [14], duration of operation of appliances and also the randomness of ON time of appliances. It is clearly observed that with complete randomization of appliances over the day the diversity factor is larger (3.8386) than the diversity factor with the randomization of operation of appliances around peak period which is only 1.97.

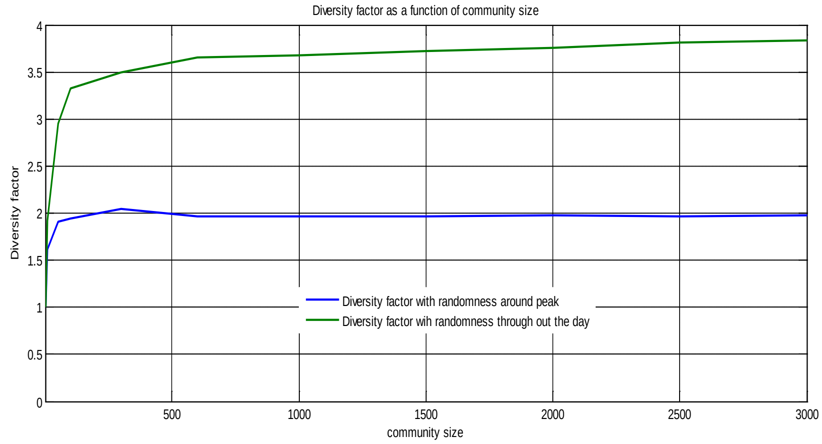

Figure 1. Diversity Factor as a Function of Community Size

4.1. Peak to Average Ratio

Peak to Average ratio is also an important factor to be considered in power system to determine the size of the power plant and the unit price. Peak to average ratio is defined to be the ratio of peak power and the average power of the system. When the diversity of consumers and appliances increase the average power increases which results in small peak to average ratio. We also considered the peak to average ratio for each community size and plotted the results.

$$Peak\ to\ Average\ ratio = \frac{Peak\ power\ of\ the\ community}{Average\ power\ of\ the\ community}$$

Our simulation results in Figure 2 show that it is saturated to 1.677 for the community size 1000 and above. Figure 2 also illustrates that peak to average ratio changes as the randomness of appliances changes. Peak to average ratio with complete randomization of appliances is almost one which is smaller than peak to average ratio with randomization of appliances around peak period. As the diversity increases the peak to average ratio decreases and hence the peak power is gradually reducing which in turn reduce the capacity of the plant and the unit price. The ideal peak to average ratio is 1 which is not possible to achieve.

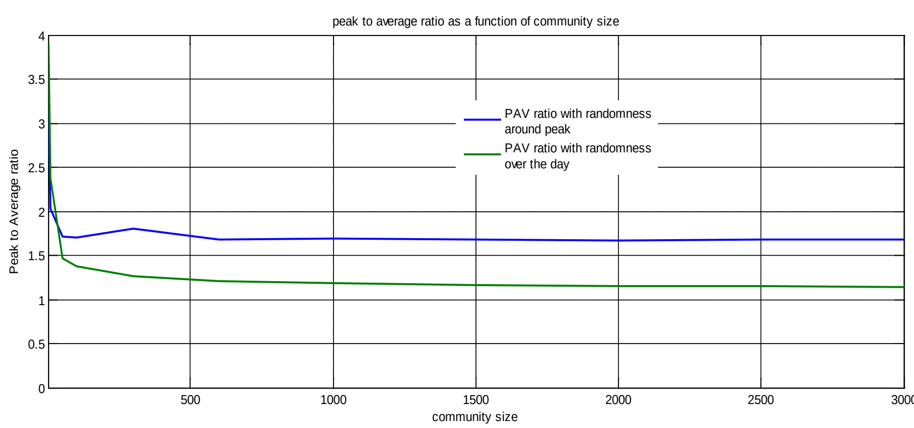

Figure 2. Peak to Average Ratio for Various Community Sizes

Since the diversity factor remains constant when the community size goes above 1500, we assumed the maximum size of the community for effective peak demand management to be 2000. Then using this community size and applying appropriate management methods we still can bring down peak to average ratio close to one which is desirable in the aspect of power plant capacity and unit price of power production.

5. Smart Energy Community Architecture

Figure 3 depicts the proposed smart energy community architecture. Each house is incorporated with a house agent containing policy rules for the appliances. The house agent will communicate with all the smart home appliances through Zigbee network. Each appliance will have a smart interface so that it can send its power consumption details to the house agent. The house agent will send control information to the appliance based on the available energy and actual consumption and correspondingly the policy rules will be executed until the actual power is less than available power. In the smart community architecture, there will be a number of houses which are connected together by a community agent through existing power lines. Each house will send its instantaneous power consumption details through smart interface and the community agent will aggregate the individual house power consumption to determine total community power consumption. We developed few peak reduction algorithms for a community. The community agent using one of the proposed peak reduction algorithms will control the power consumption of all the houses based on the total available energy.

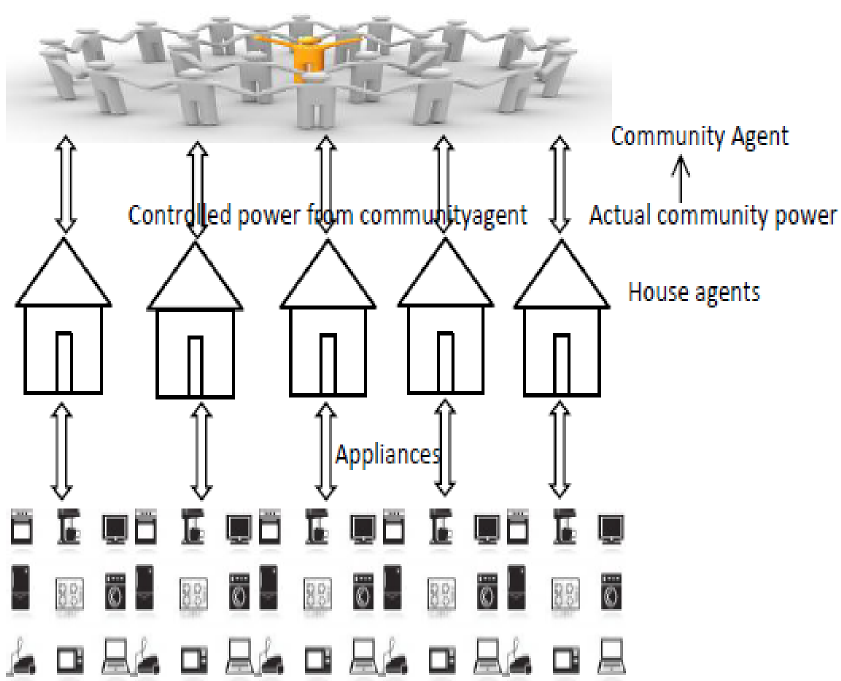

Figure 3. Smart Energy Community Architecture

6. Centralized Algorithm for Peak Reduction

In this approach global optimization criteria is divided into several local optimization goals and each agent in the environment is only concerned about a local optimization goal. The global optimization is achieved through a combination of these local optimizations. This kind of methodology is suitable for those complicated problems in which there are too many constraints or goals to define a global optimization criterion clearly and exhaustively in advance. House agents have their own power limit. So the agents operate their appliances based on the user preferences and comfort level ensuring that the power consumption at any instant doesn't exceed the power limit. When the house agents act in a community they need to satisfy their local goals as well as the goal of the community.

Definition: Assuming n number of houses **(h_1, h2, h3, ..h_n)** in a community , when the community power consumption **$P_{act}(t)$** exceeds the available power **($P_{avail}(t)$)** at any time t the deviation **Δ (t)** which is the difference of actual power consumption **$P_{act}(t)$** and available power **($P_{avail}(t)$)** is divided equally among n number of house agents and the house agents are expected to reduce their power consumption by **Δ (t) /n** at that time.

6.1. Advantages

- Since the exceeded power is divided equally by a number of houses in a community the total power that has to be reduced by an individual house will be comparatively less.
- The main characteristic of a centralized model is that major decisions are made at the top and the main reason for choosing this centralized management model is to maintain consistency across the organization.

6.2. Limitations

- Sometimes the comfort level may come down and the user is very much forced to reduce their power consumption though he is achieving his local goal.
- There is no coordination between house agents. Sometimes some houses can reduce their power consumption more than what is asked by the community agent without affecting the individual comfort so that few of the other houses need not participate in peak reduction that time due to their need to use power due to some unavoidable circumstances.
- When the management decisions come from the top it is sometimes very difficult or not possible for the house agents to react quickly to changes or circumstances and adjust its consumption behavior.
- Centralized approach will not improve the ability of individual agents to optimize their own operations. This approach bothers about the system not the requirements of the local house agents.
- All the house agents are treated in the same way which may be reasonable but treating single person in a house hold and many persons in a house hold same may not be fair.

7. Round Robin Algorithm

Definition: Assuming **n** number of houses **(h_1,h_2,h_3,..h_n)** in a community if community power consumption **$P_{act}(t)$** at any time instant t exceeds the available power **$P_{avail}(t)$,** the community agent starts requesting house agents starting from $\mathbf{h_1}$ to $\mathbf{h_n}$ to reduce their consumption until the power consumption stays below the available power. Then the next time when the community consumption exceeds the available power the community agent will start requesting from house agent next to the house agent where it stopped earlier.

House agents work in a community and when the total community consumption exceeds the available power the community agent will start requesting all the house agents one by one to turn off one of their appliances. For example the music if turned on will be turned off in all the houses in turn until the stability is reached. If the power becomes less than the available power then the process will stop. If the actual power is still above the available power then during second round all the houses will be requested to turn off their ac if they have switched it on. In third round the community agent might tell the house agents to turn off their washing machines (if turned on). This process will continue until the community agent brings the power consumption to less than the available power.

Once the power consumption is brought to less than the target then next instant when power exceeds the available power, the request should start from a house next to the house which contributed lastly.

7.1. Advantages

In this method

- The house agents are not forced to reduce it consumption and the algorithm make sure that most of the house agents are participating in peak reduction.
- It starts from turning off entertainment and grade 3 appliances with minimum discomfort. Sometimes peak demand problem is solved by simply turning of music in all the houses.
- Individual Comfort level is improved and more peak reduction is possible for the same amount of community discomfort compared to centralized algorithm.

7.2. Limitations

- Sometimes the houses which consumed more did not even participate in peak reduction and other houses take the responsibility which is not fair.

8. Balancing Responsible Agent Algorithm for Peak Reduction

In order to overcome the limitations mentioned in the above two algorithms we tried to develop an algorithm which can coordinate the house agents effectively so that total power consumption is managed without affecting the individual comfort and over all comfort of the community. This algorithm is applicable to a decentralized management system where there is no community agent or supervisor agent. The performance of the system depends on each agent’s functions. Autonomous agents cooperate to accomplish a common goal.

Definition: Assuming **n** number of houses $(\mathbf{h_1, h_2, h_3, .. h_n})$ in a community when community power consumption $\mathbf{P_{act}(t)}$ exceeds the available power $(\mathbf{P_{avail}(t)})$ at any instant t one of the house agents whose Balancing Responsible Factor **(BRF)** is maximum will volunteer to be the balancing responsible agent and reduces its power consumption as much as possible using policy based framework embedded in it, then the house agent having second most BRF will be elected as a balancing responsible agent and this process will continue until the stability is reached. Every instant when the total power exceeds the available power an election rule is used to select a number of coordinators to participate in peak reduction.

8.1. Election Rule

In electing a coordinator or a balancing responsible agent we used a factor called balancing responsible factor which is the ratio of energy consumption of the house at any instant and the max power consumed by any house at the same instant.

$$Balancing\ Responsible\ Factor\ (BRF) = \frac{E_{(h,t)}}{E_{max}(h1, h2, h3, h4 \ldots hn, t)}$$

The house agent with a larger BRF is more likely to volunteer to become a balancing responsible agent (BRA). In order add a decreasing function of Eh/Em to reflect this we used a linear function 1- $E_{(h,\ t)}$ / $E_{max\ (h1,\ h2,\ h3,\ h4\ldots hn,\ t)}$

This election rule ensures that

1. Minimum number of balancing responsible agents is selected so that the overall comfort level is improved.
2. Enough number of coordinators is selected for peak demand reduction
3. The Balancing Responsible agents are selected based on the local information (not centralized)
4. This approach prevents the house agents who do not consume more power from being participating in peak reduction.

8.2. Advantages

1. In this approach the houses who are elected as coordinators (BR agents) need to reduce their energy consumption by executing all the possible rules on appliances during that period. This helps other houses continue to consume the same amount of energy (No need to participate in peak reduction).

2. This reduces the probability of a house to participate in peak reduction from 1 to a desired value which helps to improve the overall comfort of the community. We defined a factor called User participation factor which is the ratio of number of houses participated in peak reduction to the total number of houses in a community.

$$User\ Participation\ Factor(UPF) = \frac{No\ of\ houses\ participated\ in\ peak\ reduction}{No\ of\ houses\ in\ the\ community}$$

When community size = 1
Probability of participation = 1 the chance for the house (community) to participate in peak reduction =100%
As the community size increases from 1 the chance for the house to participate in peak reduction can be reduced from 100% for the same amount of peak reduction.

Limitations

- Individual comfort of the House agents who acted as balancing responsible agents is very much affected though over all community comfort is improved.

- The Balancing responsible agents have nothing to say about whether they are willing to be balancing responsible agents to the community agent

9. Pareto Efficiency Allocation Algorithm of the Available Resources

In order to overcome the limitations mentioned in above algorithms we introduce a simple negotiation based on which the available resource is allocated to the house agents in a community so that Pareto efficiency is reached.

In a Pareto efficient economic allocation, the resources are distributed in the most efficient way. Pareto improvement means a part of people is made to obtain more comfort without declining the comfort of others [15]. When there is no further Pareto improvement can be made then it is called Pareto efficiency or Pareto optimal allocation of the available resources.

In a production possibility frontier curve (PPF) which is a combination of distribution of a resource between two persons so that the available resource is fully utilized. We assume that 8000 watts is the available resource and needs to be distributed among two users in the most efficient way.

The users can demand any amount of power as long as the total request is less than the available power of 8000 watts. If the points lie below the PPF is not the focus of our research work and they are not Pareto efficient since the available resource is not utilized by both the agents. But the points lie above the PPF is not possible. In order to bring the point on the PPF we followed this simple strategy.

Example: A and B request 3000 and 8500 respectively and is represented by R in Figure 4. So the total demand exceeds 8000 watts. Therefore the community agent divides the power 8000 watts equally among the agents and that is the disagreement point represented by S (4000, 4000) which is also one of the Pareto efficient points lie on the PPF curve.

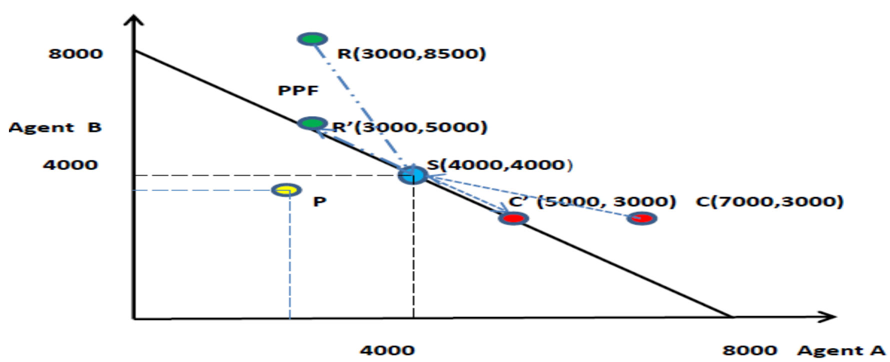

Figure 4. Pareto Efficient Allocation of Available Resource among Two House Agents

Comfort of A will be 100 %. But comfort of B will be reduced because it doesn't get the amount of power it required. A and B will get 4000 watts. Then they start to negotiate between them. Since A needs only 3000 watts that time it gives 1000 watts to agent B. B will get 5000 and the comfort of B will be improved without affecting the comfort level of the agent A and at the same time the total demand is equal to the available power which lies on the PPF. So the point R which was outside the PPF is now moved to R' on the PPF. This way the available resource is allocated between agents. We extended the approach to a number of houses in a community so that after the community agent divides the available power equally then by negotiation the agents will try to improve their comfort without affecting the comfort of other agents so that Pareto optimality is obtained.

Definition: Assuming **n** number of houses **($h_1,h_2,h_3,..h_n$)** in a community when community power consumption **$P_{act}(t)$** exceeds the available power **$P_{avail}(t)$** at **t**, then the available power will be equally divided to n number of houses. Then the houses who need less than the available power will release their surplus power and cumulatively considered as the total credit at that instant and that will be distributed to houses who need more than available power based on Pareto improvements and while doing it ensures that the total power is less than the available power so that Pareto optimality is reached. In this way available power is efficiently allocated to all the houses.

1. Calculate community power consumption. If less than available power then community agent let the house agents consume power independently irrespective of how much each house consumes.

2. If community power consumption >available power, then the Community agent divides the available power equally to all the house agents.

3. Some of the houses who do not need that much power will release the remaining so that the available credit is accumulated as total credit for that instant.

4. Then the community agent allocates the total credit to houses that need power more than the average power and the amount of power each house agent gets depends on how far it is close to average power, the individual credit power it has and the amount of total credit. If a house agent is close to average but little more, then the probability of it gets served by the community agent is more.

10. Effect of Peak Reduction Algorithms over Diversity Factor

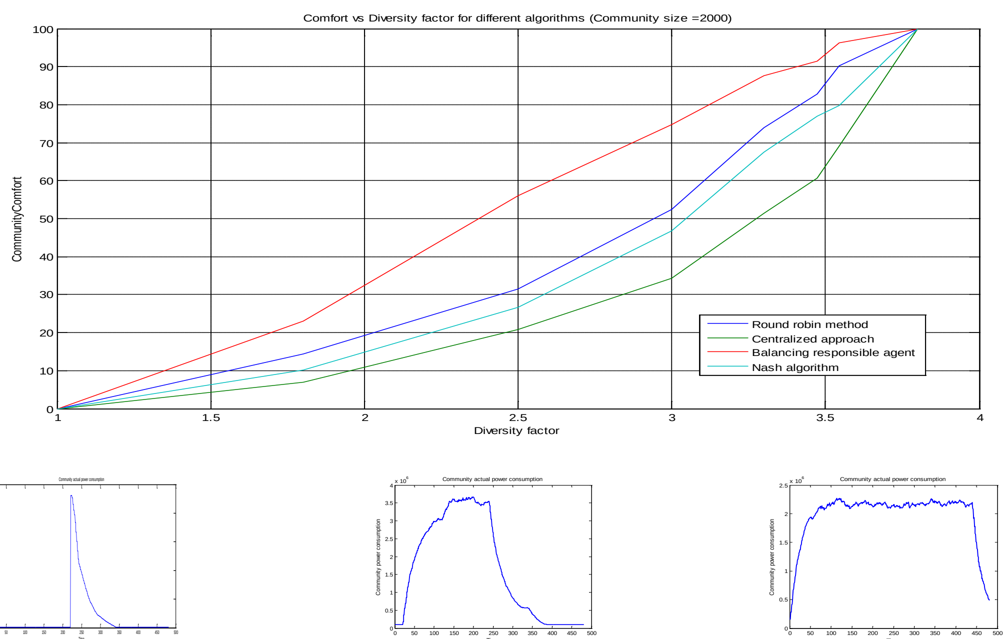

Figure 5. Community Comfort for Various Diversity Factors Keeping the Community Size Constant

In order to analyze the effect of our peak demand management techniques over various diversity factors, we varied the diversity of the community from 1 to 3.8 (this is the maximum value for complete randomization of ON time of appliances for 14 appliances with different power rating) by changing the randomness of ON time of house hold appliances between 0 and 24 hours. We also assumed that the appliances are operated only once during a day. In this case the community demand curve will have only one peak.

The utility always plan to design the power plant with larger diversity factor so that the capacity of the plant is minimum and fully utilized. So we assumed that the peak power of the community with largest diversity factor (3.83 in this case) is the Power generated in the power plant which is available to this community with 2000 houses and 14 appliances in each house. Then for each diversity factor we implemented all the algorithms and determined the minimum comfort of the community and plotted the results. The Figure 5 shows that as the diversity factor increases from one the algorithms give better comfort and for maximum diversity factor the comfort is maximum and there is no need to have peak demand management since there is no peak power observed. The order of our algorithms will be: 1.Balancing Responsible agent method 2.Round robin method 3. Nash negotiation and finally Centralized approach.

In practical life the appliances are biased to operate between two peak periods (usually people tend to operate their appliances before going to work and after coming from work). In order to get the real time demand curve with two peaks we assumed that some appliances like electric cooking, Microwave, coffee maker and AC are switched on twice in a day and when we simulated the profile we got the community of 2000 houses with the diversity factor 2.0.

11. Simulation Results for Centralized Algorithm

A community size of 2000 is assumed for implementing our peak reduction algorithms. In order to plot the actual power consumption of the community we first randomized the operation time and duration of all the appliances and simulated the load profile of the community [4] as shown in Figure 6. We identified the peak power (5.5 MW) of the actual power consumption and calculated 90% of the actual power (5 MW) and assumed that as the available power (in order to achieve 10% peak reduction).

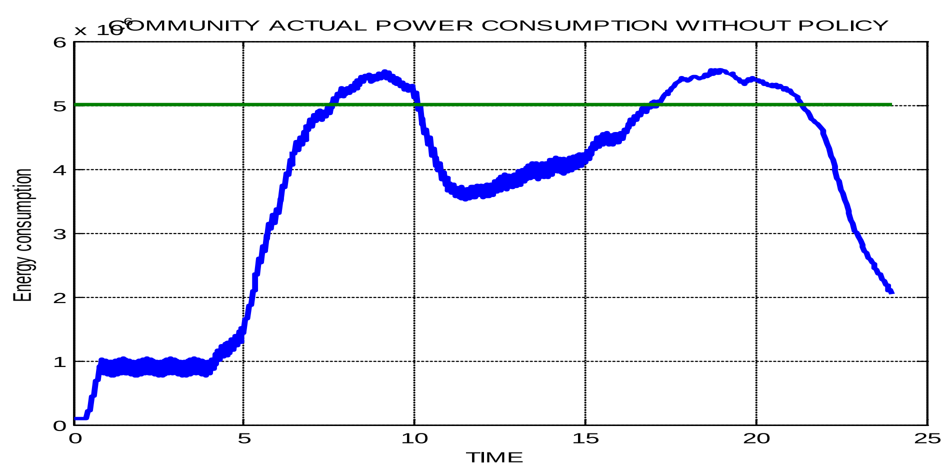

Figure 6. Community Power Consumption without Peak Reduction Algorithm

Then using the centralized algorithm we brought down the actual power consumption below the available power which is shown in Figure 7. Whenever the power consumption goes above the available power the deviation is divided equally among all the houses and each house is forced to reduce their power consumption by that amount. When implementing peak reduction algorithm all the house agents will execute policy rules and the comfort of individual houses may get affected and we modeled the individual comfort and determined the average comfort at every instant and termed as overall community comfort.

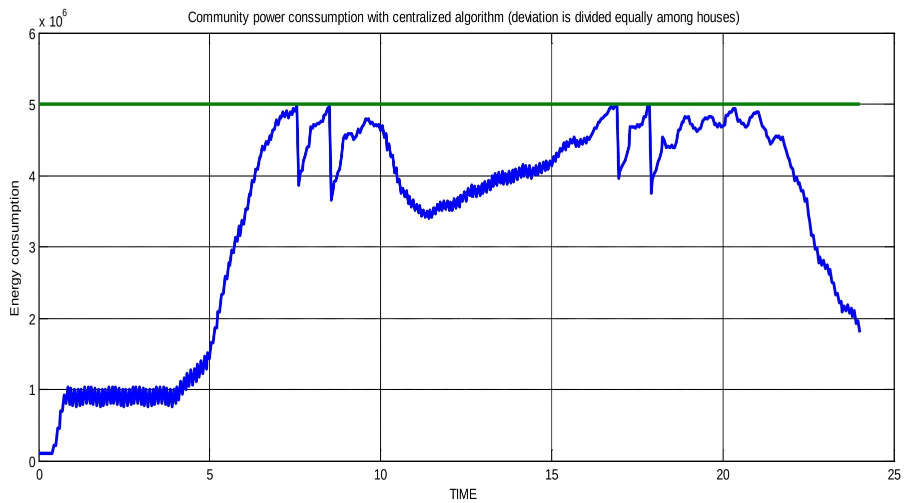

Figure 7. Community Power Consumption after Peak Reduction Algorithm Implemented

In Community comfort model we can understand that whenever the actual power exceeds the available power the house agents apply rules to appropriate appliances and that is the reason only around peak period the comfort level get affected and particularly in this approach the minimum comfort it can go to achieve 10% peak reduction is 69.95% as shown in Figure 8.

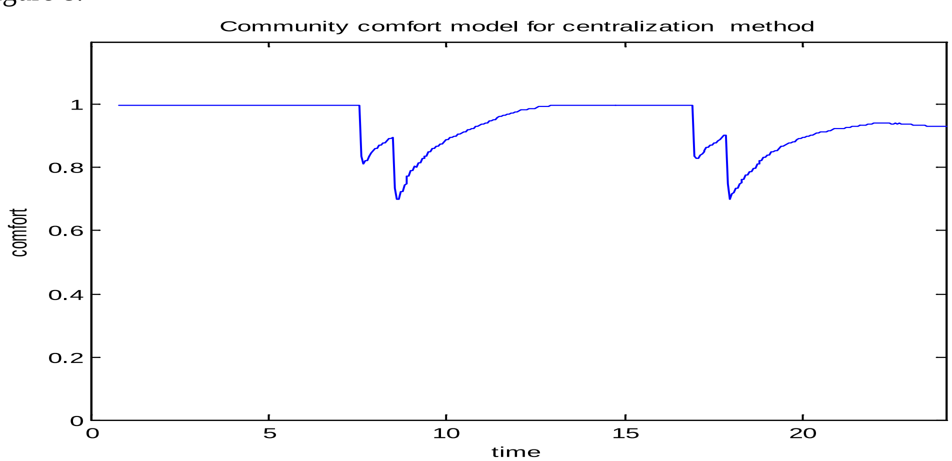

Figure 8. Community Overall Comfort after Peak Reduction Algorithm

12. Performance Analysis of Algorithms

We evaluated the performance of these algorithms in terms of overall community comfort, community involvement and percentage of peak reduction and diversity factor. Keeping the diversity factor of the community (2.0) constant we performed peak reduction algorithms for the following different scenarios.

Case 1: Keeping percentage of peak reduction constant (say 10 % peak reduction). We implemented all the peak reduction algorithms for various community sizes and plotted the overall community comfort against community size.

Figure 9 clearly shows that as the community size increases for the same percentage of peak reduction community comfort increases because of the increased diversity factor. Then when community size goes beyond 2000 because of the constant diversity factor community comfort also keeps constant. Balancing responsible agent algorithm provides maximum comfort over all the other algorithms with the reason that only a few numbers of houses is participating in peak reduction and though their individual comfort is affected the overall comfort is not affected. In Round robin method since number of houses participate in peak reduction is more than the balancing responsible agent method it results in reduced overall comfort of the community.

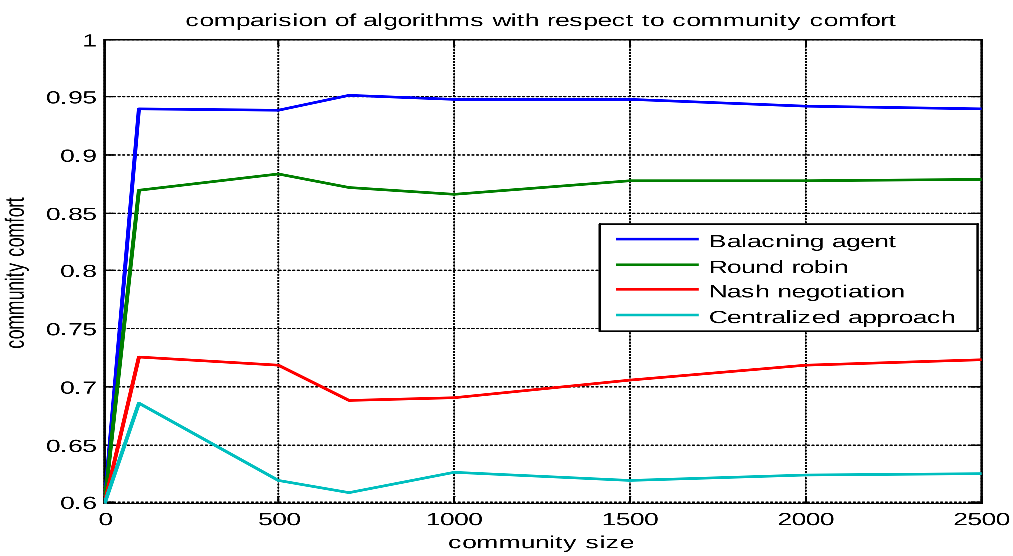

Figure 9. Community Comfort vs Community Size

In Pareto allocation when total consumption is more than the available energy the available energy is divided equally among n number of houses which is the original allocation and then reallocated to houses using Pareto allocation. In centralized algorithm the deviation is divided equally between the houses and all of the houses need to participate in peak reduction and hence the overall comfort is least among all the algorithms.

Case 2: Keeping community size constant (2000), we implemented four peak reduction algorithms for peak reduction varying from 0% to 100 % and plotted the comfort results which are shown in Figure 10. As percentage of peak reduction is increased from 0 to 100% in steps (5%) it is realized that the overall comfort of the community reduces with increased peak reduction. When we tried to order our algorithms based on community comfort it follows as; 1. Balancing responsible method 2. Pareto resource allocation 3. Round robin algorithm 4. Centralization algorithm.

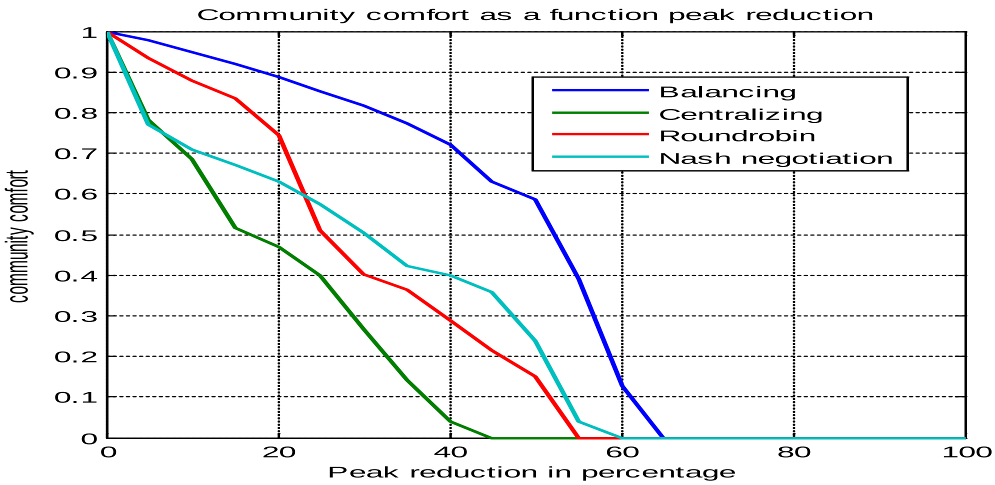

Figure 10. Analysis of Algorithms with Respect to Peak Reduction and Community Comfort

Case 3: Keeping the community size constant (2000) we implemented all the four peak reduction algorithms for various percentages of peak reduction and calculated the community involvement.

In order to analyze the performance of our algorithms we define a performance index called community involvement which is the ratio of number of houses participated in peak reduction and number of houses in the community.

From Figure 11 it is clearly understood that as the percentage of peak reduction increases for a given community size community comfort decreases with the corresponding increase in community involvement. These two parameters never conform to each other.

Peak reduction factor P= Community peak power/ max power fixed by user (which can go up to 1).

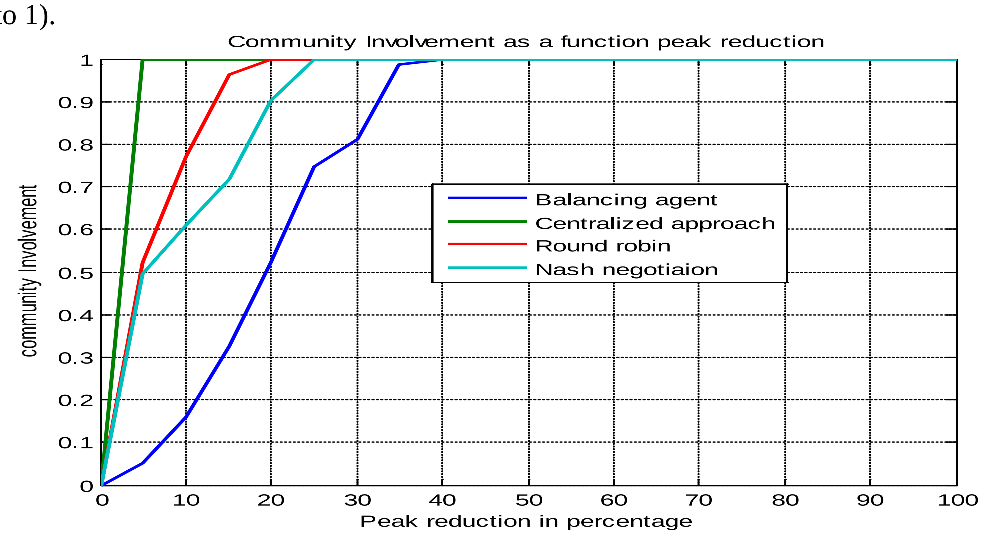

Figure 11. Comparison of Algorithms based on Community Involvement

If peak reduction factor P = 0.95 (5%peak reduction).
Community involvement is less but comfort will be more.

If peak reduction factor P = 0.3 Community involvement will be more but comfort will be reduced very much. So the larger Peak reduction factor is the lesser the peak reduction requirement is with better community comfort and less community involvement. Smaller P means more peak reduction requirement and involvement affecting community comfort.

12.1. Finding the Best Algorithm

In order to find the best of all our proposed algorithms we used performance indices such as community comfort and community involvement. In this we referred the ideal algorithm to be the one with 100% community comfort and 100 % community involvement and then we measured the distances of all proposed algorithms to this point and the algorithm with the minimum distance is selected as the best one. In our simulations when we compared our algorithms with respect to overall community comfort the order was found to be 1.Balancing responsible, 2.Round robin 3.Negotiaion and the last one was centralized approach. When we compared them with respect to overall community involvement, the algorithms were arranged as 1.Centralized approach 2. Round robin algorithm 3. Nash negotiation algorithm and 4. Balancing responsible agent which is shown in Figure 11.

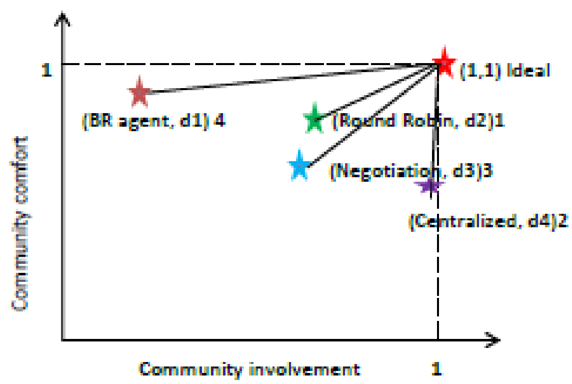

Figure 12. Finding the Best Algorithm Keeping the Ideal Point as the Reference

So in order to find the best one we considered community comfort and community involvement as the coordinates of the x-y plane and the algorithms associated with their comfort and involvement such as Balancing responsible agent algorithm(community involvement, community comfort) are located in the x-y plane as shown in Figure 12. We also have one more reference point ideal algorithm (1, 1) which yields maximum comfort and involvement. The distances d1, d2, d3, and d4 are the distances of each algorithm to the ideal one. In this we found that d2 is the minimum distance between ideal and the round robin algorithm and declared to be the best algorithm among others.

13. Conclusions

In this paper we propose different types of peak reduction algorithms for smart energy community. We implemented our algorithms for a community size of 2000 to achieve peak reduction in percentage and plotted the graphs showing actual consumption curve, peak reduced curve and the comfort model We summarized their advantages and limitations hence based on the type of community and the amount of power to be saved we could choose the desired one. Community comfort model is developed based on the significance of the appliances to the consumers with respect to priority and power reduction capability of the appliance. We compared our algorithms in terms of community comfort, amount of peak reduction and community involvement and finally able to decide the best among them. Our simulation results for different scenarios show that by having a proper size of the community and implementing one of the peak reduction algorithms we can save significant amount of peak power without the need to have additional infrastructure for the utility to meet peak demand and thus help saving the environment. Our future work will be focused on improving Nash negotiation algorithm so that it can be used as an effective algorithm for peak reduction by means of proper negotiation.

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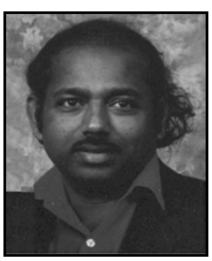

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