An Intelligent Home Energy Management System to Improve Demand Response

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***Abstract*—Demand Response (DR) and Time-of-Use (TOU) pricing refer to programs which offer incentives to customers who curtail their energy use during times of peak demand. In this paper, we propose an integrated solution to predict and re-engineer the electricity demand (e.g., peak load reduction and shift) in a locality at a given day/time. The system presented in this paper expands DR to residential loads by dynamically scheduling and controlling appliances in each dwelling unit. A decision-support system is developed to forecast electricity demand in the home and enable the user to save energy by recommending optimal run time schedules for appliances, given user constraints and TOU pricing from the utility company. The schedule is communicated to the smart appliances over a self-organizing home energy network and executed by the appliance control interfaces developed in this study. A predictor is developed to predict, based on the user's life style and other social/environmental factors, the potential schedules for appliance run times. An aggregator is used to accumulate predicted demand from residential customers.**

***Index Terms*—Appliance scheduling, demand response, home energy management, time-of-use pricing.**

I. Introduction

IN CURRENT regulated energy distribution systems, the electricity rate is generally averaged over the entire year and cost-of-service pricing is the norm. Though true cost of electricity varies over time, most customers pay rates based on average electricity costs [1]. With the vision to achieve seamless delivery, generation, and end use that benefits the nation, the concept of a smart grid has been proposed to revolutionize the electric system by integrating 21st century technology [2], [3]. The U.S. Energy Policy Act of 2005 mentions that each electric power company should provide customers with time-based rates [4]. A report submitted to the United States Congress by the Department of Energy discusses benefits of Demand Response and makes recommendations for achieving these benefits [28].

Modern buildings and houses have started incorporating digital control systems to enable users to take advantage of time-based rates by controlling each device generating or consuming electricity. Direct digital controls for building heating, ventilation, and cooling systems (HVAC), and dimmable ballasts [5] are commonly available. Modern building control systems enable optimum start/stop, night purge, maximum load demand, supervisory functions for lighting, sun-blind, energy metering, and many other applications [6], [7]. Standardization of communication protocols and widespread adoption of the BACnet protocol enabled the integration of commercial building control products and offered the connectivity among systems made by different manufacturers [8]. BACnet is a communication protocol developed under the auspices of the American Society of Heating, Refrigerating and Air-Conditioning Engineers for building automation and control networks.The acceptance of Zigbee and Powerline for connecting appliances in residential buildings is increasing at a rapid rate. A limited number of connected smart appliances which have been released by General Electric (GE) and other manufacturers, offer time-of-use (TOU) pricing control to a limited extent. However these do not offer an integrated solution involving both utility company and the residential customer.

A demand response (DR) strategy coordinates the requirements and needs between the energy provider and the customer [9], [10]. It encourages the customer to reduce the peak-demand in response to the incentives [11]. However, existing home energy management systems are primarily designed to improve the energy efficiency and comfort within single residential home. They often do not take into account the utility data (such as load forecasts or TOU pricing) for the scheduling of appliances. There is also no coordination among multiple dwelling units to simultaneously manage DR in a residential community. We envision that aggregating the demand from individual residential customers will enable us to expand DR programs to residential customers. Here, DR is defined as change in electricity usage by the end-use customers from their normal consumption patterns in response to a change in the price of electricity over time [5], [28]. This study demonstrates that, with a closed loop integrated solution, customer participation in DR programs can be increased; thus the cost of energy production can be controlled. This study also formulates energy management as a scheduling problem where energy is considered as a resource shared by residential appliances, and periods of energy consumption are considered as tasks. An intelligent scheduling algorithm is designed in this study to reduce the total consumption while satisfying a maximum energy resource constraint.

Several DR schemes have appeared in the literature for scheduling the load. In [12], an adaptation of the static Resource Constraint Project Scheduling Problems (RCPSP) is presented to

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improve the management of electric heating systems while satisfying the maximum power resource constraint. In [13], the authors formulate an optimization model which utilizes the mixed integer nonlinear programming (MINLP) technique for minimizing the electricity cost and reduce the peak demand. In [14], a weighted average price prediction filter is designed, which is evaluated on a weekly basis by using the actual hourly price; a linear programming scheme is also presented for optimal load control of appliances. A scheduler maximizing the benefits to the end user is presented in [15] using a co-evolutionary version of particle swarm optimization. In [26], an appliance commitment algorithm that schedules thermostatically controlled appliances based on user comfort settings and price consumption forecasts is proposed. However, the studies cited here do not provide an integrated solution to the DR problem space.

In this paper, we present a solution that involves both the residential customer and the utility company. We present a closed loop solution that forecasts the electricity demand of individual residential customers, aggregates the demand from residential customers in a neighborhood, and presents the aggregated demand to the utility company. The utility company can use this demand forecast for DR management and TOU price decisions. Based on the TOU pricing offered by the utility company, the residential loads are then scheduled within user comfort zones to optimize the power consumption by the residential users. Over time, the utility will learn the effect of varying TOU price on user demand and will therefore be able to predict the change in user demand as a result of TOU price. This will enable the utility to determine the TOU price based on the predicted demand and available power supply on a given day.

The focus of this paper is on the load forecasting in the home as well as in a neighborhood and presenting a novel appliance scheduling scheme which uses TOU or differential pricing.

A residential customer's daily activities are characterized by a list of tasks to be scheduled at preferred time intervals. Some of these tasks are persistent, as they consume electricity throughout the day (e.g., refrigerator), while others may be scheduled within a defined time interval (e.g., washer/dryer or oven). In this paper, the demand-side energy management problem is considered as the scheduling of a customer's daily tasks according to user-specified constraints and the TOU pricing offered by the utility company to achieve cost savings and peak demand reduction. An intelligent power management application is discussed for controlling appliances in the home and as well as for gathering data about the past usage schedules of the appliances. A branch and bound algorithm is formulated to schedule the appliances as per the customer's usage preference. A self-organizing home energy management network is developed based on IEEE 802.15.4 to control appliances remotely. The appliance controllers developed in this project offer a zero configuration appliance network with no user configuration.

The proposed system provides continuous interaction between the residential customer and the utility company by employing an adaptive neural-fuzzy learning algorithm. The solution presented in this paper would enable the utility to predict and tailor the electricity demand in multiple dwelling units in a given residential community: a) by providing suitable incentives (such as differential or TOU pricing) to customers, and b) by scheduling and controlling appliances to smoothen the demand. The residential customer is offered the following advantages: i) improved energy efficiency for electricity usage resulting in cost savings; ii) maximum usage of solar power locally within the home by shifting operation of certain appliances to times when solar power is available; iii) maximum user comfort by learning from user inputs, usage patterns, and weather conditions; and iv) effective customer education and interaction—information can be provided to the customer about the daily, weekly, and monthly energy consumption patterns and advice on energy savings to meet the customer's monthly energy budget.

II. Overview of the System Architecture

The proposed energy management solution learns and adapts to the residential energy usage patterns. The adaptive neuro-fuzzy learning algorithm developed in this study makes DR decisions based on the following factors: 1) peak load forecast, 2) differential electricity prices, 3) customers usage patterns and energy budget, 4) social and environmental factors, and 5) available solar power. The conceptual diagram capturing data and control flow in the proposed system is shown in Fig. 1. The system is composed of components that reside in the home and a regional aggregator which provides connectivity between the homes and the utility company. The aggregator accumulates the demand and enables the utility company to engineer a TOU pricing program to the customer. The aggregator also participates in demand bidding programs. The in-home system components consist of an intelligent home energy controller which is referred to as Master Controller (MC) and the appliance control nodes forming the self-configuring home energy control network. The system can be seamlessly interfaced to the utility (via advanced metering infrastructure or AMI) as well as through the Internet.

MC is the heart of this system and provides connectivity to both the aggregator and to the utility company for submitting future demands and retrieving TOU pricing information. The MC will configure, control, and schedule the operation of all the home appliances through individual, inexpensive wireless appliance controllers developed as part of this study. The system is scalable and requires zero configuration from the customer. The MC is a cognitive and intelligent unit capable of scheduling the operation of all the home appliances and HVAC, based on the user and utility inputs to meet DR objectives. For example, when a user schedules the operation of the washer/dryer, the MC may determine that a two hour delay in starting the appliance would result in cost savings. This information, along with the actual savings, will be available to the user on the appliance panel or the MC panel.

The user can either accept this advice or choose immediate operation. When a new appliance controller node is powered up, it registers with the MC and supplies information related to appliance(s) operation settings, appliance make, model and power ratings, modes of operation, etc. All the appliances in a house are inter-connected through a self-organizing wireless network based on IEEE 802.15.4 standard. The appliance network communicates with the MC through a Bluetooth to IEEE 802.15.4 gateway developed in this project. The gateway implements network management policies, address assignments, delivery of data to destination appliances and connects the appliance network to the external world through the MC. An appliance in this network receives all its schedules through the gateway and the appliances report their operation status through the same gateway.

Crossbows TelosB motes have been used to emulate the appliances in the home and host appliance controllers; a relay module is developed and interfaced to the TelosB motes to control the household appliances. Additionally, each mote has been programmed to emulate the behavior of an appliance and perform various operations when instructed to operate in a supported mode. The appliances are networked using a self-organizing cluster tree topology network; hence, they not only act as appliances but also act as routers to forward packets from other appliances to the gateway. In addition, the network is self-healing; thus removal of some appliances from the network does not affect the network.

The user's input is limited to scheduling appliances to turn on/off at particular times or complete a task within a specified duration. The user also provides one time information related to dwelling unit type and size, installed solar PV and thermal power generation capacity, and target monthly energy budget (presumably depending on household income). The MC continuously collects data regarding usage patterns of appliances from the user's interaction with the system. The customer's usage patterns take into account the history of energy demand considering the following parameters: i) time and season (time of day, day of week, month of year effects), and ii) weather including the effects of persistent extreme weather.

The MC interacts with the user and generates appliance schedules, allows the user to edit and add his/her own schedules, delivers schedules to the respective appliances, monitors and logs the operation status of the appliances over a period of time and generates data for the predictor algorithm. It provides a final schedule to the respective appliances through a home energy network gateway and monitors the state of each appliance in the network.

Aggregation is the process in which energy is sold to customers who have joined together as a group. They may also participate in demand bidding programs instituted by the utility company to shift peak load. We have developed a simplified power aggregator following the OpenADR standard [2], [16] to provide an open interface to in-home MCs and aggregate the demand from the residential customers to close the loop in our solution. The bulk estimated energy may be priced by the aggregator accordingly to enable a shift in the peak power load through price incentives. We must emphasize that all interactions between the MC and aggregation server take place with no user intervention. In this study, keeping the user intervention to a minimum is a key objective. As shown in Fig. 1, the hourly projected energy demand by the MC is used by the aggregator (or by the utility company itself acting as aggregator) to determine the TOU prices which will be communicated to the MC to make scheduling decisions.

III. Intelligent Appliance Scheduling

In [17] Boucher *et al.* developed a modular adaptive scheduling approach for minimum energy usage. Using the principle of thermodynamics and the impact of actuators on the energy system, a simple control strategy was developed and tested on a raised floor data center. While the results presented in [17] are promising, the study employed very specific sensor data, actuator models and environmental conditions. Energy management is a complex task as the dynamics of the system of systems are nonlinear, the compensation is naturally decentralized, and the environment and user demands change with the time and season. In this study, we have employed non-parametric techniques for forecasting the energy demand in the home by using the past usage patterns, solar energy production and other environmental/social factors. First we note that learning must integrate the customers' needs, the utility provider's requirements and the hardware capabilities (sensors and actuators with delays and limitations). Fig. 2 illustrates the synergy of this interaction.

At the local level, each customer's MC uses a simple adaptive neural fuzzy inference system (ANFIS) as explained below. The inputs to the MC include user preferences (appliance settings and schedules), TOU and other utility data, and the outputs include the predicted energy usage which updates the utility DR data. For this purpose, the utility may divide the 24 hour duration in one-hour time slots. Each MC communicates to the utility (via AMI) the predicted energy demand in a home for any given time slot. This data is aggregated at the aggregator from all the homes being served by it.

Inputs to the utility controller include the power availability on the grid, predicted solar power generation, and the predicted energy demand in a residential community, together with other energy demand data (e.g., industrial and commercial energy demand), and weather. Outputs include the DR data to the customers (e.g., cost incentives and/or differential pricing). The utility acts on a database of residence types and the customers' likely response (i.e., change in demand) to a change in electricity price. The change in the price of electricity will enable the utility to further tailor the energy demand by encouraging the customers through MCs to reschedule for more cost effective appliance operations. Note that the user influences the optimization and scheduling decisions for cost vs. comfort level vs. DR.

A. ANFIS Predictor to Model Residential Customer Profiles

The heart of the learning is the ANFIS [18], [19]. The ANFIS algorithm is implemented in two parts: *i*) the neural network provides the learning mechanism to identify the unknown or changing plant, *ii*) the fuzzification component compensates the uncertainties or inaccuracies of the plant as well as of the environment. As shown in Fig. 3, the first layer takes various customer and utility inputs and fuzzifies the data. Layer 2 weighs the different inputs according to some priority while layer 3 normalizes the resulting weighted data (layer 2 and 3 are the neural network components). In layer 4, the inputs are evaluated according to predefined rules and, in layer 5, the rules are combined to produce a numeric response which is the output. Two sets of parameters need to be tuned, the premise parameters (in layer 1) and the consequence parameters (in layer 4). For a system with a large number of input variables, it is necessary to carefully select the input variables that are relevant to the output. As the system is not well known, the Group Method

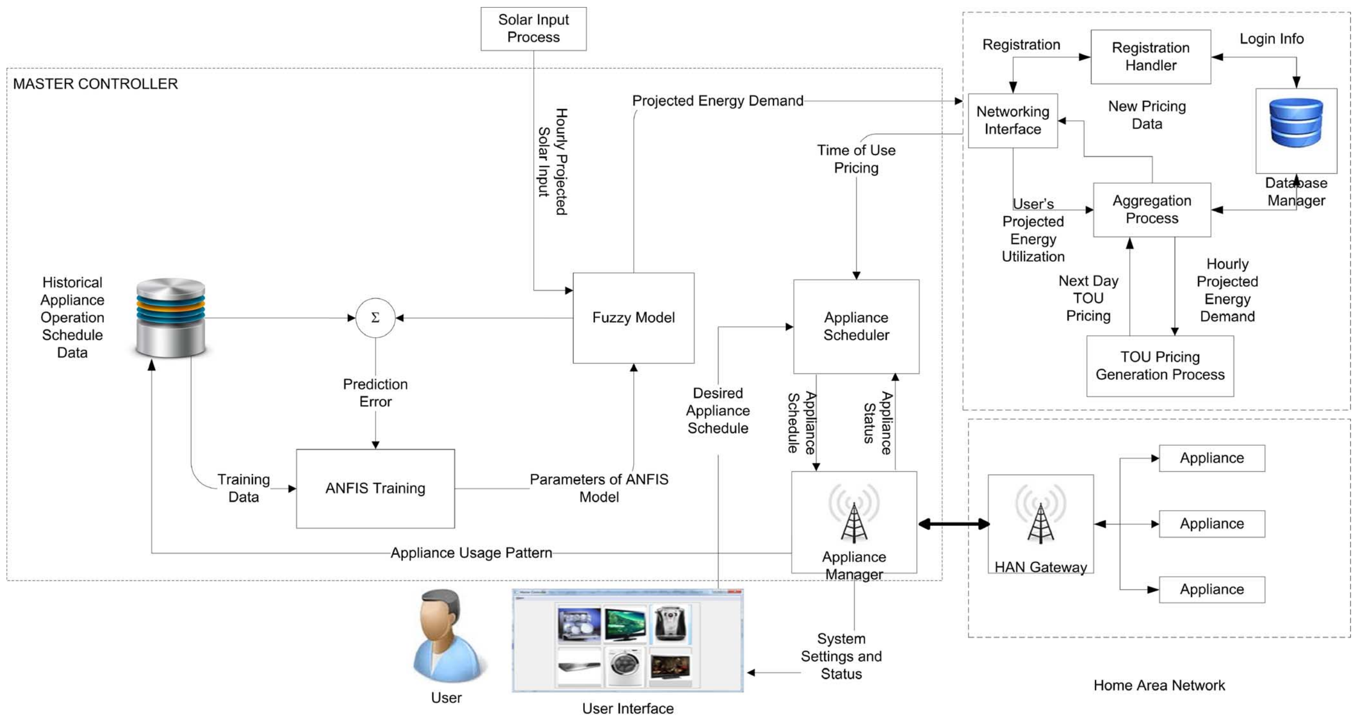

Fig. 1. Data flow in the home energy management system.

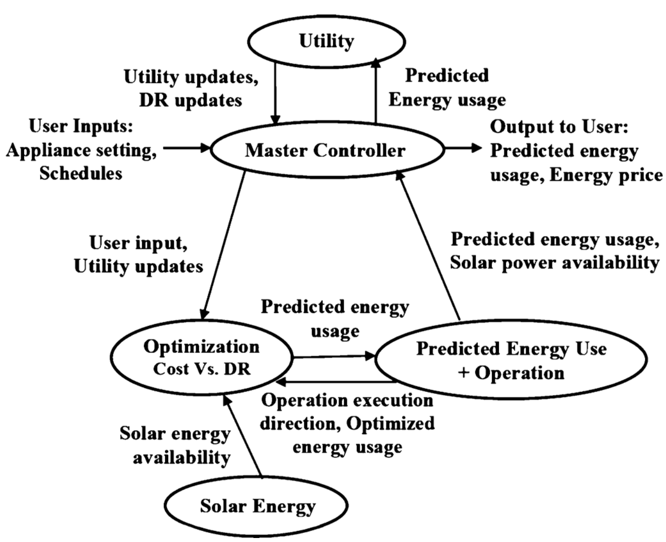

Fig. 2. Hierarchical adaptive learning control architecture.

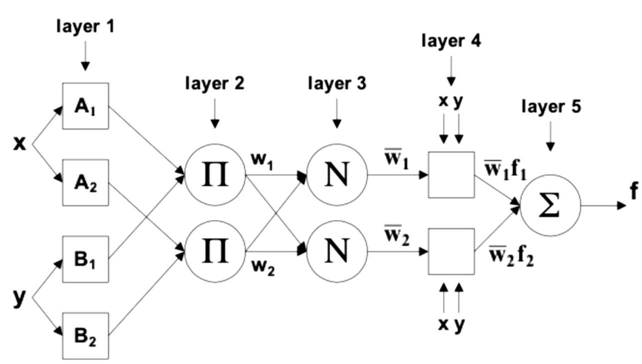

Fig. 3. An adaptive neural fuzzy inference system (ANFIS).

for Data Handling [20], [21] with the regularity criterion (RC) is used to identify the significant input.

The identification data must be divided into two groups and the regularity criterion is defined as:

$$RC = \frac{\left[\sum_{i=1}^{k_A} \frac{\left(y_i^A - y_i^{AB}\right)^2}{k_A} + \sum_{i=1}^{k_B} \frac{\left(y_i^B - y_i^{BA}\right)^2}{k_B} \right]}{2} \tag{1}$$

where k_A and k_B are the number of data points in group A and B, respectively, and y_i^A and y_i^B are the output data of group A and B. y^{AB} (y^{BA}) is the model output for group A (group B) input estimated by the model identified using group B (group A) data. Let us consider the system with n inputs.

The identification is carried out as follows:

i) The input-output data set is divided into two groups A and B.
ii) Using the two groups of data, two fuzzy models $\mathrm{M}_\mathrm{A}^\mathrm{n}$ and $\mathrm{M}_\mathrm{B}^\mathrm{n}$, are built for each group, starting with only one input and two membership functions. At this stage, a fuzzy model is built for each input in consideration.
iii) After training, the reference networks $\mathrm{M}_\mathrm{A}^\mathrm{n}$ and $\mathrm{M}_\mathrm{B}^\mathrm{n}$ are tested using data sets A and B, respectively.
iv) Compute the RC using the relation given in (1).
v) The input with the minimum RC is considered as important variable and is fixed with that number of membership function.
vi) In the next stage, consider all the input variables $i = 1, \ldots, n$. If the input variable i is already fixed, increment the number of membership functions, and if the input variable i is not fixed include it, one at a time. In this stage, a fuzzy model is built for change in each input variable and the RC is calculated. The same process is repeated until the minimum value of RC increases.

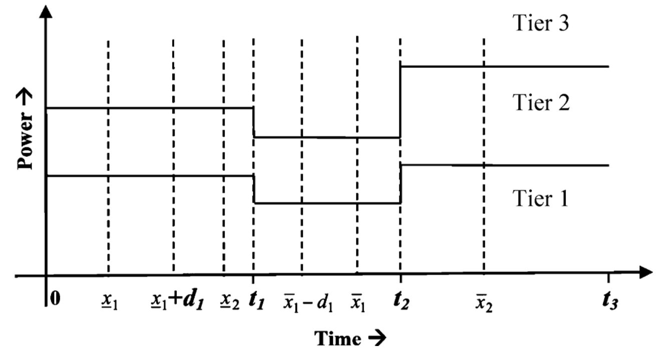

Fig. 4. Representation of differential or TOU pricing, based upon time of day and power usage (tiers). Partitions in the time duration are used in the branch and bound algorithm.

B. Intelligent Appliance Scheduling: The Branch and Bound Technique

The differential or TOU pricing provides financial incentives to customers for shifting their demand from peak to off-peak periods. In differential pricing, the cost of electricity is charged at different rates during different times of the day for different power levels and it is determined using the estimated demand. The concept of differential pricing is shown in Fig. 4, where a day is divided in three time periods $0 - t_1$ (normal demand), $t_1 - t_2$ (off-peak demand) and $t_2 - t_3$ (peak demand). Also, the cost of electricity in each time interval is divided in three tiers where tiers 1, 2, and 3 represent the low, normal and heavy usage, in that order. Using the differential pricing, an efficient energy management schedule can be constructed that minimizes the demand during peak hours and higher tiers while providing reduced costs to the residential customer. In this study we implement an appliance scheduling scheme, using a branch and bound algorithm, based on the given pricing information and the customer's constraints on schedulability of the tasks.

The branch and bound is a global optimization technique used for non-convex optimization problems [22], [23], [25]. It typically relies on *a priori* knowledge about the problem. The basic concept underlying the branch and bound technique is *divide and conquer*. The original "large" problem is divided into smaller and smaller sub-problems until these sub-problems can be *conquered*. The approach estimates upper and lower bounds (UB, LB) of the original problem and discards the subset if the bound indicates that it cannot contain an optimal solution. After the problem is divided into a set of smaller sub-problems, the algorithm is applied recursively to the sub-problems. The search proceeds until all nodes (sub-problems) have been solved or pruned.

Assume n appliances need to be scheduled between the time $\underline{x}_i$ and $\overline{x}_i, (i = 1, 2, \ldots, n)$, where $\underline{x}_i$ and $\overline{x}_i$ represent the lower and upper limit of the appliance operating time, respectively. The cost of operating an appliance is based upon the time of day (peak, off peak, and normal period) and the tier. The power consumed by the appliance i is q_i and its operating duration is d_i. The problem is to find the optimum value of the appliance switching-on time x_i such that the total operating cost is minimum. Also the appliances need to be scheduled such that the power required by them is less than the maximum power availability.

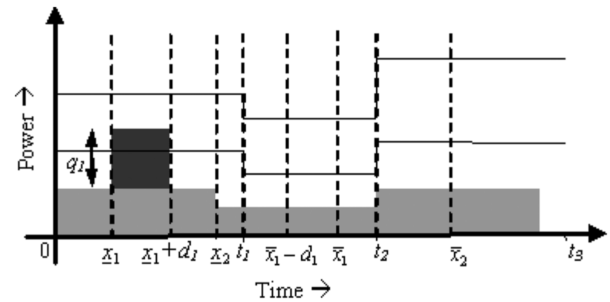

Fig. 5. Region and the power availability for schedulable appliances. Typical power consumption of the *must-run* appliances is lightly shaded.

Consider an appliance, labeled appliance 1, which must operate between the time $\underline{x}_1$ and $\overline{x}_1$. In Fig. 5, the duration between $\underline{x}_1$ and $\overline{x}_1$ is divided as $[\underline{x}_1, \underline{x}_1 + d_1]$, $[\underline{x}_1 + d_1, \underline{x}_2]$, $[\underline{x}_2, t_1]$, $[t_1, \overline{x}_1 - d_1]$, and $[\overline{x}_1 - d_1, \overline{x}_1]$. Between 0 and $\underline{x}_1$, the appliance must be in the "OFF" state. During the intervals $[\underline{x}_1, \underline{x}_1 + d_1]$, $[\underline{x}_1 + d_1, \underline{x}_2]$, $[\underline{x}_2, t_1]$, $[t_1, \overline{x}_1 - d_1]$, and $[\overline{x}_1 - d_1, \overline{x}_1]$ the appliance state is "ON" or "OFF." After the time $\overline{x}_1$, the appliance is in the "OFF" state.

If the appliance is "OFF," the lower and upper bounds of power is 0. For the appliance states, "ON/OFF" and "ON," the lower bounds are 0 and q_1, and the upper bound is q_1 for both the cases. The bounds of power for all the appliances are calculated in the same way. The bounds of the cost are calculated using the bounds of power for all the appliances and the cost per kWh in different intervals of time.

The available power for the schedulable appliances is calculated by subtracting the power consumed by the *must-run* services from the total available power. In Fig. 5, typical power consumption by the *must-run* services is shown by the lightly shaded region. The region above the lightly shaded region is available for the schedulable appliances. Between the interval $\underline{x}_1$ and $\underline{x}_1 + d_1$, the appliance 1 needs q_1 KW power as shown by a dark shaded region. Let w portion of power q_1 come under the lower power tier(tier 1) and the remaining portion $(q_1 - \mathrm{w})$ come under the higher power tier (tier 2). In this case, the cost for operation of the appliance between $\underline{x}_1$ and $\underline{x}_1 + d_1$ is given by the $wc_{1a} + (q_1 - \mathrm{w})c_{1b}$, where c_{1a} and c_{1b} are the electricity cost per KWh in tier 1 and tier 2, respectively. The cost for operation of appliances is thus calculated for all the appliances in all the intervals.

In any interval, if the lower bound of available power is q_1, then the appliance is "ON" in that interval. The remaining time of operation of the appliance is obtained by subtracting all such interval(s) from d_1. Now the remaining duration is distributed in the intervals where the lower power bound is q_1, starting from the interval where the cost per kWh for operation of the appliance is low. The sum of the operating cost of the appliance in all these intervals gives the lower bound of the operating cost of appliance. The lower bound of the operating cost for all appliances is calculated by adding the lower bounds of the operating costs for all the appliances.

The upper bound of the operating cost is calculated in a similar way. The only difference is instead of distributing the appliance operating duration in the intervals with low cost per kWh, it is distributed in the intervals where the cost is maximum. While calculating the lower and upper bounds, the appliances are considered to be operating with a discontinuity for each cycle. As the branching progresses and when the interval reduces, the discontinuity will reduce. When the interval is close to zero, the appliance operation will be continuous for each cycle of operation.

A branching rule is used to split the current problem into sub-problems. The efficiency of the branch and bound algorithm depends on the branching rule and the bound calculation method.

As mentioned earlier, the duration of operation of an appliance is d_i $(i = 1, \ldots, n)$ and the bounds of the appliance switching ON time is between $\underline{x}_i$ and $\overline{x}_1 - d_i$. The branching operation is performed on the sub-problem, where the lower bound is minimum. Next the value of i needs to be found for the branching operation. The optimization is carried out to minimize the cost associated with

$$\{\mathrm{P}\left((\overline{x}_i - d_i) - x_i\right)\}, \quad i = 1, \ldots n \tag{2}$$

where P(.) denotes the power associated with the time interval. For the optimization function in (2), the constraints are the operating time duration d_i of each appliance and the must run services. The decision variables are the lower and upper bounds of each appliance operating time.

The lower and upper bounds of the new sub-problems are calculated and the branching operation is stopped when the minimum of the lower bound is closer to the upper bound.

IV. Simulation Results

In this section, we present simulation results when using the ANFIS predictor and a branch and bound based appliance scheduler by using the TOU pricing for the home electricity management system.

A. Prediction

We use the ANFIS model to predict the appliance switching ON time and its operating duration in a home [24]. To reduce the complexity in training, the input training data is divided into three sets, viz., working day, weekend, and holiday data. For each set of data two ANFIS models are built—the first model is used to predict the appliance switching ON time and the second model is used to predict the operating duration of the appliance. For predicting the appliance ON time, the input variables considered are the day of the week, season, room temperature and the time interval between each operation of the appliance during the last two days. Similarly, for prediction of appliance operating duration, the input variables considered are day of the week, season, room temperature and the different operating duration of the appliance in the last two days. We used five weeks of data for training and testing the ANFIS model. The first four weeks of data was used for training the ANFIS model which was then tested using the last one week of data.

The power profiles of different appliances were gathered in volunteer homes using Watts Up power meters. The power profiles were stored in a database and used during the prediction and scheduling of appliances. Certain appliances, such as a washing machine, may be operated once in two to three days. Such appliances are assumed to follow a weekly pattern.

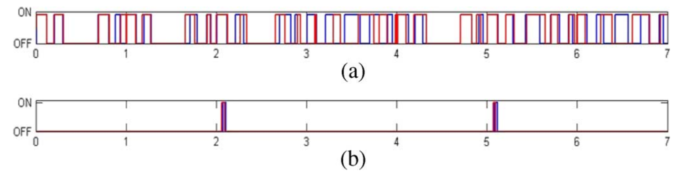

Fig. 6. Prediction result for home appliance usage for (a) air conditioner, and (b) washing machine. Here, blue line and red line represent the patterns for generated data and the predicted results, respectively.

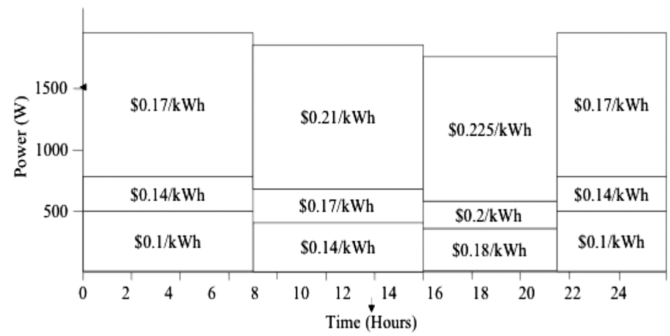

Fig. 7. An example of power availability and cost of electricity during different times of the day used in our simulation.

The prediction results over one week period for two schedulable home appliances—air conditioner and washing machine—are shown in Fig. 6 to illustrate the effectiveness of our ANFIS based prediction scheme. Here, days of the week, beginning with Monday, are shown on the X-axis. The Y-axis shows the appliance OFF state and ON state. The blue pulses represent the training data from the previous week while the red pulses represent the ANFIS prediction. In this test scenario, Thursday was considered as a holiday. The results show that the ANFIS model can be used to effectively predict the home appliance usage patterns.

B. Scheduling

Assume that we want to schedule some appliances in a home. Let the power consumed by the *un-schedulable* appliances be 0.1 kW during 12:00 A.M.–6:00 A.M., 0.15 kW during 6:00 A.M. –9:00 A.M., 0.175 kW during 9:00 A.M.–9:00 P.M. and 0.125 kW during 9:00 P.M.–12:00 A.M.. The graphical representation of the cost of electricity and the power availability during different periods of the day is shown in Fig. 7. The time between 07:30 P.M.–07:00 A.M., 07:00 A.M.–02:00 P.M. and 02:00 P.M.–07:30 P.M. is considered as peak, normal and off peak periods, respectively. The power availability and the cost per kWh during the off-peak period are considered to be {0.5, 0.25, 2.5} kW and {0.1, 0.14, 0.17} \$/kWh, respectively.

Similarly the power and cost during peak period are {0.4, 0.2, 2.5} kW and {0.18, 0.2, 0.225} \$/kWh, respectively. For normal period, these values are {0.45, 0.25, 2.5} kW and {0.14, 0.17, 0.21} \$/kWh, respectively.

Assume that we want to schedule the dishwasher, washing machine, and dryer. The lower and upper bound of the operating time is 08:30 A.M.–11:00 A.M. for the washing machine and 09:00 A.M.–12:00 P.M. for the cloth dryer. The dishwasher needs to be scheduled twice: between 08:00 A.M.–11:30 A.M. and between 7:00 P.M.–10:00 P.M.. The branch and bound algorithm discussed in Section III [38] was applied to this scheduling problem. The optimal time of operation for the appliances

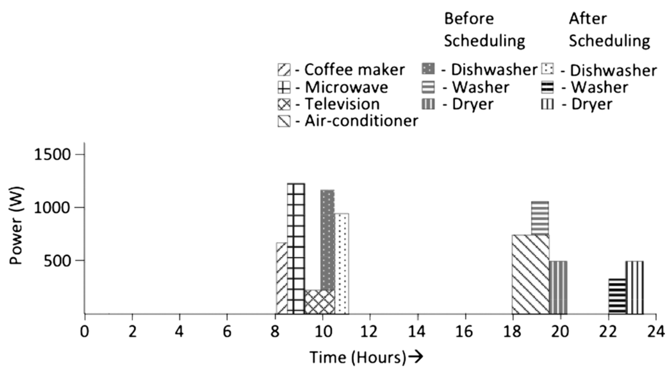

Fig. 8. Results of appliance operation when using the scheduling algorithm.

TABLE I
COST OF APPLIANCE OPERATION WITH AND WITHOUT SCHEDULING

Appliance	Cost ($) – before scheduling	Cost ($) – after scheduling
Dishwasher	0.080	0.075
Washer	0.044	0.020
Dryer	0.063	0.045

as given by the algorithm is 08:00 A.M. for the dishwasher, 09:08 A.M. for the washing machine, 10:30 A.M. for the dryer, and 07:45 P.M. for the second operation of the dishwasher.

As another example, consider the case when a user has four un-schedulable appliances, which must be turned on at a certain time, and three schedulable appliances that have flexible starting times. Suppose the user decides to start these appliances as shown in Fig. 8. Using the scheduling algorithm with a typical pricing profile, the scheduler provides an alternative set of times, also shown in Fig. 8. The pricing differences are shown in Table I.

The results indicate that by using a TOU pricing scheme and an optimal scheduling algorithm the cost of electricity can be reduced while smoothing the energy demand.

This study leads the way to offer DR solutions to residential customers by aggregating the demand. The results we presented through simulations suggest that both customers and utility company may benefit from demand response programs extended to residential customers.

V. SOME REMARKS ON PRICING

In the home management system discussed in this paper, the assumption is that the utility uses a TOU pricing scheme, based upon DR. In this section, the pricing scheme used in this study, is summarized, for completeness sake. Details of the pricing scheme are provided in [27]. We note that several pricing schemes exist and the method summarized here is just one example of such an approach.

Consider a pricing strategy that is based on maximization of a society's welfare. The basic idea of this pricing method is that the electricity price at the generation side depends on its consumption and the electricity demand on the customer side is related to the price (elasticity). If the profit to the utility company is set to zero, the cost of power generation equals the cost paid by the customer. Assuming a quadratic power generation cost curve, the objective is to maximize the consumer surplus subject to the constraint that the power generation costs should be less than or equal to the total revenue from the consumer. This can be written as:

$$\max \sum_{i=1}^{24} P_i(\Delta P_i) \tag{3}$$

where $\mathrm{P_i}$ is power consumption, over a 24 hour period and ΔP_i is the percentage change in power consumption which can be written in terms of the elasticity and change in consumer costs. Then the pricing problem can be formulated as an optimization problem:

$$\max_{\Delta\bar{\beta}} \sum_{\mathrm{i}=1}^{24}\sum_{\mathrm{j}=1}^{3} \mathrm{P_i}\varepsilon_{\mathrm{ij}}\Delta\bar{\beta}_{\mathrm{j}} \tag{4}$$

subject to

$$\begin{aligned} &\sum_{\mathrm{i}=1}^{24} \mathrm{a}+\mathrm{bP_i}\left(1+\sum_{j=1}^{3}\varepsilon_{ij}\Delta\bar{\beta}_j\right)+\mathrm{c}\left(\mathrm{P}_i\left(1+\sum_{j=1}^{3}\varepsilon_{ij}\Delta\bar{\beta}_j\right)\right)^2 \\ &\quad< \sum_{i=1}^{24}\beta_i(1+\Delta\beta_i)\mathrm{P}_i\left(1+\sum_{j=1}^{3}\varepsilon_{ij}\Delta\bar{\beta}_j\right) \\ &\quad P_i(1+\Delta P_i) < P_i^{\max};\ i=1,\ldots,24 \end{aligned} \tag{5}$$

where ε is elasticity coefficient, (a, b, c) are the coefficients in the quadratic power generation cost curve, and β is the price of electricity paid by the customer. The Δ terms are changes in the respective variables. We note that if there is a built-in profit to the utility, the left hand side of the first inequality would be multiplied by that profit factor.

VI. CONCLUSION

This paper presented a solution to DR for residential customers. An ANFIS-based MC was developed to forecast power demand based on the user's life style (i.e., usage patterns) and environmental/social factors impacting power consumption. An aggregator was used to gather the electricity consumption profiles from residential MCs to estimate the aggregated demand for energy in a region. A self-organizing home energy network with appliances as the end nodes was implemented. The MC communicates with the appliance nodes via a home energy network gateway node developed as part of this study. A scheduling algorithm was designed for managing the appliance schedules based on the branch and bound algorithm. The TOU pricing communicated to the customer is used by the MC to optimize scheduling of the appliances. The appliance scheduling algorithm is driven by the electricity price and the customer actions, and operates within the boundaries established by the customer. The customer can modify the appliance schedules, which may, however, result in the customer paying a higher price for the energy consumed. Results show that the proposed system is an effective solution for home energy management.

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