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Intelligent Agent-Based Architecture for Demand Side Management Considering Space Heating and Electric Vehicle Load

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Abstract

Contraction of resilience on generation side due to the introduction of inflexible renewable energy sources is demanding more elasticity on consumption side. It requires more intelligent systems to be implemented to maintain power balance in the grid and to fulfill the consumer needs. This paper is concerned about the energy balance management of the system using intelligent agent-based architecture. The idea is to limit the peak power of each individual household for different defined time regions of the day according to power production during those time regions. Monte Carlo Simulation (MCS) has been employed to study the behavior of a particular number of households for maintaining the power balance based on proposed technique to limit the peak power for each household and even individual load level. Flexibility of two major loads *i.e.* heating load (heat storage tank) and electric vehicle load (battery) allows us to shift the peaks on demand side proportionally with the generation in real time. Different parameters related to heating and Electric Vehicle (EV) load e.g. State of Charge (SOC), storage capacities, charging power, daily usage, peak demand hours have been studied and a technique is proposed to mitigate the imbalance of power intelligently.

Keywords

Demand Response (DR), Electric Vehicles (EVs), Heat Storage, Smart Grids

1. Introduction

Wide penetration of non-flexible intermittent renewable energy sources in the power grid is going to reduce the flexibility for power balance between generation and consumption of electrical power in real time. One way is to

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manage the power consumption according to the generation by shifting some of the flexible loads, *i.e.* Demand Side Management (DSM). Altering generation with the demand to keep frequency of the network in acceptable limit was the old concept of matching demands with supplies. Presently, there is a need to solve several problems simultaneously related to these intermittent renewable energy sources in the power grid and the penetration of more flexible loads in the network like EVs. In order to capture more EV penetration in the market we should first provide with their charging solutions in each scenario, *i.e.* for normal trips and long trips. Charging solutions for EVs on highways have been studied in detail in [1]. With the increased penetration of EVs in the market it would be wise to schedule their charging to support the grid in managing intermittent generation [2]. EVs have a very great potential in them since besides the environmental benefits [3] achieved from them, they are aimed to deliver more in context of optimized energy usage [4] and active participation in demand response [5]-[7]. Now with the advent of more intelligent systems and advanced communication technologies, it has encouraged researchers why not to control these flexible loads to optimize the energy usage. With this regard we suggest to introduce a domestic energy management system at consumer level based on intelligent agents. Three layers demand side management architecture is proposed in which the first layer agents are the EV agent, heating load agent, non-flexible load agent and domestic energy management agent. Second layer agents are the local market agents while the third layer agents are the distributed generation agents including forecast agents, environmental agents and source agents. Generation forecast agent estimates the generation for the upcoming time slots based on the installed capacity and the weather forecast (in case of PV or wind turbine units) and gives the information to local market agent. Local market agent then sets the pricing based on generation forecast and demand forecast from DEM agent. DEM agent then controls the flexible loads according to generation forecast and price of energy for particular time slot. Every agent has some degree of freedom, allowed by the environment and system which helps it to make decisions. Degree of freedom is a power to determine actions without restraints given to agents for making decisions on consumer's behalf. It is obvious that we don't expect the agent to make stupid decisions to sacrifice consumer's comfort but to be on the safer side in more advanced Multi-Agent Systems (MAS) degree of freedom could be adjusted in order to fix the risk factor. Risk factor increases with the increase in degree of freedom. This paper has been divided into different sections starting with nomenclature and introduction to idea; it follows the basics for multi-agent systems and demand response. A case study is then simulated using Monte Carlo simulations in Matlab.

2. Intelligent Agent and Multi-Agent System (MAS)

An agent can be a piece of hardware or software whose presence in a system makes the system more intelligent and autonomous [8]. Agents are intelligent and rational entities, *i.e.* they perform right things at right times [9] [10]. Generally, an agent-based system is composed of more than one agent and is called Multi-Agent System (MAS). In this way, the control is distributed among different agents in the same system. In MAS, each agent has its unique ID for communication between the agents. MAS is implemented to break a complex problem (which is supposed to be done by a single entity), into many simple tasks to be handled by many entities in order to achieve distributed processing [8]. An agent-based system is one in which the core entity used is an agent. Conventionally, Supervisory Control and Data Acquisition (SCADA) system have been used for the control and communication in power system [11]. Multi-Agent Systems (MAS) have many advantages over the SCADA system for the implementation of smart grid because of its distributed control nature. We will propose a model to control the loads at domestic level using intelligent agent-based system. Consider an example scenario of a colony of consumers where each household has intelligent agent-based energy management system installed in its premises containing, Heat Load (HL) agent, Electric Vehicle (EV) agent, Non-Flexible Load agent and Domestic Energy Management (DEM) agent. These agents are considered to be the first layer or component level agents whereas DEM agent is the second layer agent. Now we will proceed by explaining the functionality of these four agents:

- **Electric Vehicle (EV) Agent:** Its goal is to coordinate with DEM agent to store power from the source in low demand times or deliver power to the load in case of low generation times when the source is not able to provide the demanded power to the load. It keeps record of the daily vehicle usage for transportation and the time of use. EV agent could also help to provide DEM agent with the available capacity of EV to support the household for electricity use irrespective of use of EV as vehicle.
- **Heating Load (HL) Agent:** Optimized usage of energy for climate control is the ultimate goal of HL agent.

It controls the temperature of the environment in the house within acceptable pre-set limits and fetch energy continuously either to store it for peak demand hours or for real time consumption for heating depending upon available charging power. It coordinates with the DEM to inform about its flexibility to shift charging in accordance with its State of Charge (SOC) and weather forecast from forecast agent.

- **Non-Flexible Load Agent:** It gives information to DEM agent about the connected load which is most critical load in a particular household in real time. Degree of flexibility of various critical loads could also be estimated by this agent based on past knowledge and experiences of this agent.
- **Domestic Energy Management (DEM) Agent:** It is a second layer agent in Domestic Energy Management (DEM) system; all the three first layer agents communicate with DEM agent in order to inform it of their status, demands and needs. DEM agent performs the status check of three agents and collects information about their demand for the near future. For instance, EV agent provides with the available capacity and SOC, HL agent tells DEM agent about its capacity and stored energy which would be available and Non-flexible load agent based on connect load sends demand request. Now having all this required information from the sub-agents, game of making final decision comes to DEM agent, and after coordinating with the upper level local market agent for available peak power in during next time window DEM agent accepts or delays the charging power for EV and HL agent. DEM agent could also change the level of charging for both the flexible charging loads in order to meet the requirement of LM agent.
- **Local Market (LM) Agent:** It keeps all information regarding generation capacity of the source, expected generation in the near future, coordinates with the forecast agent to know about the weather condition and other related metrological data. It also communicates with the DEM agent on second layer to inform about the available power during the next time stamp. Figure 1 depicts the interaction of these agents to carry on the demand response. There are some terms which need to be addressed before we move further towards demand response using intelligent agents.

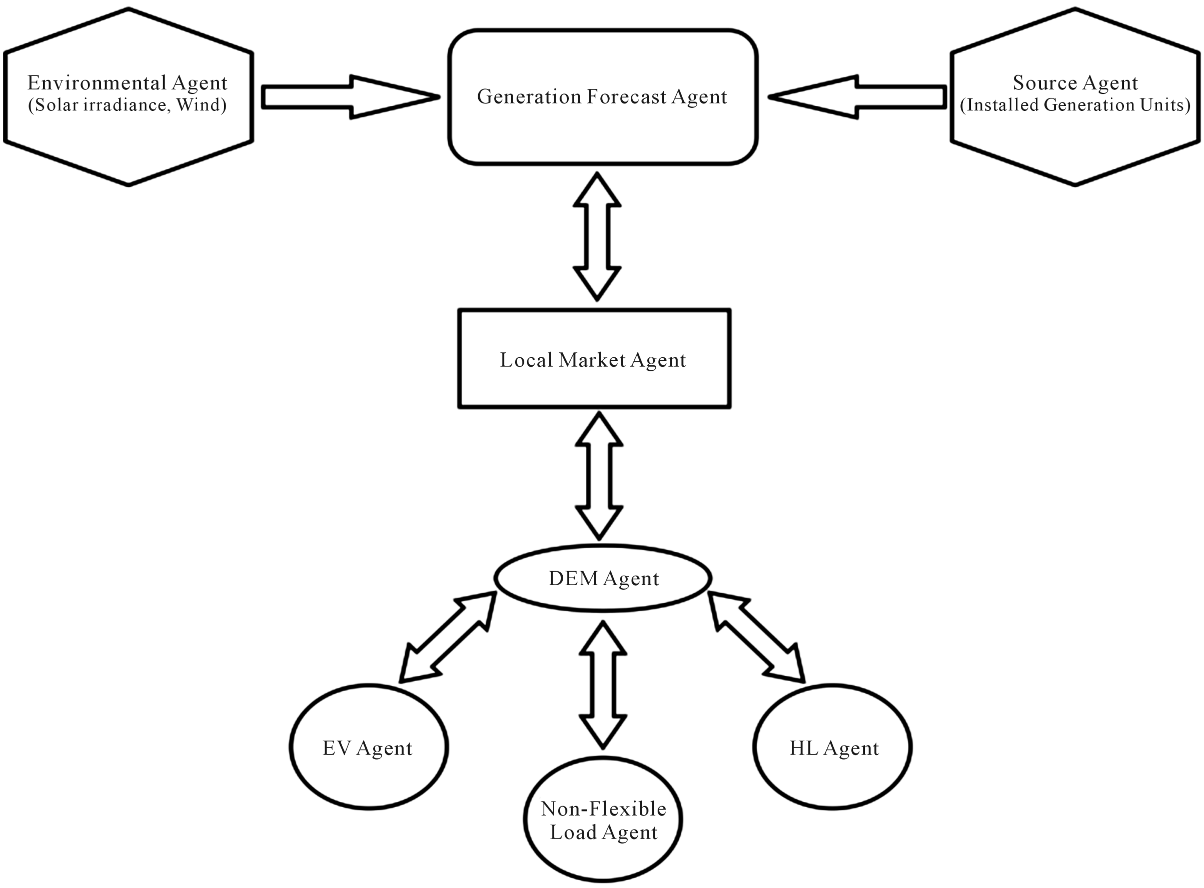

Figure 1. Coordination of agents to make a Domestic Energy Management System (DEMS).

2.1. Load Addressing or Tagging System

Loads even at appliances level could be controlled and shifted better by assigning them a proper addressing or tagging. Nomenclature for loads suggested is to be standardized in order to get more control on them. Loads at appliances level when tagged can help agent-based energy management system to adjust power balance in the entire system.

2.2. Prioritizing the Loads in Agent's Mind

Prioritizing the loads as important, critical or noncritical helps load agent to shift and switch loads accordingly. This thing not only has to do with the energy management system but also in case of emergency measures and abnormal conditions in the system, like faults or very low generation. After having a prioritized list of loads in mind, agents can better consider consumers comfort as well as economics of the electricity and can participate efficiently in the electricity market.

2.3. Supply Forecasting on the Basis of Environment Agent

Source agent is assisted by environment agent in order to estimate its generation in the near future. Environment agent forecast the weather conditions based on the metrological data, for example in case of solar panels, it informs source agent about the expected solar insolation and for wind turbine it estimates the speed of wind and other necessary parameters which help source agent to have an estimate of its generation for upcoming time slots.

3. Demand Response and Flexible Loads

According to [12] [13] Demand Response (DR) is defined as "changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at time of high wholesale market prices or when system reliability is jeopardized". Flexibility to alter the time of energy consumption for different is load important in demand response. In household there are two major loads that could help achieve demand response effectively *i.e.* heating load and electric vehicle load.

Heating Load: In order to maintain the climate control in the household continuous energy is needed either for cooling or heating the space. The heating load is flexible because we could have a temperature range to satisfy the comfort level and also with heat storage tank this flexibility could be extended. Time of charging for the heat storage tank could be shifted to achieve demand response.

EV Load: How much an EV in a particular household could support demand response depends on the capacity of the battery and the daily usage of EV as vehicle. Most of the time EVs are parked and this thing allow the flexibility to shift the charging time for different EVs depending upon the usage pattern of the EV. Flexibility to shift charging time is also dependent on the SOC of the battery.

4. Case Study

In this case study we have considered 100 households all of them having both EV and space heating load. We studied the behavior of limiting the peak power demand according to available generation. Monte Carlo Simulation has been employed to study different parameters involving demand response.

4.1. Monte Carlo Simulation (MCS)

Whole day has been divided into three Time Regions (TRs) *i.e.* TR-1 (from 17:00 to 22:00), TR-2 (from 22:00 to 07:00) and TR-3 (07:00 to 17:00). Each time region has been assigned a maximum peak power, in order to ensure consumption to be limited during each time region to a particular value. After fixing the peak power for the overall system now the allowed peak for individual households could be assigned equally to all households under consideration e.g. if the peak power for the system is 1 MW then it could 10 kW for individual households (in case of 100 households). This assumption was considered for the sake of simplicity in the simulation. In a real case allowed peak could be different for different households. Number of time regions could be increased to get higher resolution. Depending upon the generation forecast during each time slot peak power limits could be adjusted proportionally. In this case study our focus is on two flexible loads *i.e.* heating load and EV load. It has been considered that during Time Region-1 both the loads would be present along with other loads (lightning etc.) so less peak power is allowed to feed heating and EV load but during Time Region-2 other loads start to decrease the allowed peak power limit for heating and EV load could be increased. But during Time Region-3 there is no EV charging load but only heating of these two loads so the peak power limit could be reduced during this time. Important thing is that both heating and EV loads have the storage capacities which allow us to charge them or get back energy when needed. Flexibility of different charging rates could help in limiting peak powers according to generation. **Figure 2** illustrates the idea of limiting peak powers for different time regions.

4.2. Assumptions

There are some parameters and assumptions which have been considered for Monte Carlo simulations:

- Number of households taken into account are 100.
- Time window is 15 minutes, *i.e.* four slots per hour.
- SOC_{EV} may have any value from 5% to 95%.
- SOC_{HT} may have any value between 5% and 95% because heating system is continuously fetching energy.
- B_C could have any value between 20 kWh and 30 kWh.
- H_C could have any value from 20 kWh to 30 kWh.
- H_D the average heating demand per hour may vary from 1 kWh to 2 kWh.
- EV_{DU} daily usage of individual EVs may vary from 30 km/day to 50 km/day.
- Mileage of individual EVs may vary between 5 km/kWh and 6 km/kWh.
- Time Region-1 is from 17:00 to 22:00 which is the most peak load region on the distribution transformer.
- Time Region-2 is from 22:00 to 07:00 which could be the best charging region for EV and heat storage.
- Time Region-3 is from 07:00 to 17:00 which does not containing any EV charging load only heat storage load.
- $maxP_1$ is set to 2 kW, $maxP_2$ is set to 4 kW and $maxP_3$ is set to 3 kW (could be any value depends on generation forecast for upcoming time slot).
- Level of charging power for heat storage depends on SOC_{HT} and peak allowed power for particular time region.
- Level of charging power for EV depends on SOC_{EV} and peak allowed power for particular time region.

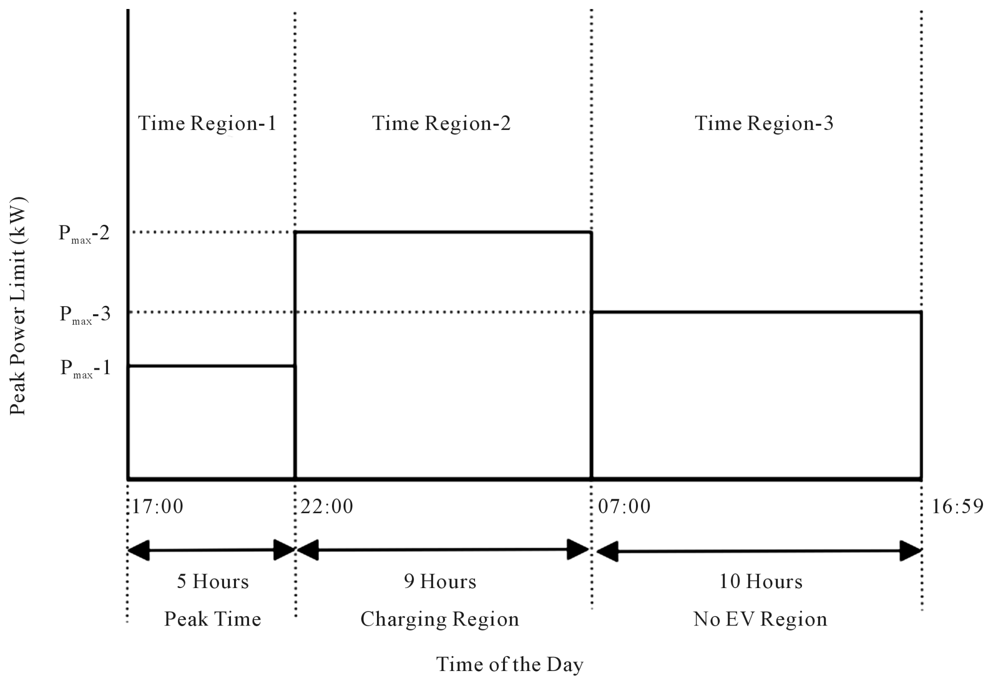

Figure 2. Division of the whole day into different regions to limit the power during each time region.

- Charging power decreases with the increase in state of charge.
- Priority is given to charging of heat storage during Time Region-1 and to charging of EV during Time Region-2.
- There is no EV charging load during Time Region-3.

Table 1 is a lookup table to select the charging power level for both EV and heating load with respect to the state of charge of both storages. The less is the state of charge the higher would be the charging power. Charging power decreases with the improvement in state of charge of storages (EV and heat storage).

4.3. Control Algorithm for Demand Response

Figure 3 shows the flow chart of the simulation model. For Monte Carlo simulation we have considered 100 households and assumed that each of the household under consideration has both EV and heating loads along with other loads.

Different parameters (SOC_{EV}, SOC_{HT}, B_C, H_C, H_D, EV_{DU} and M) for all households are fetched using pseudo-random numbers within predefined range using uniform distribution. Time window for the simulation is 15 minutes, meaning that it fixes the selected charge power for next 15 minutes. Time counter starts at 17:00 hours and increments after every 15 minutes until 24 hours have been completed. Peak power P_{max} is set based on generation forecast for next time slot. After fixing the peak power for the whole system of 100 households it assigns the peak power to each of the individual households for next time slot. Parameters value for the kth household are fetched and time region is also recognized from the time counter, then based on state of charge the charging power for EV and heating is selected from the lookup table. If the sum of both selected charging powers is within the assigned peak power then it starts charging otherwise it would select the next lower level of charging power of one of the loads from lookup table until it satisfies the peak power limit. After charging powers have been finalized for a particular time slot it updates the state of charge for both loads and then moves to the next household with the same procedure. At the end of each time slot it increments the time counter until one day has completed.

4.4. Simulation Results

Figure 4 shows the simulation result of the technique to limit the peak demand power according to generation. The result is obvious, at 17:00 when both charging loads are in the system, a fraction of available power is given to both charging loads while giving priority to heating load over the EV load during Time Region-1 until 22:00 hour. At the start of Time Region-2 we can see a sharp rise of power which is because of the increased allowed peak power during this time region and the priority of EV charging load over the heating load. It is clear that as the EV batteries are getting fully charged they are going out of the system by switching off their chargers as seen with the negative slop of power curve during Time Region-2. During Time Region-3 only heating load out of

Table 1. Lookup table to select the charging power for EV and heating load based on SOC.

Level	SOC_{EV}	Max. P_{CH_EV}	Energy per 15 minutes	SOC_{HT}	Max. P_{CH_HEAT}	Energy per 15 minutes
1	<20%	4 kW	1 kWh	<20%	4 kW	1 kWh
2	20% to 30%	3.5 kW	0.875 kWh	20% to 30%	3.5 kW	0.875 kWh
3	30% to 40%	3 kW	0.75 kWh	30% to 40%	3 kW	0.75 kWh
4	40% to 50%	2.5 kW	0.625 kWh	40% to 50%	2.5 kW	0.625 kWh
5	50% to 60%	2 kW	0.5 kWh	50% to 60%	2 kW	0.5 kWh
6	60% to 70%	1.5 kW	0.375 kWh	60% to 70%	1.5 kW	0.375 kWh
7	70% to 80%	1 kW	0.25 kWh	70% to 80%	1 kW	0.25 kWh
8	80% to 95%	0.5 kW	0.125 kWh	80% to 95%	0.5 kW	0.125 kWh
9	>95%	0 kW	0 kWh	>95%	0 kW	0 kWh

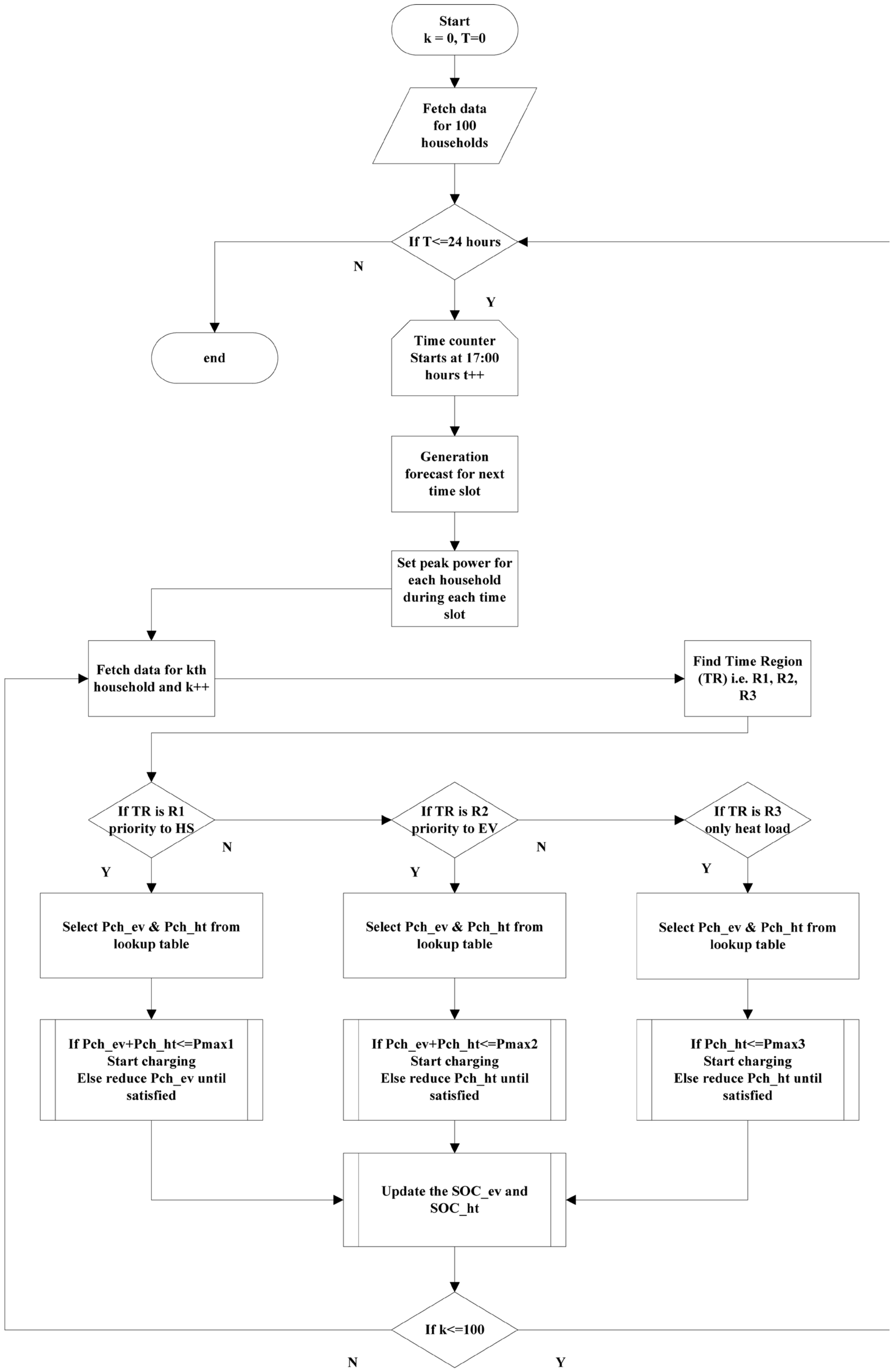

Figure 3. Algorithm for Demand Side Management (DSM).

these two loads (EV and heating) is present so it would try to charge the heat storage tank until 95% state of charge along with the constant power consumption for maintaining the temperature.

Figure 5 and Figure 6 clearly reveal the behavior of state of charge for EV and heating storage at two different times of the day. It is important to note that at 17:00 when EVs arrive back home the SOC is very low depending upon the individual usage of EVs but at 7:00 in the morning the batteries are almost fully energized and almost all of them have more than 80% of the charge of the full capacity of the battery. In case of heat storage the overall SOC for heat storage tank remains between 40% to 60% of the full capacity of heat storage tank on average, the reason for this is that heating SOC is more dynamic throughout the day. Heat storage needs continuous feeding of power to maintain the climate control and also to keep the SOC level for the heat storage tank in reasonable limits.

5. Conclusion

This paper discussed the demand response at domestic level utilizing the flexibility of EV charging and space

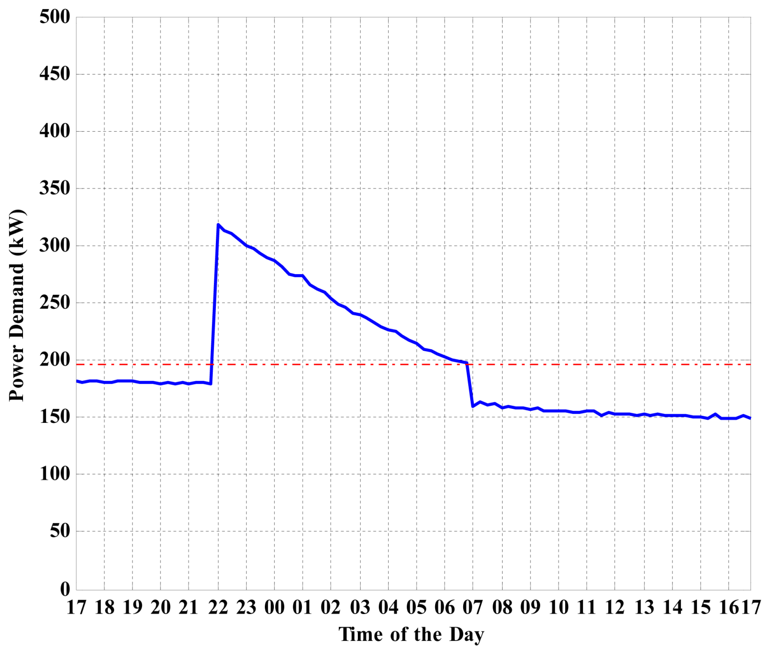

Figure 4. Example case scenario for demand response by the limiting the peak power and varying the charging rate for EV and heating load.

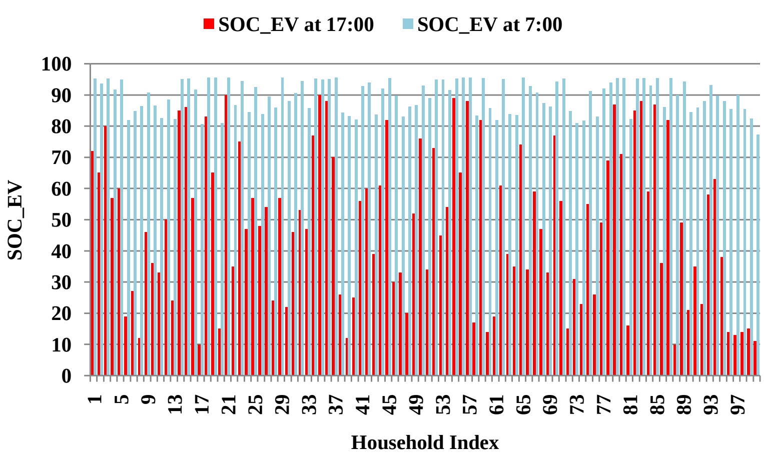

Figure 5. Behavior of SOC_EV at 17:00 and 7:00 hours for each household.

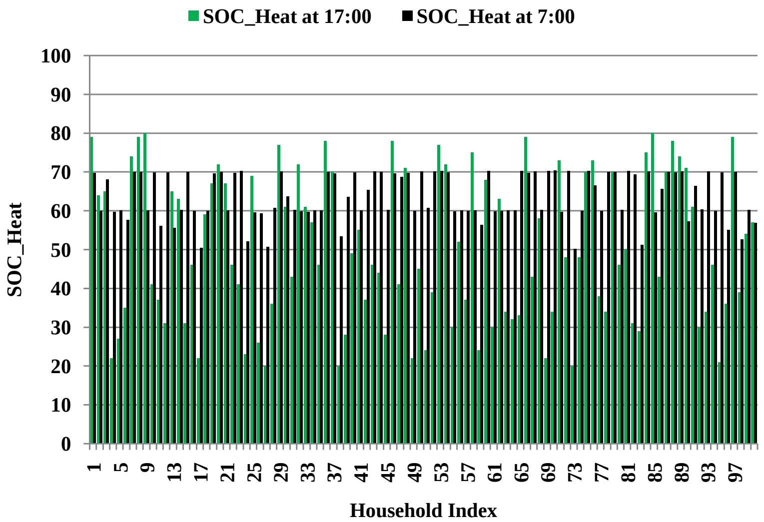

Figure 6. Behavior of SOC_Heat at 17:00 and 7:00 hours for each household.

heating load in context of intelligent agents. Agent-based three-layer demand response architecture was proposed. In example case scenario one day has been divided into three time regions assigning different power peaks and prioritizing the loads for each region. Based on real-time generation forecast we could have more defined time regions with shorter time slots with more realistic demand response behavior from both generation and consumption side. Allowed peak power for different households could be different for individual households depending upon the daily energy usage pattern of the household. Varying charging rate for both EV and heating load allows us to schedule not only the charging time but also the level of charging for both loads depending upon the available power in real time. Limiting the peak power for each time region ensures the generation to match with the consumption with optimized utilizing of energy without altering the generation side *i.e.* when the generation is high increasing the charging level of each of the flexible EV or heating load and vice versa.

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Nomenclature

MAS	Multi-Agent System
DR	Demand Response
DSM	Demand Side Management
DEMS	Domestic Energy Management System
HL	Heating Load
EV	Electric Vehicle
k	Number of Households in Consideration
SOC_{EV}	State of Charge of Electric Vehicle
SOC_{HT}	State of Charge of Heat Storage
B_C	Battery Capacity of Electric Vehicle (kWh)
H_C	Heat Storage Capacity of Heat Storage Tank (kWh)
H_D	Average Heat Demand (kWh per hour)
EV_{DU}	Electric Vehicle Daily Usage (km)
M	Mileage of EV (km/kWh)
P_{CH-EV}	Charging Power of EV
$P_{CH-HEAT}$	Charging Power for Heat Storage
TR_1	Time Region-1 of the day
TR_2	Time Region-2 of the day
TR_3	Time Region-3 of the day
$maxP_1$	Maximum allowed Peak Power during Time Region-1 for each household
$maxP_2$	Maximum allowed Peak Power during Time Region-2 for each household
$maxP_3$	Maximum allowed Peak Power during Time Region-3 for each household