Smart Demand Side Management of Low Voltage Distribution Networks using Multi–Objective Decision Making

Farhad Shahnia[1], Michael T. Wishart[2], Arindam Ghosh[3], Gerard Ledwich[3] and Firuz Zare[3]

[1] Centre for Smart Grid and Power Systems, Department of Electrical and Computer Engineering, Curtin University, Australia

[2] Ergon Energy, Australia

[3] School of Engineering Systems, Queensland University of Technology, Australia

Corresponding Author: f.shahnia@qut.edu.au

Abstract

A novel intelligent online demand side management system is proposed for peak load management in low voltage distribution networks. This method uses low cost controllers with low bandwidth two–way communication installed in costumers' premises and at distribution transformers to manage the peak load while maximizing customer satisfaction. A multi–objective decision making process is proposed to select the load(s) to be delayed or controlled. The efficacy of the proposed control system is verified by simulations of three different feeder types.

Keywords- Demand side management, Direct load control, Decision making, Peak load shaving

Introduction

Distribution networks must be designed to supply peak loads to ensure acceptable reliability, despite the fact that these peak loads typically occur for a small fraction of the year [1]. This means that the overall electricity infrastructure cost is largely determined by the peak load on the network. Consequently, there is strong motivation to minimize peak load growth throughout the electricity network. In many parts of the world peak load growth in residential areas is higher than the consumption growth. As an example, in Queensland Australia, electrical utilities Energex (supplying the high population density south–east) and Ergon Energy (supplying the remainder of Queensland) experience an average annual residential peak load growth of 10–13% compared with an annual residential consumption growth of 3% due to a number of factors including the proliferation of air–conditioning [2–3]. This has resulted in large annual capital expenditures on system upgrades. In the future the introduction of plug–in electric vehicles (PEVs) (which include plug–in hybrids and battery electric vehicles) is expected to further increase the peak load especially in residential areas [4–6]. This has the potential to significantly impact on the distribution network assets, especially on assets closer to the end user, where the load diversity decreases.

Much work has been historically done on demand management [7–12]. Schemes can generally be classified into either direct or indirect. Direct demand management schemes, often called Direct Load Control (DLC) systems, typically make use of a control signal from the utility to directly control loads. The water heater ripple control systems currently used in many parts of the world are an example of a traditional DLC system [13–14]. Other more recent schemes often propose using a real time price as the control signal to trigger automated action from home automation controllers [15–16]. Some pilot projects are also being conducted of individual house load management [17]. In addition, direct control methodologies for PEV charging have recently been proposed to minimize the impact of PEV charging [18–19]. Indirect demand management schemes use price as a control variable to influence consumers' behavior and thus indirectly control the load. For example, time of use tariffs typically increase the price of power during peak periods thus encouraging consumers to shift their consumption to off–peak [20–22].

In this paper, an intelligent direct demand management system is proposed for low voltage (LV) distribution networks. The main objective of the proposed method is to prevent overloading of distribution and upstream transformers at peak load periods. This method works based on instantaneous load levels and requires installation of smart controllers with local communications capability.

The load control choice during peak periods (i.e. which load to delay or control) is complex, depending on multiple different criteria such as customer priority, load operation satisfaction, overloading level and number of loads to be controlled. This paper proposes using a Multi–Objective Decision Making (MODM) method [23] to achieve the load control objective with minimal impact on customers.

In Section II, a brief description of modeling of different LV type loads is given along with the methodology of analysis. In Section III, the proposed control method is described along with the required hardware and control algorithm. The decision making process is presented in Section IV. The final section presents some simulation results of the network with and without the proposed control method. The effectiveness of the proposed method in controlling the peak demand while maintaining customer satisfaction can be seen from the results.

Network Modeling and Analysis

Fig. 1 shows the schematic of a typical radial distribution network in a suburban area. The network supplies several residential and small business loads. Three 11kV/400V 100kVA transformers supply residential feeders. Additional dedicated 100kVA transformer supplies a small business feeder.

The network assets are traditionally chosen for a certain peak load level based on standardized After Diversity Maximum Demand (ADMD) figures [1]. For example, Ergon Energy, the distribution utility in regional Queensland Australia, uses an ADMD of 5kVA per detached dwelling for suburban houses. This figure is based on historical peak load data (and obviously neglects PEVs). Transformer and conductor ratings are also calculated using these ADMD values along with the associated voltage drop.

In practice, the peak load value in residential and small business networks is season and area dependent but generally occurs in the evening (6–7pm). Uncontrolled Level I charging of PEVs (from a house outlet at 230V 10/15A) is expected to be added to this peak since it is thought that customers will generally plug in their vehicles for charging as they return back home.

If the traditional network design methodology is followed, penetration of PEVs will have significant implications on the network infrastructure cost.

A. Residential Type Load Modeling

To investigate these potential implications a detailed system model is required. The load models were built up in Matlab from individual device/appliance models which later were aggregated to form a house and then a residential feeder. Seventeen different appliance types were modeled. Each device was allocated a power rating and power factor as well as a time usage pattern. The time usage pattern of many appliances is linked to seasonal sunrise and sunset times as well as temperature. Therefore a simple "climate model" was constructed to vary the temperature throughout each day.

Each house was assigned a floor area according to a Gaussian distribution with mean $240m^2$ and standard deviation $20m^2$ corresponding to the Australian 2008 new house data [24]. The floor area is used in the calculation of many appliance loads below.

The power ratings of appliances were generally determined using mean values based on the ratings of common models in Australian market while usage patterns were typically derived from an informal assessment of typical behavior patterns. The detailed models of the main devices/appliances, including all parameters used in the study, are presented in Appendix A and are briefly discussed below:

1- Lighting

The total lighting load of each house was assigned according to a Gaussian distribution with the mean proportional to the house floor area. The morning and evening turn–on and turn–off times were based on informal observations as well as accounting for sunrise and sunset times (which vary seasonally).

2- Fridges and Freezers

The number of fridges in a house was related to the house size, with the probability of more than one fridge being proportional to the floor area. Similarly the probability of a separate freezer is proportional to the house size.

In reality, refrigerators and freezers operate at ON/OFF duty cycles determined by hysteresis temperature controllers. In this study, in order to limit the computational complexity, the thermal dynamic model is neglected and both fridges and freezers are modeled as loads operating at ambient temperature dependant duty cycles.

3- Cooking appliances

Stove–top cookers, conventional ovens and microwave ovens were modeled separately. Every house was assumed to have one stove top cooker and one oven, however a certain percentage of these are assumed to be gas powered. In addition, each house was assumed to have a microwave oven.

4- Air Conditioners (AC)

ACs can have a major impact on residential peak load, so they were modeled in some detail. In this study, a residential market penetration of 70% was assumed, split between traditional hysteresis ACs and inverter ACs as described in Appendix A. A small percentage of the inverter ACs was assumed to represent ducted air conditioning (air conditioning the entire dwelling).

All ACs are modeled as closed loop temperature controlled devices (either hysteresis or proportional), attempting to force internal house temperature to follow a set point. A second order dynamic thermal model of the house, taken from [25], was used and is explained briefly in Appendix D. The ACs only operate if the internal temperatures rise above preset thresholds.

5- Clothes washers, Dryers and Dishwashers

All houses were assumed to have clothes washers, with 30% assumed to have clothes dryers and 50% dishwashers. Clothes dryer operation was assumed dependent on weather (i.e. a rain parameter) and operated only once clothes washing were completed. All washers and dryers are modeled as constant power loads; the variation of power through different washing and/or drying cycles was not modeled.

6- Water heaters

Electric water heaters are still common in many parts of the world including in Australia, although certain plans are in place to phase them out over a number of years. In this study a market penetration of 85% was assumed. The thermal dynamics of the water heater are modeled and it is assumed that they are not operating under a pre–existing direct load control system.

7- Swimming pool pumps

Swimming pool pumps represent large loads that operate for long period of time (e.g. 1.5kW for 6– 8 hours per day). In this study a 50% penetration of swimming pool pumps was assumed. The pool pumps were assumed to operate each day with the total operation time varying from a mean of 6 hours in winter to a mean of 8 hours in summer.

8- Electric vehicles

Electric vehicles are widely thought to be a significant future load for residential power systems, especially when high clusters of PEV owners occur in a certain area. In this study a total of 15 EVs (25% penetration) were modeled with a mean battery capacity of 20kWh (corresponding to the average of the Chevy Volt and Nissan Leaf battery capacities) [26]. It was assumed that the vehicles travel an average of 50km per day and the batteries charge at a constant rate of 15A at 230V until either fully charged or the householder departs.

9- Televisions and Personal Computers

The number of Televisions (TVs) and Personal Computers (PCs) per household was assumed to be in relation the house floor area. The operational times are assumed to be a small amount in the morning and much larger durations in the afternoon and evening to model both adult and children occupants.

10- Stand–by power and miscellaneous appliances

A small random constant power was allocated to each house to account for stand–by power and miscellaneous continuously operating appliances (e.g. broadband modems). This amount was changed each day.

11- Period of no occupancy

During week days, there is a high probability that many of the houses will be unoccupied for significant periods of the day. During these unoccupied periods it is highly unlikely that ACs, lighting, cooking appliances, TVs and PCs will be operated (albeit that occasionally some people may leave some loads on). To simulate this effect 90% of the houses were allocated a stochastic "no occupant" period during each week day where operation of the aforementioned appliances was excluded.

B. Small Business Type Load Modeling

Several small office and shops were modeled on a small business feeder. This included Takeaways, Restaurants, Coffee shops, Drugstores, a Bookstore, a Grocery, a Fruit shop, a Florist, Clothes Shops, a Bank, Offices, Bars, a 24–hr shop, a Butcher, a Tailor, a Bakery and a Laundry. Their modeling is based on detailed modeling of the main appliances used within each shop/office. The models used are identical to the residential appliances, only with different parameters (rating, number and operation time) as given in Appendix B. Each device was allocated a power rating as well as a time usage pattern. The time usage pattern of many appliances is linked to shop/office working hours.

Having discussed the main appliances modeled, the next section describes the developed software program to simulate the LV network.

C. Analysis method

A Matlab–based simulation was developed to simulate the LV distribution network with an arbitrary number of houses/offices, each containing a number of the above mentioned electric appliances with different time usage patterns. Since most appliances turn ON, run for a certain time at constant power/impedance and then turn OFF, the simulation was made event–based. The simulation comprised a main routine plus a number of appliance modules which simulate the power characteristics of all appliances of that type. In addition, a calculation is made of the timing of next switching event of that appliance type, and that appliance module is run at that time. The active and reactive power consumptions (or load impedances) are maintained constant between switching events. The simulation also has a fixed time step clock which generates regular events at a user defined interval (typically 5 minutes). All continuous models (such as the "climate model" and inverter AC) are run at this fixed time step. Note that at each event, only the appliance module which contains the next switching device is run since the power of other appliances is not changed at that time instant. This makes the simulation computationally efficient. The flowchart of the program is shown in Fig. 2(a).

Note that the simulation does not include a detailed network model nor load flow. Network and transformer loads are calculated based on the algebraic sum of active and reactive load power consumption and losses are neglected. A more accurate network model could possibly be considered, however this would come at a considerable computational expense.

Proposed Control Scheme

The main requirements of the proposed controller are:

- Effectiveness: the control system should limit peak load while assuring customer satisfaction.
- Low cost: the system should utilize low cost hardware.
- Scalable: the system should be easily scalable to larger networks.
- Robustness: the system should be fault tolerant.

Consider the distribution network depicted in Fig. 1 where a 33/11 kV substation is feeding several 11 kV/400 V distribution transformers. The main objective of the control system is to ensure that all the transformers and conductors do not exceed their ratings while minimizing the negative impact on consumers. If a transformer loading is below its rating, no control action is taken.

It is proposed that a micro–processor based intelligent controller is installed in each house/shop, called end–user controller, to measure and control loads and communicate with the controllers located at the transformers. All controllers have low–bandwidth two–way communication capability. The end–user controllers measure the power consumption of each device in the house/shop and send that information to the relevant transformer controller every 2 minutes. The schematic diagram of the proposed control system is shown in Fig. 1.

When the transformer controller detects an overload in a transformer, it decides which load(s) should be controlled and sends a command to the end–user controller in the related house/shop to delay/adjust that load. The load selection procedure is discussed in the following section. After the selected load is delayed or adjusted, the end–user controller sends back a confirmation command to the transformer controller. Upon receiving this, the transformer controller re–measures the total load. If the load is now below the threshold, no further action is taken. If the loading still exceeds the threshold, the transformer controller will again choose another load to be delayed or adjusted. This process continues until all controllable loads are delayed or reduced.

The specific control action depends on the load type. Most loads (e.g. Pool pumps, washers/dryers, water heaters and electric vehicle chargers) are delayed by 15 minutes and then reconnected, while the set point of locally controlled loads (such as inverter ACs, water heaters) are adjusted for 15 minutes and then reset.

Several incentive methods can be used to encourage the householder or business to participate in this control scheme. While not the focus of this paper, this could be as simple as free installation of controllers along with rebates or discounts on monthly energy bills.

In this paper, the control signals are generated as soon as the load reaches the steady state transformer rating. However, this rating limit can also be made dynamic based on a transformer thermal model which considers the transformer rating, the overload magnitude and period, and the ambient temperature [27]. This would generally allow a greater load before limiting, while still maintaining the transformer overload protection.

Multi–Objective Decision Making (MODM) Process

Multi–objective decision making (MODM) is a methodology for selecting the best action (or decision) from a large number of alternatives given multiple (often competing) objectives. A decision matrix is used to weight different alternatives and derive the resulting action. The interested reader is referred to reference [23] for a survey of different MODM techniques.

When the controller of a distribution transformer determines that the total load of that transformer exceeds its rating (i.e. the transformer is overloaded), the controller will decide which load(s) on that transformer should be delayed or controlled.

In this study, eight controllable loads are considered as alternatives for delay or control by the distribution transformer controller. In residential feeders, swimming pool pumps, PEV, electric water heaters, dish washers, clothes washers, dryers and ACs (both hysteresis type and inverter type) are assumed as controllable devices. In business feeders, only ACs are assumed as controllable devices. The inverter type ACs and water heaters can be adjusted by changing their temperature set point while the delay type of control (ON/OFF) will be applied to other alternatives.

The hardware required to implement this system will form part of a future study. However, it should be noted that the required hardware is relatively low cost since the processing requirement and communication bandwidth are low.

The decision making process consists of the following stages:

A. Defining Criteria and Weighting

A multi–objective decision making process is utilized in the control system. In this way, it is possible to consider the effect of several criteria, each with a different weighting value on prioritizing the loads to be delayed or adjusted. The criteria which have effect on prioritizing the loads are:

1– User Priority

Customers may set the general priority of load delay or adjustment i.e. the order in which their appliances are delayed or controlled during peak load periods. The user priority is converted to a numerical value in range of [0 1] for their eight controllable devices, where 1 and 0 show the highest and lowest priority for delay/control, respectively.

2– Flexibility

Inherent characteristics of different load types result in different flexibilities for disconnection and reconnection of appliances. For example, a swimming pool pump can work any time of the day if it satisfies its desired total hours of operation per day. Therefore, it has a high flexibility. Clothes/ dish washers have a lower flexibility. This is due to this fact that if they are disconnected while working, the heated water inside will cool down; needing to be warmed up again next time it starts. Water heaters and ACs are considered to have a high flexibility (subject to their satisfaction criterion discussed next).

3– Satisfaction

A satisfaction index is defined to represent how close a device/appliance is to its optimum state of operation. The index is dynamic, being updated every 5 minutes. This index is calculated differently for the appliances as follows and is shown schematically in Fig. 3.

- AC satisfaction index depends on how close the room temperature is to its set point.
- PEV satisfaction depends linearly on battery state of charge.
- Clothes washer, dryer and dishwasher satisfaction depends on the ratio of remaining operational time and available time. Available time is based on constraints set by the user i.e. washing/drying must be finished by a certain time.

- Swimming pool satisfaction depends on total operational time in the last 24 hours compared with set time.

4– Power similarity

It is more desirable for the transformer controller to delay a load which closely matches the required power decrease than one which is highly dissimilar. Therefore, the controller calculates a dynamic power similarity criterion for each load at each decision making step. All loads are normalized in range of [0 1] where 1 shows the power consumption of a specific load is very close to the required power reduction.

5– High power consumption

Assuming all customers are on the same tariff, it is desirable for the controller to first control an appliance from the house/shop with higher total electric power consumption rather than with lower total power, since the houses/shops with the highest consumptions are the biggest contributors to the overload. Therefore, at each decision making step, a numerical value in range [0 1] is allocated for all controllable devices in each house/shop expressing the ratio of total power of the house/shop compared to other houses/shops, where 1 and 0 show the house/shop with highest and lowest total power consumption at that moment, respectively.

Each of the above mentioned criteria have a different weighting. These weightings (in range [0 1]) are defined based on which criterion is more important than others when selecting a load to be delayed or adjusted.

Note that the MODM approach is ideally suited for the inclusion of time varying wholesale energy market costs of primary interest to energy retailers. Thus if purchased wholesale power cost is added to the decision making process, energy retailers can use this scheme to shift some of the network load to periods with lower energy cost. The authors intend to add this cost as part of future research; however this paper focuses on reducing or delaying network augmentation cost by reducing peak load. This will hence result in reducing the network component of electricity bills, thus creating downward pressure on electricity prices and indirectly economically benefiting the customers. This economic benefit mechanism to customers can be as simple as a lower tariff if they accept this load control scheme. Alternatively, for example if there was a time of use (TOU) tariff, reducing customers load during peak times would result in lower bills.

In addition, the algorithm could in concept be extended to consider loss minimization as a further objective considering that feeder loss can typically vary from 3% during off–peak hours to even 20% during peak periods. This would of course require network loss calculations, not presently considered in the simulation.

Note also that this algorithm can be modified to support ancillary services in the network, as well as Distributed Energy Resources (DER), which will be a part of future research.

It is to be noted that the maximum load allowable for each customer or order of load control can also depend on some payment mechanism. If such a tariff adjustment is available in the network, it will be easy to be applied to the proposed MODM method by adjusting new weighting values for the criteria.

B. Defining Decision Making Matrix

For prioritizing the loads to be controlled, a decision making matrix is calculated. For this purpose, a numerical value in range [0 1] is allocated for all alternatives (each controllable device in the network) based on the different criteria. All these data are set in a matrix as shown in Table 1.

In this table, B_j ($1 \leq j \leq 5$) represents the weighting values for j^{th} criterion. This weighting represents the importance of each criterion for load control in comparison with the other criteria.

In Table 1, $H(i,j)$ (where $0 \leq H(i,j) \leq 1$) is the rank of i^{th} alternative among other alternatives in the same house/office from the j^{th} criterion point of view. Therefore, for i^{th} house/office and a specific j^{th} criterion, $H(i,j)$ is calculated. Then values of $H(i,j)$ are calculated for other criteria in that house/office. Similarly, $H(i,j)$ is calculated for all controllable devices in the other house/offices. Finally D_i, the control priority value for i^{th} criterion, is calculated independently for each alternative in the network as

$$D_i = \sum_{j=1}^{5} H(i,j) \times B_j \tag{1}$$

The alternative in the network with highest D_i will be chosen as the first alternative for control (delay/adjustment).

The flowchart of the proposed control scheme including MODM process is shown in Fig. 2(b). This flowchart is used for each transformer within the network individually.

Simulation Results

For verifying the efficacy of the proposed control, several cases were studied of which a few sample results are given below. It is assumed the network consists of a 400kVA 33/11 kV transformer feeding 3 residential feeders and 1 business feeder. Each residential feeder is fed through a 100 kVA 11kV/400V pole–mounted transformer and supplies 20 houses (i.e. designed with an ADMD of 5kVA per house). One similar transformer is used to feed separately a business feeder. There are 24 different types of small business/shop/offices assumed on the business feeder. The load parameters of the residential and business feeders are given in the Appendix. The simulation also included a total of 15 PEVs (25% penetration level) which are plugged–in as the owners return to their houses. The simulation was conducted over a 48–hr week–day summer period (max ambient temperature of 35˚C at 2pm).

The assumed weighting of the MODM criteria in this study is as shown in Table 2. In addition, the flexibilities assumed for each controllable device in this study are listed in Table 3. Note that, these values are used just as an assumption and can be changed depending on stakeholder feedback. In Table 3, each device is given a number of 1–8 which represents that device in the simulation results figures. Note that the final device selection in each house is dependent on the priority (randomly generated), flexibility and criteria weightings.

Fig. 4(a) shows the total aggregated apparent power supplied by a 100 kVA residential feeder transformer in the presence of PEVs. Since the specific load shape will vary somewhat stochastically from day to day and from area to area, no attempt was made to quantitatively match the resulting load shape to a measured one. However the load shape roughly matches measured profiles in Ergon Energy as well as published profiles [12] which provide confidence in the bottom up modeling approach. As seen from this figure, although the average apparent power supplied by the transformer is around 60 kVA per day, it reaches a peak of 150 kVA. The transformer is overloaded by 50% for a 2–hr period per day.

The total apparent power of the upstream 400 kVA transformer without the controller is shown in Fig. 4(b). As seen in this figure, the transformer has a peak value of 550 kVA and overloaded for about 5 hrs during the second day.

Let us now assume that the proposed control system is applied to the network. The total aggregated apparent power supplied by the residential distribution transformer is shown in Fig. 4(c). As seen in this figure, the peak load power is limited to 100 kVA hence verifying the efficacy of the proposed control system in controlling load. The total aggregated apparent power supplied by the upstream transformer is shown in Fig. 4(d). As seen from this figure, the peak load power is now limited to 400 kVA and this verifies the efficacy of the proposed control system in controlling loads. Comparing Figs. 4(b) and 4(d), a load increase is seen after the control operation period which is the result of the delay/adjustment of specific loads by the controller.

As seen in Figs. 4(c) and 4(d), the load varies "instantaneously" around the transformer rating. This is due to the fact that the control action occurs in 2–min time intervals whereas load changes can occur at any time. Therefore, after a control action at t_1, some load might increase (or turn on) during the 2 min time interval which will cause the load to exceed the rating of the transformer until the control action at t_1+2 min.

For investigating the effect of the proposed control method on the upstream network another case study is carried out. In this study the network in Fig. 1 is simulated assuming the 33/11 kV substation supplies 20 transformers each with 100 kVA nominal rating. Fig. 4(e) shows the total apparent power of the substation in 48–hr period. As it can be seen from this figure, in the uncontrolled case, the substation transformers experience an overload around 30% for a period of 3–hours. However, if the proposed control method is applied for all the residential loads which are supplied by each distribution transformer, the peak load is limited to 2 MVA as shown in this figure. This demonstrates the potential for savings in the upstream network electrical infrastructure. The slight difference in the load profiles following the peak is a result of some peak loads being transferred to off peak periods.

It is important for the control scheme to have a minimal impact on consumers. To verify this, sample operation states of PEVs and swimming pools as (delayed) controllable loads are given below. Fig. 5(a) shows the ramp waveforms indication the battery charging state of a few PEVs of the network. It is to be noted that each color line in this figure represents the charging status of a sample PEV within the network. The increasing section shows that they are being charged from an arbitrary initial value to full (100%) before their departure time. This value is reset to an arbitrary value at 12 pm everyday and they start being charged at an arbitrary time in the evening when the cars return back home. The flat sections of the traces show that they are disconnected by the controller at some stages and again reconnected, nevertheless all vehicles complete charging. This figure verifies that even though the controller has delayed the charging for some of them, they have all been fully charged before departure time.

Fig. 5(b) shows the swimming pool pump remaining operation time for a few houses in the network, which is reset every day. It is to be noted that each color line in this figure represents a sample swimming pool within the network. As seen in this figure, each swimming pool has a randomized required operational time per day (around 7–9 hrs) and they have all completed operation (i.e. they fall to zero) within each 24 hour period. All other controllable devices have the same operational characteristic.

Inverter type ACs and water heaters are large loads in the network and have adjustable characteristics based on changing the set points of room temperature and tank water temperature.

Based on assumption in this study, inverter ACs will operate when the internal house/shop temperature exceeds its set point providing it is occupied. If an inverter AC is selected, the transformer controller will increase the temperature set point by 1ºC. Fifteen minutes later this set point will be reset to its original value, thus preventing set point divergence from the householders desired level. In Fig. 5(c), the AC inverter set point increase and reset is shown for three sample houses. The set point increase results in less electric power consumption by the AC as shown in this figure.

However, this set point change should not appreciably worsen the customer satisfaction. This is investigated in Fig. 6. In Fig. 6(a), the ambient and internal temperature in 48–hr period is shown. As it can be seen the internal temperature is kept around 25 ºC (set point). In Fig. 6(b), the electric power consumption of the AC is shown. It can be seen that when the internal temperature rises beyond the set point limit, the AC turns on and turns off when the internal temperature is reduced to the set point. In Fig. 6(c) the AC satisfaction is shown. When the people are away, the AC is off so “satisfaction” is decreased but when the people are at home, it is kept close to 100%. In Fig. 6(d), the set point and its variation based on the controller command is shown. It can be seen that around 43:00 hr, there are several commands for set point increase.

The same behavior is evident for other ACs and water heaters in the network.

It is of interest to study the number of control commands applied by the transformers' controller. In Fig. 7(a), the number of control commands applied to each controllable device is shown for 4 sample houses in a residential feeder. The controllable device number was given in Table 3. From this figure, it can be seen that the number of control commands differs from house to house based on the status of any controllable device running in each house, as well as their objectives (power, satisfaction, priority and flexibility).

In Fig. 7(b), the total number of the low level control commands applied for each customer in each feeder individually and for each type of controllable device in that feeder is shown. It can be seen that the number of commands for load control differs from a house to house. It is also shown that inverter type ACs experience the highest number of control actions.

Conclusion

A novel intelligent direct demand side management system has been proposed for peak load reduction in LV distribution networks. The system utilizes low cost controllers with two–way communications capability, installed in each house/office and at the supply transformers, to monitor and control the loads. A multi–objective decision making process has been proposed to select which load(s) to be delayed or reduced. The algorithm uses several criteria, each with different weightings to reduce the load while minimizing the impact on consumers. An event–based simulation was developed in Matlab and results were presented to show the capability of the system to control overloads while maintaining the required load objectives.

Appendix

A. Residential Load Data

Residential load modeling data was taken from references [28–32] and from manufacturers' websites. Extensive use was made of the Gaussian or Normal distribution to generate appliance power data and usage times. Specifically N(μ,σ) denotes the Normal (or Gaussian) random function generating a value according to a Normal distribution with mean μ and standard deviation σ. Note that the decision to use Normal distributions was largely intuitive based on the central limit theorem [28–32] although [29] presents a good case for using the Beta distribution for some loads.

1- Lighting

The total lighting load of each house was determined by:

$$P_{li,i} = \frac{A_i}{240} \cdot \mathrm{N}(322,20) \tag{2}$$

where $P_{li,i}$ is the lighting load in kW of house i and A_i is the floor area of house i in m^2. The power factor is assumed to be unity. The mean morning and night lighting loads were calculated as 50% and 80% of the total lighting load. The turn–on and turn–off times were determined as follows:

Table 4. Lighting Load Turn–on and Turn–off Times

	TURN–ON TIME T_{ON}	TURN–OFF TIME T_{OFF}
AM	N(06:00,1:00) or no turn–on if $T_{SUNRISE}>T_{ON}$	Earliest of T_{ON} + N(02:00,0:20) or $T_{SUNRISE}$
PM	Latest of N(18:00,0:30) or T_{SUNSET}	N(23:00,01:00)

2- Fridges and Freezers

Each house was assumed to have at least one fridge. The probability of second fridge was related to house floor area as:

$$\begin{aligned} &P(fr2,i) = \min(0.1 + (A_i - 240)/240, 1) \\ &N_{fr,i} = 1 + (\mathrm{rand} < P(fr2,i)) \end{aligned} \tag{3}$$

where *min(.)* is the minimum function, *rand* is a uniformly distributed random variable and *rand*<P(*fr2*,i) = 1 if true or 0 if false. The fridge period and duty cycle were

$$Per_{fr,i} = N(0{:}50,0{:}05)$$
$$D_{fr,i} = N(0.18,0.02).T_{amb}/298 \quad (4)$$

where $Per_{fr,i}$ is the period in minutes, $D_{fr,i}$ is the duty cycle and T_{amb} is the ambient temperature in Kelvin. The turn–on time of the fridge within the period was assumed to be random.

The probability of each house having a separate freezer was similarly related to the floor area. In addition, the freezers duty cycle and period were similarly modeled except the mean period was 60min and the mean duty cycle 0.16.

The power ratings of the fridges and freezers (in kW) were determined by

$$P_{fr,i} = N(0.47,0.04)$$
$$P_{fz,i} = N(0.4,0.04) \quad (5)$$

The power factor was assumed to be 0.85.

3- Cooking Appliances

The probability of any house having an electrical stove top cooker and oven was taken as 70% and 90% respectively (assuming 30% and 10% gas stove top and oven market penetrations respectively). Each house was assumed to have a microwave oven. The table below shows the calculation of the power ratings and times of use.

Table 5. Cooking Appliance Power Ratings and Times of Use

	STOVETOP COOKER	CONVENTIONAL OVEN	MICROWAVE OVEN
POWER RATING	N(3.0,0.3)	N(2.4,0.2)	N(1.4,0.14)
T_{ON}(AM)	N(07:00,0:30)	N(07:00,0:30)) Probability = 0.1	N(07:00,0:30)
T_{OFF}(AM)	T_{ON}(AM) + N(0:30,0:03)	T_{ON}(AM) + N(0:30,0:03)	T_{ON}(AM) + N(0:05,0:015)
T_{ON}(PM)	N(18:30,0:30)	N(18:30,0:30)	N(18:30,1:00)
T_{OFF}(PM)	T_{ON}(PM) + N(01:00,0:15)	T_{ON}(PM) + N(0:45,0:10)	T_{ON}(AM) + N(0:15,0:02)

4- ACs

For the 60 house study presented, a total of 42 houses (70%) were assumed to be using AC during the hottest part of the day. The assumed split between different types of AC is presented in the table below. Temperatures T_0, T_{100} are expressed in Kelvin.

Table 6. AC Parameters

	HYSTERESIS AC	INVERTER AC	DUCTED AC
NO OF HOUSES	Total 9 houses: – 6 in a single room – 3 in 2 rooms	Total 30 houses: – 18 in a single room – 12 in 2 rooms	Total 3 house

RATING	N(2.0,0.2) per room	N(2.3,0.2) per room	N(5.2,0.2)
CYCLE	N(0:30,0:05)	N/A	N/A

5- Clothes washers, Dryers and Dishwashers

Parameters for washers and dryers were as follows.

Table 7. Washer Operating Parameters

	CLOTHES WASHER	CLOTHES DRYER	DISH WASHER
RATING	N(1.0,0.1)	N(2.8,0.3)	N(2.0,0.2)
T_{ON}	N(8:30,0:30) or N(20:00,0:30)	Clothes washer T_{OFF} + N(0:15,0:01)	N(07:30,0:30) or N(20:30,1:00)
T_{OFF}	T_{ON} + N(01:00,0:10)	T_{ON} + N(01:00,0:10)	T_{ON} + N(01:00,0:02)

6- Electric Water Heaters

Electric water heaters were modeled as dependent on ambient temperature and water consumption rate. The following parameters were used in the study.

Table 8. Electric Water Heater Parameters

POWER RATING	N(3.6,0.3)
SLOPE OF TEMPERATURE DEPENDENCY	N(–0.0125,0.001)

7- Swimming Pool Pumps

Swimming pool pumps were assumed to operate for a total mean daily period of 8 hours (during summer). The operation was assumed to be split into two equal periods of operation occurring randomly during the day. The parameters used are listed in Table 9 below.

Table 9. Swimming Pool Parameters

POWER RATING	N(1.5,0.1)
T_{ON}(AM) T_{ON}(PM)	12:00×rand 12:00 + 12:00×rand
T_{OFF}	T_{ON} + N(8–2×sin(2π×d/730),0.8)

where *d* is the number of days into the year.

8- Plug–in Electric Vehicles (PEVs)

For uncontrolled charging, the PEVs were assumed to start charging at a constant rate from when the customer arrives home until the battery is fully charged or the customer departs (whichever occurs first). An average travel distance of 50km per day was assumed with an economy of 20kWh per 100km [33] and an average charge/discharge efficiency of 85%. Parameters used were as follows.

Table 10. PEV Parameters

CHARGING POWER RATING	230V,15A, unity power factor = 3.45kW
DAILY REQUIRED CHARGE	N(11.8kWh,2kWh)
$T_{ARRIVAL}$	N(17:00,1:00)
$T_{DEPARTURE}$	N(07:30:0:30)

9- Television and Personal Computers

The following parameters were used in this study.

Table 11. Consumer Electronics Parameters

	TVS	PCS
NO. DEVICES PER HOUSE	round(N(1.5,0.3)×A_i/240)	ceil(N(1.5,0.3) ×A_i/240)
POWER RATING PER DEVICE	N(0.18,0.02)	N(0.26,0.02)
T_{ON}(AM)	N(07:00,0:30) Probability = 0.5	N(07:00,0:30) Probability = 0.5
T_{OFF}(AM)	T_{ON}(AM) + N(0:30,0:03)	T_{ON}(AM) + N(0:30,0:03)
T_{ON}(PM)	N(16:00,2:00)	N(16:00,2:00)
T_{OFF}(PM)	T_{ON}(PM) + N(2:00,0:30)	T_{ON}(AM) + N(2:30,0:30)

where *round* is a function rounding to the nearest integer and *ceil* is a function rounding up to the next highest integer.

B. Small Business Data

Shops/offices load modeling data was made based on assumptions of their working hours and different kind of electric devices used. Similar to residential loads, Gaussian or Normal distributions are used to model their working hours, electric devices ratings and number. The businesses assumed in this study with their working hours are listed in Table 12. The floor area of the Restaurants and Bars are assumed to be around 1000 m^2 while for all others it is assumed around 250 m^2.Their lighting was calculated similar to (2) based on their floor area during working hours. All shops/offices are assumed to have an AC and PC. A loss factor of 10% is applied for the AC operation for considering shops doors opening and closing. The electric power consumption of most of the devices (including ACs, and lighting) was based on working hours for each business. However, the ACs for Drug store, Grocery store, Fruit shop, Florist and 24–hr shop are assumed to be operating 24 hours. The cooking devices in Restaurants, Take–away and Bakery are assumed to be working on Gas (non–electric). The main electric appliances for each business after lighting and ACs are listed in Table 12. The power rating of these devices for each business is given in Table 13.

Table 12. Business Loads, their Working Hours and Main Electric Devices

TYPE AND NO.	WORKING HOURS	MAIN DEVICES AND NO
Restaurant (3)	N(10,0.5) to N(22,0.5)	Freezer, Fridge, Dish washer, TV
Coffee shop (2)	N(7,0.5) to N(18,0.5)	Freezer, Dish washer
Take–away (1)	N(10,0.5) to N(23,0.5)	Freezer, Fridge, Dish washer
Drugstore (1)	N(9,0.5) to N(17,0.5)	
Bookstore (1)	N(9,0.5) to N(17,0.5)	
Grocery store (1)	N(9,0.5) to N(17,0.5)	Freezer, Fridge (2)
Fruit shop (1)	N(9,0.5) to N(17,0.5)	Fridge (2)
Florist (1)	N(9,0.5) to N(17,0.5)	
Clothes shop(3)	N(9,0.5) to N(17,0.5)	
Offices (3)	N(9,0.5) to N(17,0.5)	PC (4), Printer
Bars (2)	N(18,0.5) PM to N(02,0.5) AM	Fridge (3), TV (2), Dish washer
24–7 shop (1)	24 hours	Fridge (3), Freezer
Butcher (1)	N(9,0.5) to N(17,0.5)	Fridge (3), Freezer
Tailor (1)	N(9,0.5) to N(17,0.5)	
Bakery (1)	N(9,0.5) to N(17,0.5)	Dish washer
Laundry (1)	N(9,0.5) to N(17,0.5)	Clothes washer, Dryer

Table 13. Power Rating of Main Electric Devices for Shops/Offices

TYPE	BUSINESS	RATING
Freezer	Restaurant, Take–away, Grocery store, Butcher, 24–hr shop	N(0.8,0.04)
Fridge	Restaurant, Coffee shop, Takeaway	N(0.47,0.04)
	Grocery store, Fruit store	N(0.94,0.04)
	Butcher, Bar, 24–7 shop	N(2.82,0.04)
Dish washer	Restaurant, Coffee shop, Takeaway, Bar	N(5,0.1)
TV	Restaurant, Bar	N(1,0.1)

PC–Printer	All	N(1,0.1)
AC	Restaurant, Bar	N(4.6,0.1)
	Other shops	N(9.2,0.1)
Clothes washer	Laundry	N (10,0.1)
Dryer	Laundry	N(14,0.3)

C. Indoor Thermal Modeling

The second order dynamic thermal model of a house was presented in [25]. This model takes into account the effect of AC output power, sun radiation, ambient temperature, door and window size, and floor area of the house. All ACs were modeled as closed loop temperature controlled devices attempting to keep the internal temperature around a set point. The ACs only run if the internal temperature rises above a threshold. This is shown in Fig. 8 and calculated in (6). The parameters of the indoor thermal model for houses and shops are given in Table 15.

$$\begin{bmatrix}\frac{dT_m}{dt}\\ \frac{dT_{int}}{dt}\end{bmatrix} = \begin{bmatrix} \frac{-1}{r_{int}C_m} & \frac{1}{r_{int}C_m} \\ \frac{1}{r_{int}C_{int}} & \frac{-1}{r_a C_{int}} - \frac{1}{r_{int}C_m}\end{bmatrix}\begin{bmatrix}T_m\\ T_{int}\end{bmatrix} + \begin{bmatrix}0 & 0 & 0\\ \frac{1}{r_a C_{int}} & \frac{1-LF}{C_{int}} & \frac{A_w}{C_{int}}\end{bmatrix}\begin{bmatrix}T_{amb}\\ \varphi_c\\ \varphi_s\end{bmatrix} \tag{6}$$

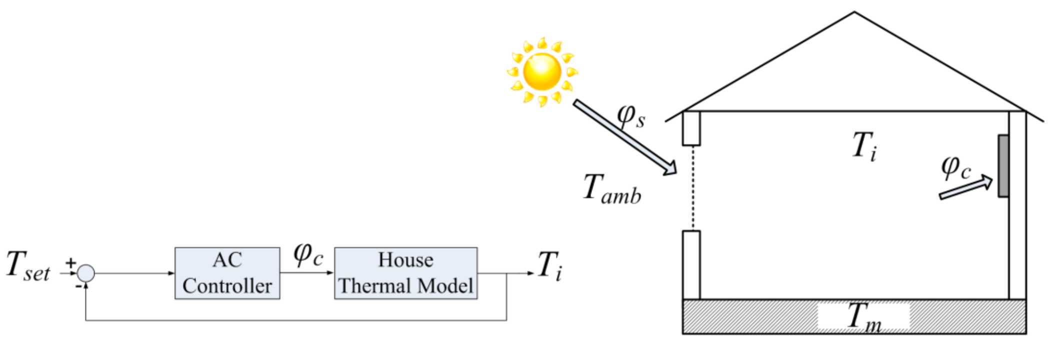


Fig. 8. Indoor thermal modeling and temperature closed loop control.

where

r_a = Outside ambient/Internal air thermal resistance [°C/kW]

r_{int} = Internal air/House slab thermal resistance [°C/kW]

C_{int} = House internal air thermal capacity [kWh/°C]

C_m = House slab thermal capacity [kWh/°C]

φ_c = air conditioning cooling [kW]

φ_s = solar radiation [kW/m^2]

T_m = House slab temperature [°C]

T_{int} = Internal temperature [°C]

T_{amb} = Outside Ambient temperature [°C]

T_{set} = Air conditioner set point [°C]

A_w = Effective window area [m^2]

LF= loss factor due to door opening and closing [%]

Table 15. Indoor Thermal Modeling Parameters

$C_{m,i}$	$N(4,0.4)\cdot A_i/240$
$C_{int,i}$	$N(1.2,0.12)\cdot A_i/240$
$R_{a,i}$	N(29.4,2.9)
$R_{int,i}$	N(0.48,0.048)
$A_{w,i}$	N(2.9,0.29) for Houses N(5.8,0.29) for Shops
LF_i	0% for houses, 10% for shops

References

[1] H.L. Willis, *Power Distribution Planning Reference Book*. New York: Marcel Dekker, 2004.

[2] Energex Annual Report 2008/2009. Available:
http://www.energex.com.au/__data/assets/pdf_file/0011/26669/2008_09_Annual_Report.pdf

[3] Ergon Energy Annual Stakeholder Report 2008/2009. Available:
http://www.ergon.com.au/__data/assets/pdf_file/0020/9218/2009–Annual_Stakeholder_Report_08–09.pdf

[4] J. Taylor, *et al.*, "Evaluation of the impact of plug–in electric vehicle loading on distribution system operations," in Proc. of IEEE Power & Energy Society General Meeting, pp. 1–6, July 2009.

[5] K. Schneider, *et al.*, "Impact assessment of plug–in hybrid vehicles on pacific northwest distribution systems," in Proc. of IEEE Power & Energy Society General Meeting, pp. 1–6, July 2008.

[6] P. Mohseni and R.G. Stevie, "Electric vehicles: Holy grail or Fool's gold," in Proc. of IEEE Power & Energy Society General Meeting, pp.1–5, July 2009.

[7] K. Bhattacharyya and M.L. Crow, "A fuzzy based load model for power system direct load control," in Proc. of IEEE 4th Conf. on Control Applications, pp. 27–32, Sep. 1995.

[8] A. Gabaldon, *et al*, "Assessment and simulation of demand–side management potential in urban power distribution networks," in Proc. of IEEE Power Tech Conf., Vol. 4, June 2003.

[9] A. Amato, M. Calabrese, V. Di Lecce and V. Piuri, "An intelligent system for decentralized load management," in Proc. of IEEE Int. Conf. on Computational Intelligence for Measurement Systems and Applications, pp. 70–74, July 2006.

[10] B. Ramanathan and V. Vittal, "A framework for evaluation of advanced direct load control with minimum disruption," *IEEE Trans. on Power Systems*, Vol. 23, No. 4, pp. 1681–1688, Nov. 2008.

[11] H.Y. Yih and S.C. Ching, "Dispatch of direct load control using dynamic programming," *IEEE Trans. on Power Systems*, vol. 6, No. 3, pp. 1056–1061, Aug. 1991.

[12] I. Richardson, M. Thomson, D. Infield and A. Delahunty, “A modelling framework for the study of highly distributed power systems and demand side management,” in Proc. of IEEE Int. Conf. on Sustainable Power Generation and Supply (SUPERGEN '09), pp. 1–6, April 2009.

[13] C.Y. Chang, *et al.*, "Experiences of direct load control using ripple signals in Taiwan Power System," 4th Int. Conf. on Advances in Power System Control, Operation and Management, Vol. 2, pp. 591–596, Nov. 1997.

[14] B.F. Hastings, “Ten years of operating experience with a remote controlled water heater load management system at Detroit Edison,” *IEEE Trans. on Power Apparatus and Systems,*, Vol.PAS–99, No.4, pp.1437–1441, July 1980.

[15] G. Inc. (2010, 5/9/2011). *Load Management*. Available: http://www.gridpoint.com/utility–solutions/load–management.aspx

[16] Y. Chee–Min, *et al*, “e2Home: A lightweight smart home management system,” in Proc. of IEEE 3rd Int. Conf. on Convergence and Hybrid Information Technology (ICCIT '08), Vol. 1, pp. 82–87, Nov. 2008.

[17] Lochiel Park, http://www.lochielpark.com.au/lochielpark/energy.htm

[18] P. Richardson, D. Flynn and A. Keane, “Optimal charging of electric vehicles in low–voltage distribution systems," To be published in *IEEE Trans. on Power Systems*, doi: 10.1109/TPWRS.2011.2158247.

[19] M. Takagi, K. Yamaji and H. Yamamoto, “Power system stabilization by charging power management of Plug–in Hybrid Electric Vehicles with LFC signal,” IEEE Vehicle Power and Propulsion Conference (VPPC '09), pp. 822–826, Sep. 2009.

[20] F.C. Schweppe, M.C. Caramanis, R.D. Tabors and R.E. Bohn, *Spot pricing of electricity*, Kluwer Academic Publishers, Boston, MA, 1988.

[21] A.K. David and Y.Z. Li; “Effect of inter–temporal factors on the real time pricing of electricity,” *IEEE Trans. on Power Systems*, Vol. 8, No. 1, pp. 44–52, Feb 1993.

[22] K. Clement, E. Haesen, J. Driesen, “Coordinated charging of multiple plug–in hybrid electric vehicles in residential distribution grids,” in Proc. of IEEE Power & Energy Society General Meeting, pp.1–7, March 2009.

[23] Umm–e–Habiba and S. Asghar, “A survey on multi–criteria decision making approaches,” IEEE Int. Conf. on Emerging Technologies, pp. 321–325, Oct. 2009.

[24] Australian Bureau of Statistics. (2009). *Average Floor Area of New Residential Dwellings*. Available: http://www.abs.gov.au/ausstats/abs@.nsf/featurearticlesbyCatalogue/8BB3F6B866BC35CECA2578A000153026?OpenDocument

[25] H. Madsen and J. Holst, “Estimation of continuous–time models for the heat dynamics of a building,” *Energy and Buildings*, Vol. 22, pp. 67–79, 1995.

[26] T. Mackintosh, H. Tataria and S. Inguva, “Energy storage system for GM Volt–lifetime benefits,” in proc. of IEEE Vehicle Power and Propulsion Conf., pp.321–323, Sep. 2009.

[27] J.A. Jardini, *et al*, “Power transformer temperature evaluation for overloading conditions,” *IEEE Trans. on Power Delivery*, Vol. 20, No.1, pp. 179– 184, Jan. 2005.

[28] H. L. Willis, *Spatial Electric Load Forecasting*, Second edition, New York: Marcel Dekker, 2002.

[29] R. Herman and S.W. Heunis, “Load models for mixed–class domestic and fixed, constant power loads for use in probabilistic LV feeder analysis,” *Electric Power Systems Research*, Vol. 66, pp. 149–153, 2003.

[30] J. V. Paatero and P. D. Lund, “A model for generating household electricity load profiles,” *International Journal of Energy Research,* Vol. 30, pp. 273–290, 2006.

[31] A. Wright and S. Firth, “The nature of domestic electricity–loads and effects of time averaging on statistics and on–site generation calculations,” *Applied Energy,* Vol. 84, pp. 389–403, 2007.

[32] S. Karnouskos and T.N.D. Holanda, “Simulation of a smart grid city with software agents,” *3rd UKSim European Symposium on Computer Modeling and Simulation*, 2009.

[33] D.J.C. MacKay, *Sustainable Energy–without the hot air*, UIT Cambridge, 2009.

List of Embedded Tables

List of Embedded Figures

Fig. 7. Number of the control commands applied for different controllable devices

(a) for 4 sample houses of residential feeder 2.

(b) for each customer in a feeder individually (left) and for a specific controllable device in each feeder (right).

Table 1. Decision Making Matrix

House/ Shop No		Criteria Weightings	Priority B_1	Flexibility B_2	Satisfaction B_3	Power Similarity B_4	High Power B_5	Control Priority Value
	Alternatives							
1	1	Water heater	$H(1,1)$	$H(1,2)$	$H(1,3)$	$H(1,4)$	$H(1,5)$	D_1
	2	Swimming pool	$H(2,1)$	$H(2,2)$	$H(2,3)$	$H(2,4)$	$H(2,5)$	D_2
	3	PEV	$H(3,1)$	$H(3,2)$	$H(3,3)$	$H(3,4)$	$H(3,5)$	D_3
	4	AC (hysteresis)	$H(4,1)$	$H(4,2)$	$H(4,3)$	$H(4,4)$	$H(4,5)$	D_4
	5	AC (inverter)	$H(5,1)$	$H(5,2)$	$H(5,3)$	$H(5,4)$	$H(5,5)$	D_5
	6	Dish washer	$H(6,1)$	$H(6,2)$	$H(6,3)$	$H(6,4)$	$H(6,5)$	D_6
	7	Clothes washer	$H(7,1)$	$H(7,2)$	$H(7,3)$	$H(7,4)$	$H(7,5)$	D_7
	8	Dryer	$H(8,1)$	$H(8,2)$	$H(8,3)$	$H(8,4)$	$H(8,5)$	D_8
2	9	Water heater	…					…
	10	Swimming pool	…					…
	11	PEV	…					…
	12	AC (hysteresis)	…		$H(i,j)$			D_i
	13	AC (inverter)	…					…
	14	Dish washer	…					…
	15	Clothes washer	…					…
	16	Dryer	…					…
⋮								

Table 2. Weighting of MODM Criteria

Priority	Flexibility	Satisfaction	Power similarity	High Power
0.8	0.5	0.7	0.7	0.9

Table 3. Controllable Device Number Allocation and Flexibility

Controllable Device	Water Heater	Pool Pump	AC (hysteresis)	AC (inverter)	PEV	Dish Washer	Clothes Washer	Dryer
Number	1	2	3	4	5	6	7	8
Flexibility	0.5	0.9	0.7	0.7	0.9	0.2	0.2	0.2

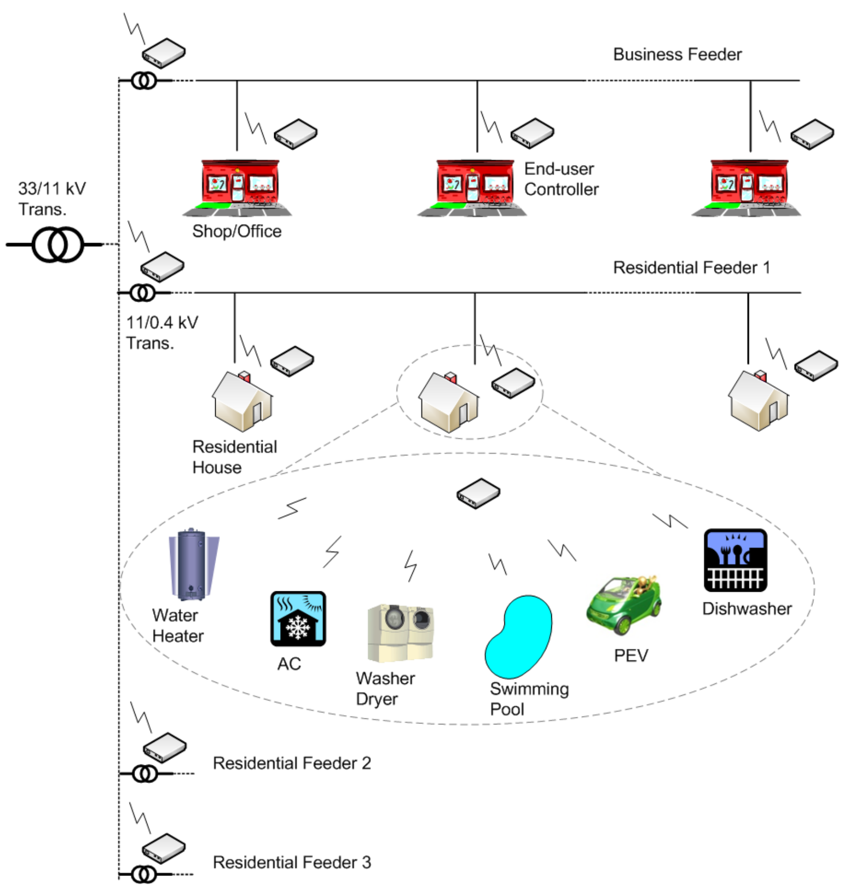


Fig. 1. Sample structure of radial LV distribution networks with the proposed control scheme.

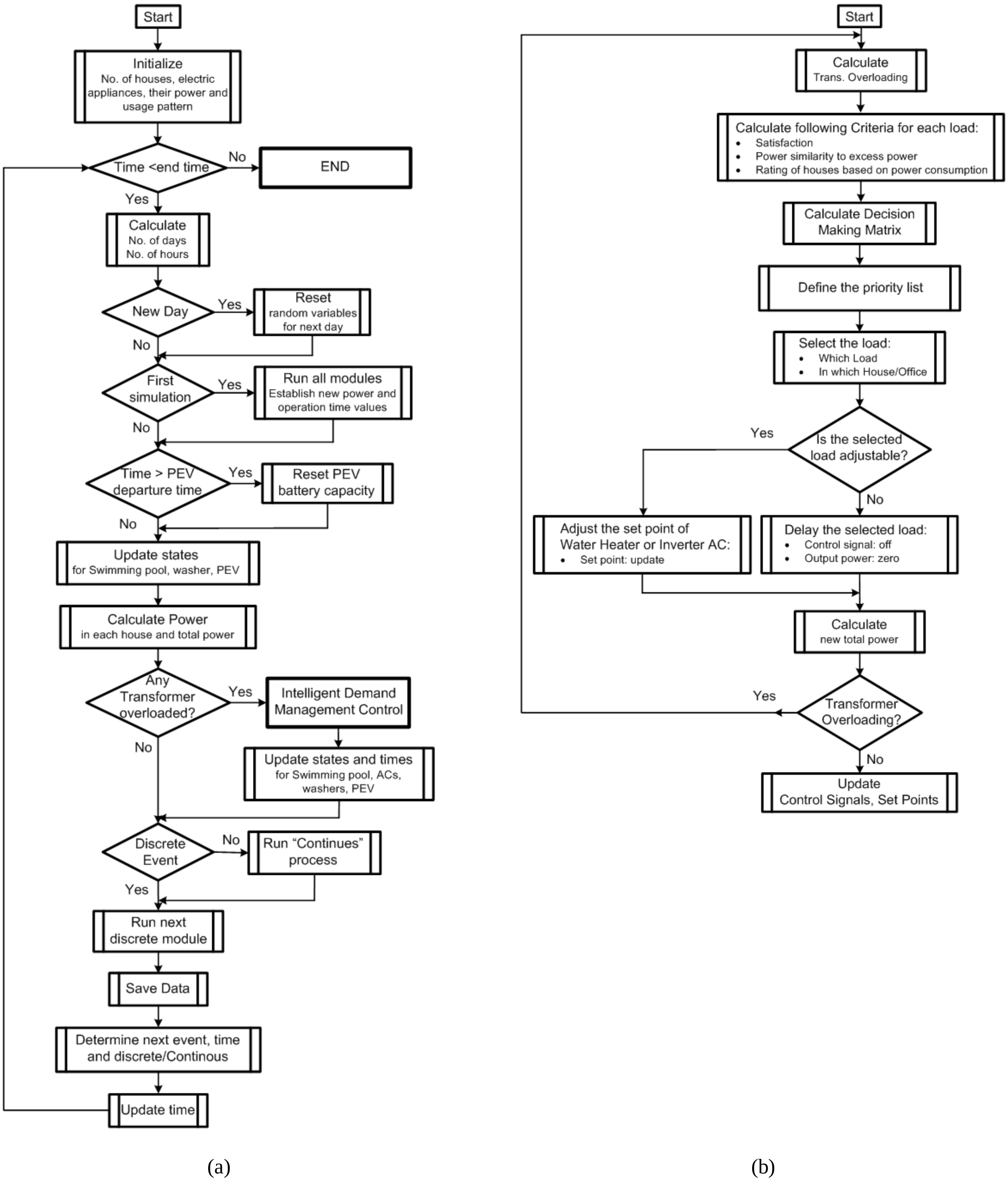


Fig. 2. Flowchart of (a) the analysis and simulation method, (b) the control scheme including MODM process.

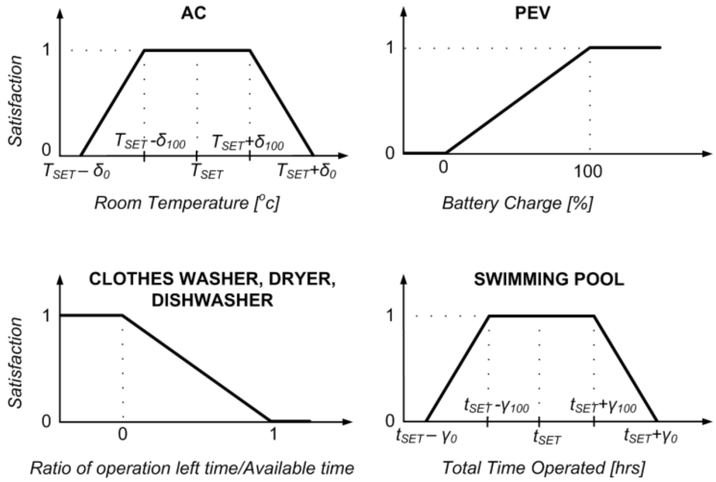


Fig. 3. Satisfaction Criteria Calculation for AC, PEV, Washer/Dryer and Swimming Pool.

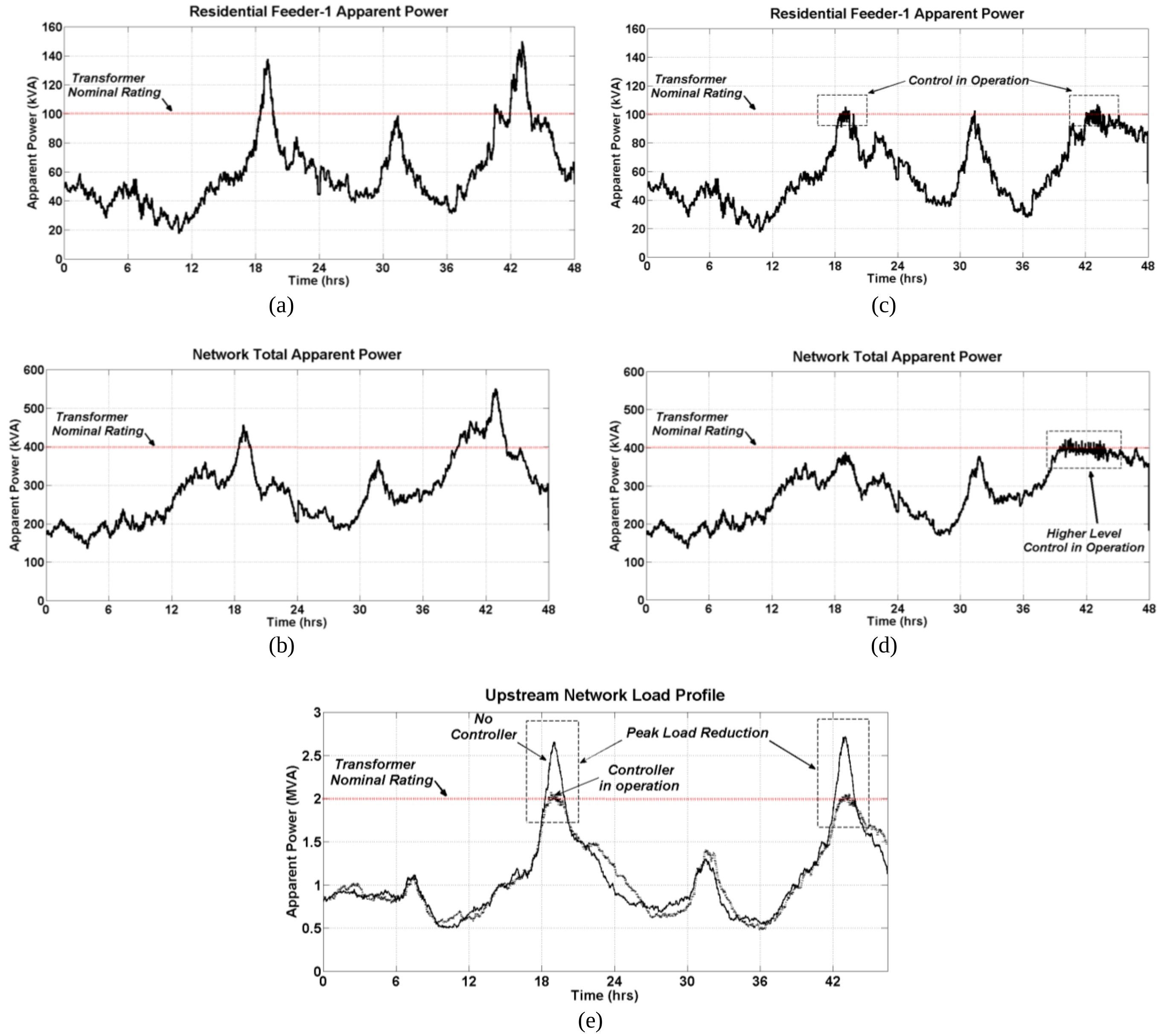


Fig. 4. Total apparent power of

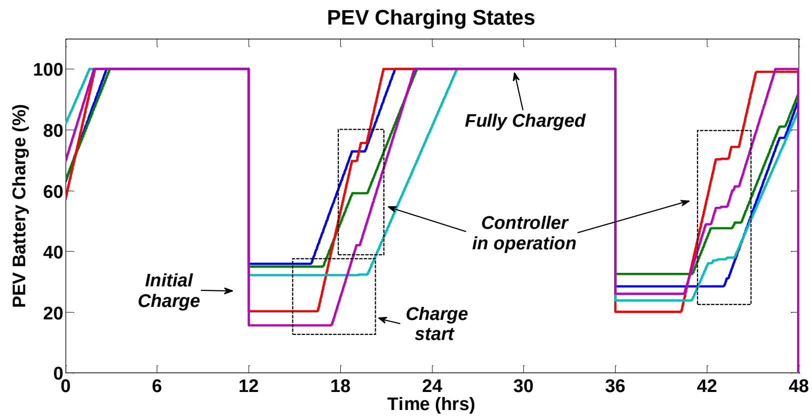
(a) one of the residential distribution transformers including 25% penetration level of PEVs without any control.

(b) the studied network without any control.

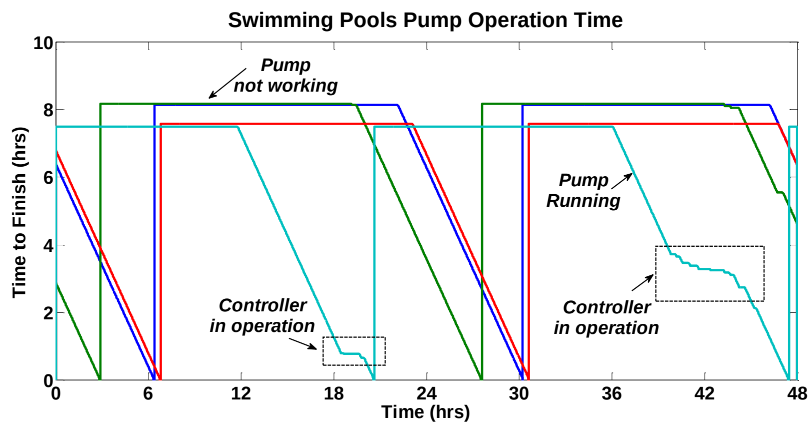
(c) one of the residential distribution transformers including 25% penetration level of PEVs with the proposed control system.

(d) the studied network with the proposed control system.

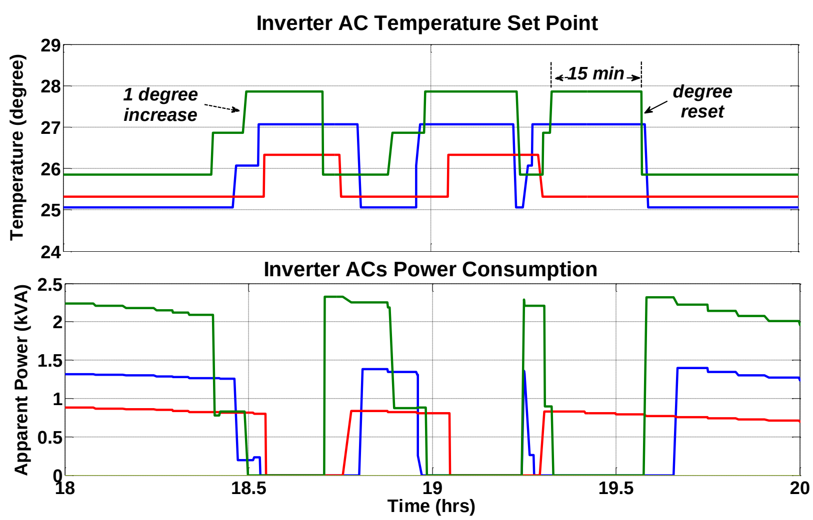
(e) the substation feeding 100 distribution transformers in an area with and without the control.



(a)



(b)



(c)

Fig. 5(a) PEVs battery charging states.

(b) Swimming pool pump operation characteristic.

(c) Temperature set point and relevant apparent power consumption change for sample residential inverter ACs in network.

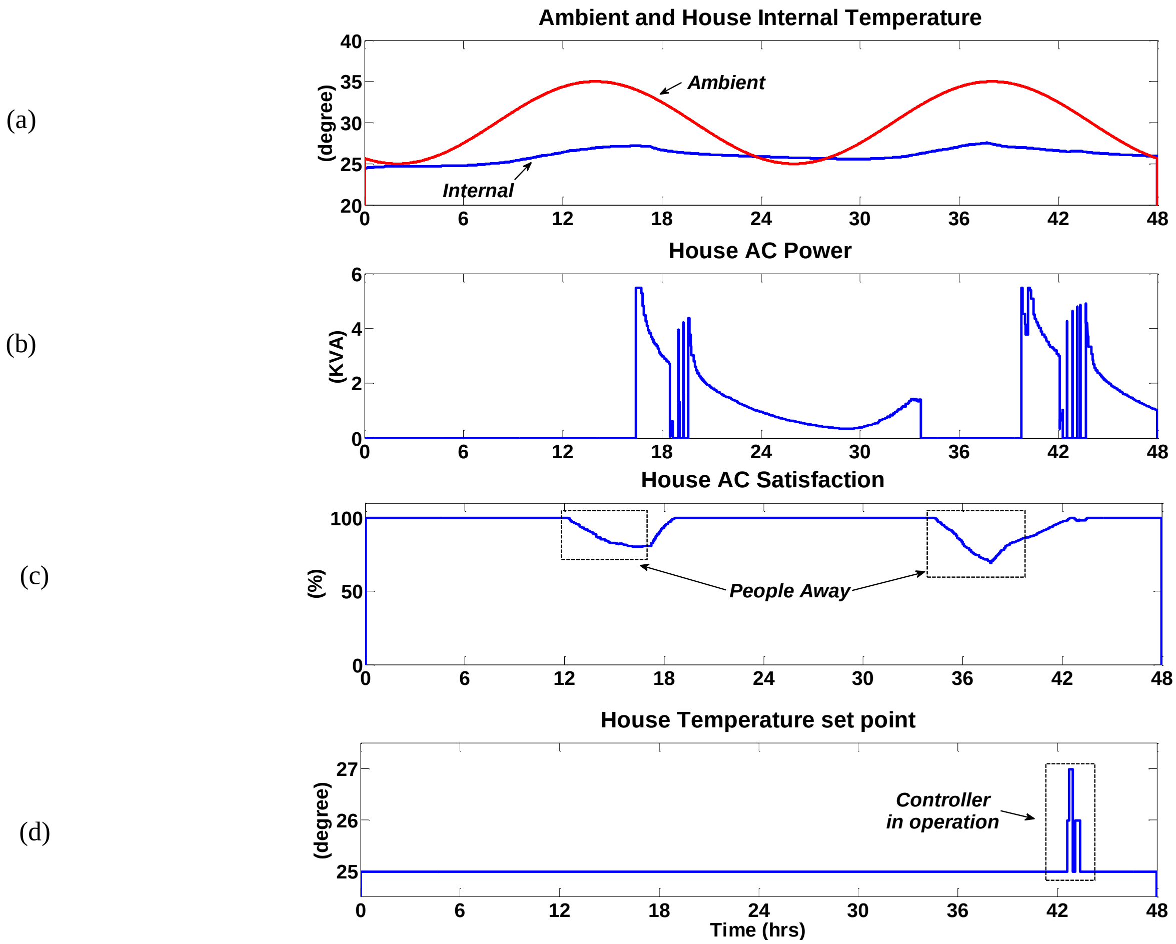
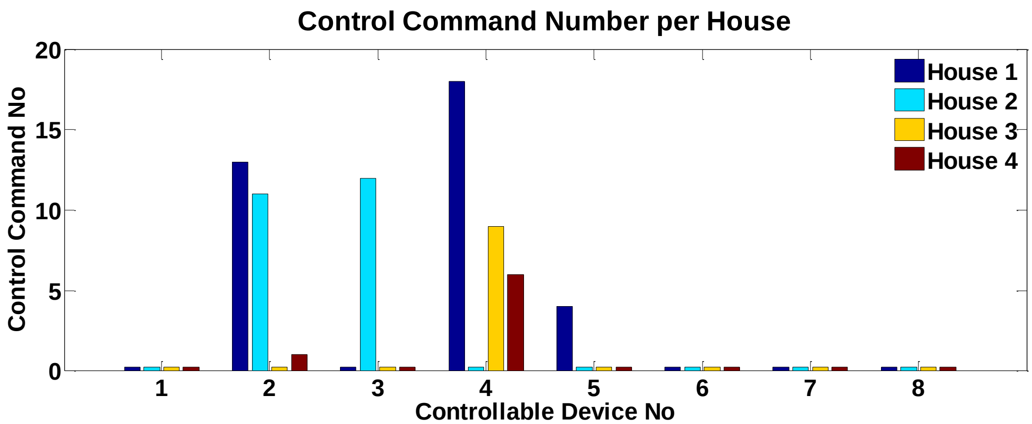


Fig. 6. (a) Ambient and house internal temperature variation,

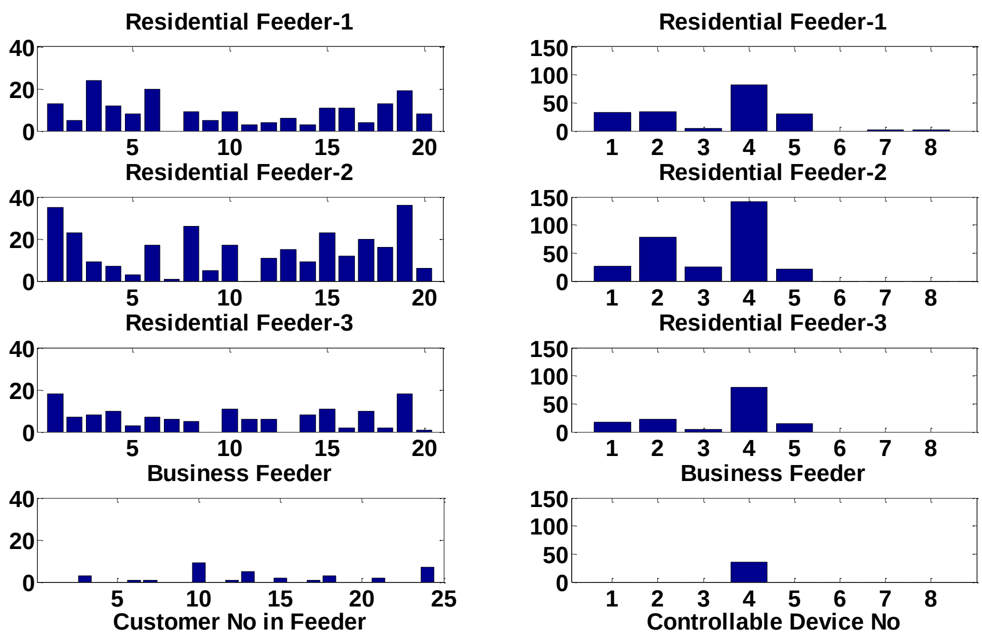
(b) AC electric power consumption,

(c) AC satisfaction,

(d) AC set point.



(a)



(b)

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