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Krishnendranath Mitra
Goutam Dutta

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INDIA

Electricity Consumption Scheduling with Energy Storage, Home-based Renewable Energy Production and A Customized Dynamic Pricing Scheme

Krishnendranath Mitra[1]
Goutam Dutta[2]

Abstract

In this paper we propose a scheduling model for electrical appliances in a dynamic pricing environment. Initially we have given a vector of price points for the next twenty four hours. We have developed an optimization model that minimizes cost to customer subject to operating time spans provided by the customer as per their requirements. The model is further modified to derive prices based on the consumption of electricity at the concerned time slot. We have also studied the effects of including energy storage and renewable energy generation at the consumer level. In this case we propose a linear price function that helps in automatically generating a price value for a time slot.

Keywords

Electrical appliance scheduling, dynamic pricing of retail electricity, price functions, use of electric battery in scheduling, in-house renewable generation

[1] Department of Business Management, University of Calcutta 1, Reformatory Street, Kolkata - 700 027, West Bengal, India, E-mail: kmitra.dgp@gmail.com
[2] Department of Production and Quantitative Methods, Wing 03, Indian Institute of Management, Vastrapur, Ahmedabad 380 015, Gujarat, India, Fax: +91 79 2630 6896, E-mail: goutam@iima.ac.in

Introduction

The electricity industry is facing an increase in demand as well as a remarkable technological development. However the supply of electricity is not increasing at the same pace as that of the demand. Demand management has thus become the need of the day. Dynamic pricing can be a good tool for demand management but due to regulated nature of the electricity market in most places, consumers face flat tariffs. This pricy policy leads to consumption of electricity by users in a way that leads to high aggregate demand at peak periods straining the capacities and low aggregate demand at off-peak periods leading to inefficiencies of generation. The problem of this demand supply mismatch can be handled by dynamic pricing and the use of automation in the scheduling of operation of the household appliances. Dynamic pricing in the form of different prices in different times of the day can influence customer behavior to consume more at low prices and less at higher prices. The time span of a day (24 hours) can be considered as a cycle for the load curve. The rescheduling of the use of electrical appliances from peak to off-peak hours eventually flattens the load profile.

The scheduling of the appliances needs a proper logic so as to operate the appliances in a way such that the expenses for electricity consumption get minimized. This scheduling process is however difficult to be done manually, especially when there are many appliances in the list and the price changes are frequent. In this context, it can be noted that the demand response can be done better with more number of price points in a day, i.e. having 48 numbers of time slots or price points, each of 0.5 hours duration, provides better demand control opportunity than 24 numbers of time slots or price points, each of 1 hour duration. When the number of price points increase further, it will be practically impossible for manually scheduling the jobs in the optimized way. Supporting technology in the form of smart meters and automatic schedulers will need to be included in the system to incorporate superior computing power that the model demands.

The use of dynamic pricing in electricity has been done in many places; however, the large scale utilization of the concept is still to be done. The use of dynamic pricing is generally done in the form of bulk pricing or time of the day pricing. In these cases the prices vary based on bulk consumption or prices at the various time slots are anticipated beforehand by the supplier by relying on consumption trends and related statistics. Thus these price points are known beforehand and allow the customer to schedule their jobs with price information available sufficiently ahead of time. The demand response can be further fine-tuned by incorporating real time pricing (RTP) in the system. The use of RTP will require faster computing and data transmitting technologies to operate the automated scheduler. In such a case the price provided at any time slot can be calculated as a predefined function of the demand at that time slot.

The provision of similar price variations to all consumers at the same time may however lead to a peaked load profile instead of a flat one. This can be due to the automated scheduling of maximum consumption in each household during the low priced time slots. In such a case, the efficiency of a scheduling model for a single home can help in minimized costs for the household but will lead to another demand supply mismatch problem. This problem can be solved by including each and every consumer or household in the scheduling model. Such a model can take care of the limiting conditions for the supplier. This problem can also be addressed by offering different prices to different customers at the same time so that their optimization goals become different. Customized pricing can be useful in this case.

This paper consists of a short literature review on scheduling of household electrical appliances and related issues like battery charging and discharging to enhance comfort level in the scheduling process. The research gap is identified and the importance of the problem is explained. The following section describes the model and expresses its formulation in mathematical notations. This model is tried and tested with the help of AMPL modeling language and the statistics of the model are provided. The scope of further work is mentioned at the end of the paper.

Literature Review

(Chen et al., 2013) use linear programming to obtain a deterministic scheduling solution and use an energy consumption adaptation variable to account for uncertainties. They used the day-ahead pricing data of Ameren Illinois Power Corporation as the input to their model and two sets of solar photovoltaic module of Kyocera Solar Incorporation as the solar energy source for the model. Their model achieves between 41% and 24% reduction of expenditure over traditional deterministic schemes and provides a schedule within 10 seconds. (Agnetis et al., 2013) identify various types of appliances with varying load types like shiftable, thermal, interruptible, and non-manageable and then schedule their operations. The authors use a Mixed Integer Linear Programming (MILP) model and a heuristic algorithm to solve the NP-hard problem. The objective functions are cost minimization and comfort maximization through scheduling preferences and climatic control. (Wang et al., 2013) present a novel Traversal and Pruning algorithm to schedule thermostatically controlled household loads to optimize an objective considering both expenditure and comfort. This algorithm has optimality, robustness, flexibility and speed. The authors propose that this algorithm can be useful in designing any automated energy management system.

(Hubert & Grijalva, 2012) incorporate electricity storage provisions in the scheduling problem by classifying loads as energy storage system, non-interruptible loads, and thermodynamic loads. They use MILP for robust optimized consumption scheduling to minimize the impact of stochastic inputs on the objective function. The objective function integrates electric, thermodynamic, economic, comfort, and environmental parameters. (Mishra et al., 2013) observe that greedy charging algorithms when used at large scales shifts the peaks causing grid instability. They present a storage adoption cycle incentivizing the use of energy storage at large scales with variable rates and peak demand surcharge. They show that consumers can flatten their demand by 18% of the minimum optimal capacity to flatten grid demand of a centralized system.

(Liu et al., 2012) emphasize the maximum use of renewable resources in a load scheduling problem. Their model depends on weather forecasts. They classify appliances based on type of energy consumption and assign dynamic priority in the scheduling process. (Dupont et al., 2012) state that the renewable energy tariff scheme can be used to increase renewable energy consumption during periods of high renewable energy generation. They use integer linear programming to optimize this scheduling problem taking into account customer preferences. This paper also emphasizes the use of automation in households for consumption scheduling over the year. (Hu et al., 2010) incorporate both active and reactive power demand and generation in the scheduling problem. The authors use a non-linear load optimization method in a real-time pricing environment. The scheduling of consumption is studied for three customer groups – industrial, commercial, and residential, and for three load periods – peak load, flat load, and off-peak load periods.

Scheduling in individual homes must be linked to the aggregate demand situation. Thus it is necessary to model the individual household scheduling incorporating the aggregate demand. (Kishore & Snyder, 2010) point out that shifting the load from peak hours to off-peak hours in each household by means of a same price signal can shift the aggregate peak to the previously off-peak zone. Thus the authors optimize electricity consumption within a home and across multiple homes. The in-home scheduling model attaches the probabilities of start and stop of operation of any appliance in the next time period. It also considers a cost for delay of start of operation. The model minimizes the total cost of electricity in a deterministic dynamic pricing environment. In the neighborhood-level scheduling model, the authors assume a well communicated neighborhood where each household has a minimum guaranteed load at each time slot. The neighborhood however has a maximum limit of energy at each time slot. The idea is to distribute this available power to all households thereby minimizing total costs. A second delay cost is associated in the model to address the delay of starting an appliance after the specified maximum delay time. (Luh et al., 1982) present a 'load adaptive pricing' philosophy formulated as a closed-loop Stackelberg game. The authors demonstrate that a team optimum can be achieved by the proposed approach since the utility company can induce a cooperative behaviour from the customer.

(Li et al., 2011) align individual optimality with social optimality by means of a distributed algorithm. Each customer has a utility function and provisions for energy storage. This allows them to forecast their total individual demand for a future time after maximizing their individual benefit. The utility company collects these forecasts from all households and generates a price based on its cost function. This price is then published and the individual households reschedule their consumption. After several iterations, the consumption schedule of each household and the price offered by the utility gets fixed. (Cui et al., 2012) describe how scheduling of household loads helps electricity suppliers to maximize their profits and the global controller to maximize social welfare. The authors use greedy algorithm for the first model with pre-announced dynamic tariffs. They also devise a model for the utilities based on consumers' schedules. Table 6 shows the different scheduling methods used in the referenced literature.

The scheduling of operation of each appliance can be done by defining various states of the operation for the appliance, like appliance not operating (either not started operation or ended operation), appliance ready to operate and appliance operating (Chapman et.al., 2013). The concept of joint state action, where one appliance operates before another appliance, is explained in the residential demand response approach following realistic assumptions in the paper. (Goudarzi et. al., 2011) propose pricing policies in two different scenarios to help facilities schedule their electricity consumption. They work with a TOU-dependent energy pricing function and a TOU and total power consumption dependent energy pricing function. They use heuristics to efficiently minimize the consumer's electricity expenditure and demonstrate demand shaping ability of the methods. (Zhou et al., 2014) develops an appliance scheduling model to use the uncertain photovoltaic energy generated in-house in a time varying dynamic pricing environment. (Dlamini and Cromieres, 2012) provide load shifting algorithms for flattening the load profile of households. They describe the flattening in terms of load-leveling effect and peak-load ratio.

Research Gap

Models for electrical appliance scheduling in a household with real time pricing options can be developed. It is possible to use different types of pricing schemes or demand management approaches in such optimization models. These demand management aspects may contain variable prices, rebates and consumption limit controls. Some research have been done in shifting the electrical load of individual household from high priced time to low priced time. But this merely shifts the peak load on the aggregate basis to the low priced periods. Thus each customer must be charged in a way so that their individual load curve flattens. This will lead to flattening of the aggregate load curve. Such aspects of household electricity appliance scheduling have not been studied extensively. Different price functions leading to customized prices in the retail electricity sector can be studied to check their applicability as effective revenue management options. Opportunities lie in the practical application of such models in the Indian context or in other developing nations.

Importance of the present Problem

The load profile of electricity needs to be flattened so as to avoid black outs and brown outs at some areas during peak hours and underutilization of generating facilities leading to lower efficiency levels during off-peak hours. Implementation of dynamic pricing in retail electricity for the residential sector can prove to be an important demand side management tool. The varying nature of pricing can induce a variance in the consumption pattern according to economic laws, i.e. to reduce demand during peak hours, price needs to be increased and to increase demand during off-peak hours, price needs to be reduced. Consumers can be stimulated to shift their electricity consumption from higher tariff periods to lower tariff periods. This shift will help to maintain or even reduce their individual electricity expenditure and in turn, on an aggregate level, will help the market experience a flatter demand profile. The consumers will normally not have the incentive to reduce their electricity consumption unless there is marked cost differences associated with the shifting of their electricity consumption to periods other than their primary preferences. Manually scheduling the operation of appliances is a tedious job and will be almost impossible for any consumer. So a scheduling algorithm is required supported by suitable supporting technology to execute the scheduling job every day. Therefore, the successful implementation of demand side management in electricity will require such scheduling algorithms to automate the optimization of expenses by scheduling of appliances. At the same time such algorithm must address the comfort needs of the individual households as far as possible. The flattening of the load profile is specifically important in developing and underdeveloped countries to slow down the requirement of capacity addition in power sector.

Assumptions of the Model

The following are the assumptions in the models:

1. There are ninety-six time slots each of fifteen minutes duration. All operations are at least one time slot long. Thus any appliance/battery must start operation at the beginning of a time slot and stop at the end of a time slot.
2. Power consumed by each appliance and battery and power discharged by battery is at a constant rate. If any appliance has different consumption rates within its operation, we will denote those different phases of operation as different appliances.
3. A battery can either charge or discharge or loose a leakage power at any time slot at constant rates and have constant efficiencies irrespective of the power stored in the battery at that time.
4. The whole amount of renewable energy generated at a time slot can either be consumed in-house or sold to the grid. There is no part use and part sell.

Mathematical Representation of the Model

The mathematical representation for the optimization model for scheduling of in-house electric appliances in a dynamic pricing environment is as follows:

Indices:

t= Index for time slots

a= Index for appliances

b= Index for battery banks

Sets:

T= Set of time slots indexed by t=1, 2, …, 96.

A= Set of appliances indexed by a=1, 2,…,A_{max} ; A_{max} is the maximum number of appliances that the user sets for scheduling in the said time horizon.

B= Set of battery banks indexed by b=1,2,…,B_{max}

Variables:

I_{ta} =Binary scheduling variable denoting which appliance, 'a', works in which time slot, 't'.

I_{ta} = 1, if appliance 'a' operates at time slot 't'.

= 0, if appliance 'a' does not operate at time slot 't'.

The nature of values of I_{ta} are tabulated below.

State of operation of appliance 'a' at time slot 't'	I_{ta}
Appliance 'a' not yet started at time slot 't'	0
Appliance 'a' in operation at time slot 't'	1
Appliance 'a' stopped at time slot 't' after completion of operation	0

$J1_{tb}$ = Binary variable that indicates the time slots for the charging of the battery bank 'b'.

$J1_{tb}$ = 1, if battery bank 'b' is getting charged at time 't'

= 0, if battery bank 'b' is not getting charged at time 't'

$J2_{tb}$ = Binary variable that indicates the time slots for the discharging of the battery bank 'b'.

$J2_{tb}$ = 1, if battery bank 'b' is discharging to supply to the in-house power demand at time 't' and thus substituting grid power consumption

= 0, if battery bank 'b' is not discharging to the in-house power demand at time 't'

The nature of values of $J1_{tb}$ and $J2_{tb}$ are tabulated below.

State of operation of battery 'b' at time slot 't'	$J1_{tb}$	$J2_{tb}$
Battery 'b' is charging from the grid at time slot 't'	1	0
Energy is consumed from battery 'b' by appliances at time slot 't'	0	1
Battery 'b' is idle at time slot 't' (energy leakage)	0	0

K_t = Binary variable that indicates the time slots for using renewable energy from in-house renewable energy generator for satisfying part of home energy demand.

K_t = 1, if renewable energy generated is used for the home power requirement at time 't'

= 0, if renewable energy generated is sold to the energy market at time 't'

The nature of values of K_t is tabulated below.

Action on the renewable energy generated (rg_t) at time slot 't'	K_t
The whole energy generated (rg_t) at time slot 't' is used in the home	1
The whole energy generated (rg_t) at time slot 't' is sold to the grid	0

s_a = The time slot at which appliance 'a' actually starts operation

p_t = Price/unit of electrical energy at time t (>=0)

$p1_t$ = Component of price of electrical energy at time 't' related to consumption of the individual household concerned (>=0)

$p2_t$ = Component of price of electrical energy at time 't' related to overall consumption level in the electricity grid (>=0)

E_t = Net electrical power consumed from the grid at time 't'

$E1_t$ = The electrical power consumed by only the appliances of the home at time 't'

$E2_t$ = The net electrical power consumed by appliances and including charging or discharging of battery at time 't'

w_{tb} = The energy stored in a battery bank 'b' at time 't'

ap = The average value of prices over all time slots

Parameters:

C_t = Limit on consumption from grid at time 't' (>=0)

T_a = Number of time slots needed to operate appliance 'a' (>=0, <=96)

e_a = Earliest time slot at which appliance 'a' can start (>=0, <=96)

l_a = Latest time slot by which appliance 'a' can stop (>=1, <=96)

rp_a = Rated power consumption of appliance 'a' (>=0)

D_t = Forecasted aggregate demand in the grid at time slot 't'

M_i = Rate of change of price component $p1_t$ with respect to in-house consumption E_t. Here 'i' represent the i th consumption slab.

N = Rate of change of price component $p2_t$ with respect to change in aggregate demand D_t.

W_b = Energy storage capacity of the battery bank 'b'

wo_b = Energy stored in the battery bank 'b' at the beginning of the time horizon

ch_b = Amount of power charged in battery 'b' in one time slot.

dch_b = Amount of power discharged from battery 'b' in one time slot for in-house consumption

$dchm_b$ = Amount of power discharged from battery 'b' as a leakage if it is not used in a time slot.

pr_t = The price/unit of renewable energy in the electricity market at time slot't'

rg_t = The forecasted power generated by in-house renewable energy source at time slot 't'

d = The duration of one time slot in hours

$f1_b$ = A fraction of the battery storage capacity used to represent triggering of battery charging

$f2_b$ = A fraction of the battery storage capacity used to represent triggering of battery discharging

ef_b = Overall efficiency of the battery 'b'

Objective Function:

The objective of the problem is to minimize the total expenditure on electricity over a period of twenty-four hours by scheduling the operation of the in-house electrical appliances, the charging and discharging of batteries and the consumption or sell of renewable energy generated in-house within a dynamic pricing setup. This in turn flattens the in-house load curve as far as possible. The objective is given as follows:

Minimize

$$z = \sum_t p_t d\left(\sum_a rp_a I_{ta} + \sum_b ch_b J1_{tb} - \sum_b dch_b J2_{tb}\right)$$

$$- \sum_t rg_t d\left(K_t p_t + (1 - K_t) pr_t\right)$$

………………………………………….……. (1)

The power consumption by all the appliances in a time slot 't' is given by

$$E1_t = \sum_a rp_a I_{ta} \qquad \text{…………………….…………. (2)}$$

Power consumption $E2_t$ at time slot 't' gives the net power consumed including appliances and the battery charging or discharging. This is given by

$$E2_t = E1_t + \sum_b ch_b J1_{tb} - \sum_b dch_b J2_{tb} \qquad \text{………….. (3)}$$

Net power consumption E_t at time slot 't' includes the appliance, battery charging or discharging and renewable energy consumption. The is given by

$$E_t = E2_t - \left(K_t rg_t\right) \qquad \text{……………………………... (4)}$$

Constraints:

The following constraints can be applied while optimizing the objective function.

1) Earliest start constraint: An appliance should not start before its user-selected earliest start time and hence the actual start time should be equal or greater than the earliest start time.

$$s_a \geq e_a \qquad ; \forall a \epsilon A \qquad \text{……………….. (5)}$$

2) Latest end constraint: An appliance should not operate after its user-selected latest end time and hence the sum of actual start time and the time of operation of the appliance

should not be more than one plus the latest end time. The one is to eliminate the second time counting of the time slot denoted by s_a which can be included in T_a .

$$s_a + T_a - 1 \leq l_a \quad ; \forall a\epsilon A \quad \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

3) Maximum power limit constraint: The net electrical power consumed in any time slot tϵT must be equal or less than the in-house consumption limit at that time slot tϵT.

$$E_t \leq C_t \quad ; \forall t\epsilon T \quad \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

4) Total operating time constraint: The sum of all I_{ta} for any appliance aϵA over all the time slots of T will be equal to the total operation time for that appliance.

$$\sum_t I_{ta} = T_a \quad ; \forall \ a\epsilon A \quad \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

5) Constraints on binary appliance scheduling variables: The binary variable I must have a value of 1 only during those time slots when the appliance is running, i.e. from (s_a) to (s_a+T_a-1).

If $s_a \leq t \leq s_a + T_a - 1$,

then I[t,a] = 1, else I[t,a] = 0 ;$\forall$ aϵA, tϵT ……………… (9)

6) Appliance sequencing constraint: The sequencing of any two appliances can be done. For example, an appliance a_1 has to be started only when another appliance a_2 has completed its operation. Then we can mathematically express it as follows.

$$s_{a1} \geq s_{a2} + T_{a2} \quad ; \forall \ a1, a2\epsilon A \quad \ldots\ldots\ldots\ldots (10)$$

Different appliances or different phases of the same appliance can be sequenced in an order by this constraint.

7) The values of parameters used for deciding the value of $J1_{tb}$ and $J2_{tb}$ can vary according to the requirements of the user. These are as follows:
   a) $J1_{tb}$ is one when the battery bank 'b' is charging at time t. The charging can occur only if the battery power at that time is less than a certain fraction ($f1_b$) of battery storage capacity and either the energy price is less than the average price over all time slots or the renewable energy generated is more than the power required to charge the battery.

$$\text{If } (w_{tb} \leq f1_b W_b) \text{ AND } \{(p_t \leq ap) \ OR \ (rg_t \geq ch_b)\}$$

then $J1_{tb}=1$, else $J1_{tb}=0$; $\forall$ $b \epsilon B$, $t \epsilon T$ ……… (11)

When t=1, $w_{tb} = wo_b$.

b) $J2_{tb}$ is one when the battery bank 'b' is discharging to the in-house consumption at time t. The discharging occurs only if the battery power at that time is more than a certain fraction ($f2_b$) of battery storage capacity and the energy price is more than the average price over all time slots.

If $(w_{tb} \geq f2_b W_b)$ AND $(p_t \geq ap)$

then $J2_{tb}=1$, else $J2_{tb}=0$; $\forall$ $b \epsilon B$, $t \epsilon T$ ……… (12)

8) Price constraint: In this model, the unit price of electricity at time 't' is generated based on the in-house consumption as well as the aggregate demand in the grid at time 't'. As the consumption of electricity in a time slot increases, the price per unit of electricity also increases and vice versa. This acts as a control measure on the amount of consumption.

a) The price component $p1_t$ is represented as a piecewise linear function of in-house electricity consumption.

$$p1_t = M_i E_t + cons_i \qquad ; \forall \ t \epsilon T \qquad \text{………………… (13)}$$

Each linear piece in the function is represented by 'i' and the values of M_i and $cons_i$ depend on the consumption slab 'i' within which the value of the associated E_t falls.

b) The price component $p2_t$ is represented as a linear function of aggregate demand.

$$p2_t = N \times D_t \qquad ; \forall \ t \epsilon T \qquad \text{....................... (14)}$$

c) The net price of electricity per unit is given by the sum of these two components.

$$p_t = p1_t + p2_t \qquad ; \forall \ t \epsilon T \qquad \text{....................... (15)}$$

9) Battery capacity constraint: The power content of the battery at any point of time must be less than its total power storage capacity.

$$w_{tb} \leq W_b \qquad ; \forall \ t \epsilon T, b \epsilon B \qquad \text{..…………. (16)}$$

10) Battery energy level constraint: The power content of the battery at any time slot is given by the sum of power content at the beginning of the time horizon and charged power minus the discharged power for all previous time slots.

$$w_{tb} = wo_b + \sum_{i=1}^{t} ef_b\, ch_b dJ1_{ib} - \sum_{i=1}^{t} dch_b d\, J2_{ib} - \sum_{i=1}^{t} dchm_b\, d(1 - J1_{ib} - J2_{ib})$$

$;\forall\ t\epsilon T,\ b\epsilon B$ ………… (17)

Here we consider battery efficiency ef_b that is constant irrespective of the charge stored in the battery.

11) Constraints on binary variable renewable energy use: The renewable energy at time ‘t’ is to be used for consumption at home only when the amount of renewable power generated is less than the power consumption by the appliance and battery at time ‘t’ and the price at that time is more than the market price of renewable energy at time ‘t’.

If $(p_t \geq pr_t)$ AND $(E2_t \geq rg_t)$

then $K1_t = 1$, else $K1_t = 0$; $\forall\ t\epsilon T$ …………..(18)

Implementation of the model

The models were implemented in AMPL (A Mathematical Programing Language) with CPLEX solver. We used feasibility pump heuristic approach in CPLEX to solve this model. The system was run in Windows 8 operating system and has taken around a couple of seconds to provide an optimal solution.

Experiments

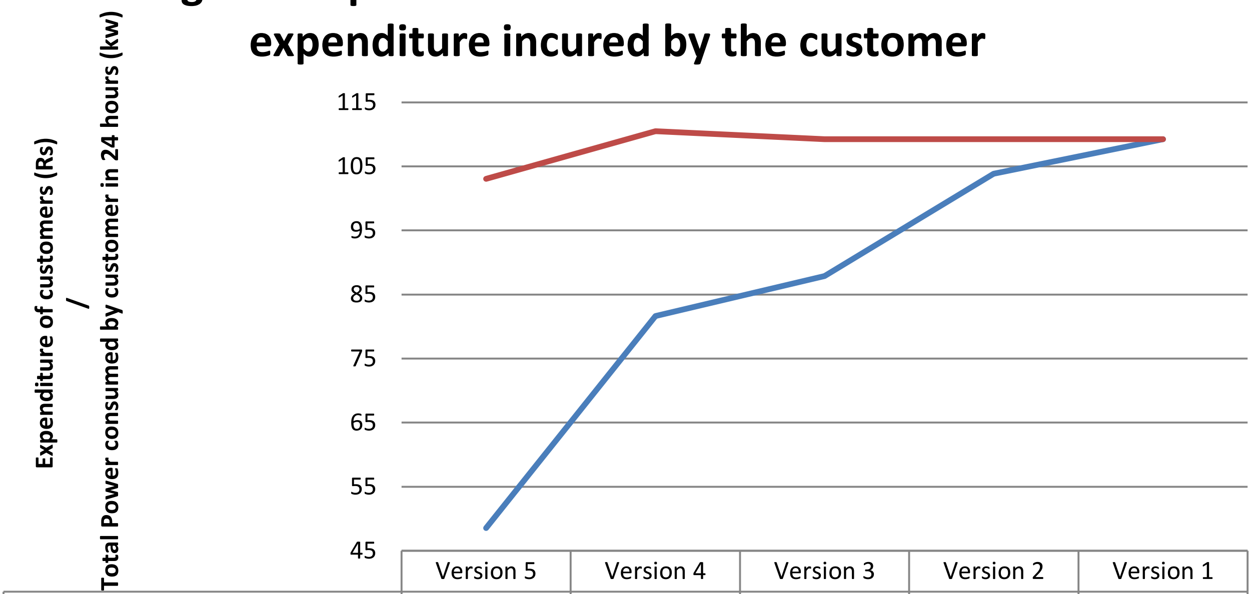
The model is developed in five versions and each version is tested to compare their effectiveness. The differences in the versions are listed below.

	Model Speciality	Assumed Values
Version 1	Flat prices are offered to the consumers. Thus price per unit of electrical energy remains fixed irrespective of the grid demand and the consumption by the concerned consumer.	We have assumed Rs 4 per unit (Kwh) of electrical energy as flat rate.
Version 2	A fixed component of per unit price is offered and a dynamic component of price is administered based on grid demand. The more the grid demand, the more is the value of the dynamic component. This dynamic component adds over and above the fixed component to give the total price per unit of electricity.	We have assumed the fixed component as Rs 3.5/Kwh and the dynamic price can vary from 0 to Rs 1/Kwh.
Version 3	There are two components of per unit price. One component is based on the grid demand and the other is based on the consumption of the concerned consumer. Both the components are dynamic in nature and price increases with increase in demand or consumption. The two components are added to get the net price per unit.	We have assumed the first price component to vary from 0 to Rs 8.5/Kwh in a piecewise linear function based on consumption of the concerned consumer (4 KWh maximum line capacity). The price component for grid demand can vary from 0 to Rs 1/Kwh.
Version 4	Maintaining the pricing scheme in version 3, we assume the use of an energy storage like battery. The battery charges from the grid when the net price is low and discharges when the net price is high. Hence it is expected to reduce consumer's electricity expenditure.	We have assumed the same pricing scheme as in version 3. We have also assumed a battery of capacity 4 Kw connected to the consumer's electric line such that in every time slot it either charges at 0.25 Kw/15 mins, or discharges at 0.5 Kw/15 mins or discharges a leakage power of 0.001 Kw/15 mins if not in use.
Version 5	Maintaining the situation in version 4 we introduce a renewable energy generator like solar panel or rooftop wind generator. The system is suppose to either utilize renewable energy generated at any time slot for in-house consumption or sell the same at Rs 2/Kwh. The ultimate objective is the minimize expenditure.	We have assumed a renewable energy generator that can generate at the most 2 Kw of power at any time slot of 15 minutes.

The results of the experiments are shown below.

The total power consumed from the grid and the total expenditure incurred by the customer over twenty-four hours in the different versions is listed below.

Fig 1: The power consumed in 24 hours and the expenditure incured by the customer



	Version 5	Version 4	Version 3	Version 2	Version 1
Expenditure of customers (Rs)	48.53234085	81.62359996	87.87945622	103.8407035	109.24
Total power consumed by customer (kw)	103.04	110.49	109.24	109.24	109.24

The Versions of the Model

The approximate computational time (varies due to the use of heuristics) by the different models is plotted in the figure below.

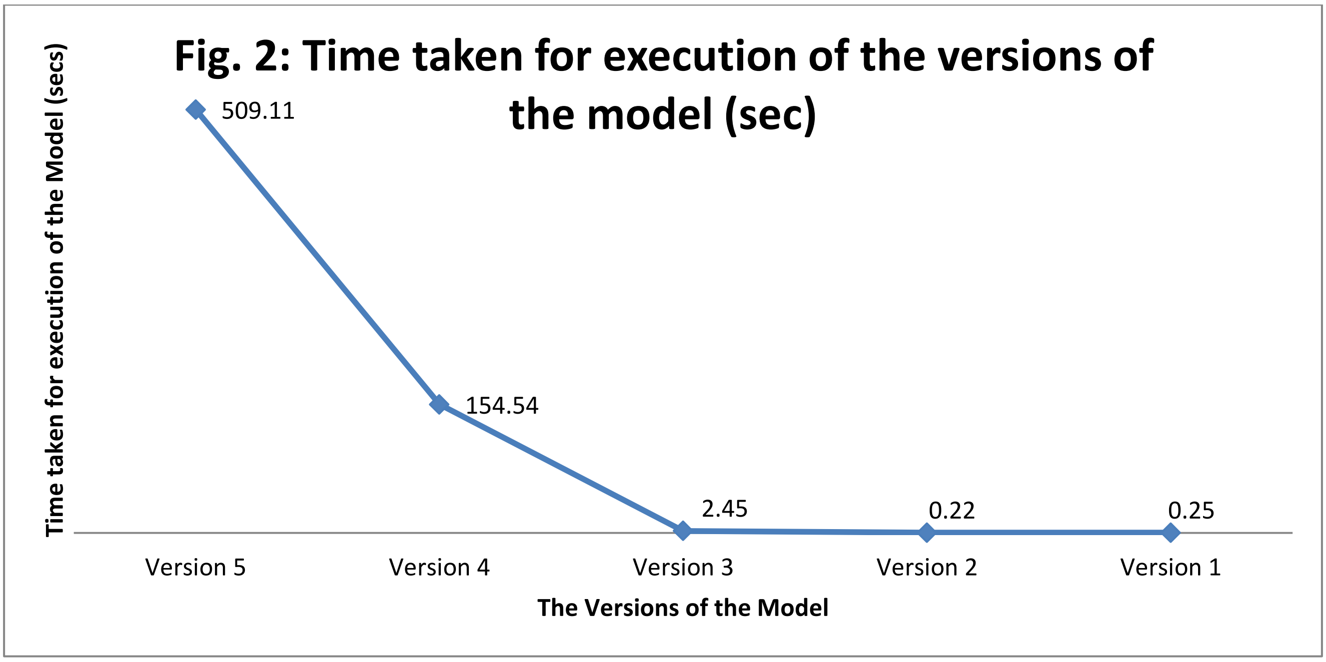


Fig. 2: Time taken for execution of the versions of the model (sec)

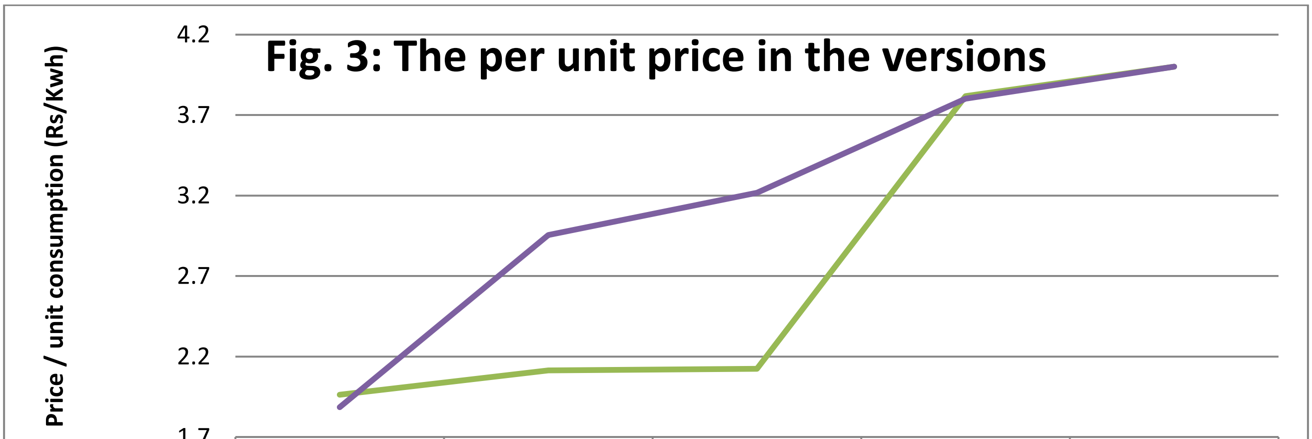
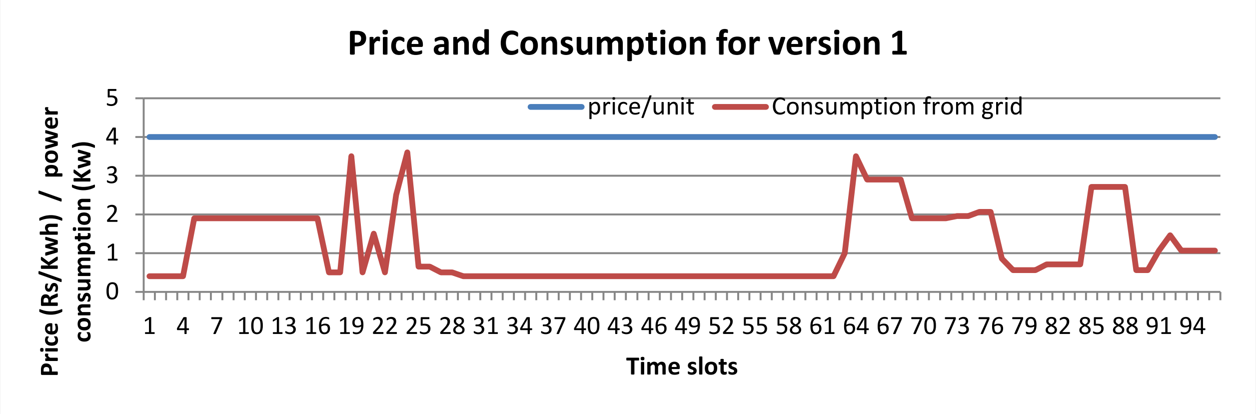


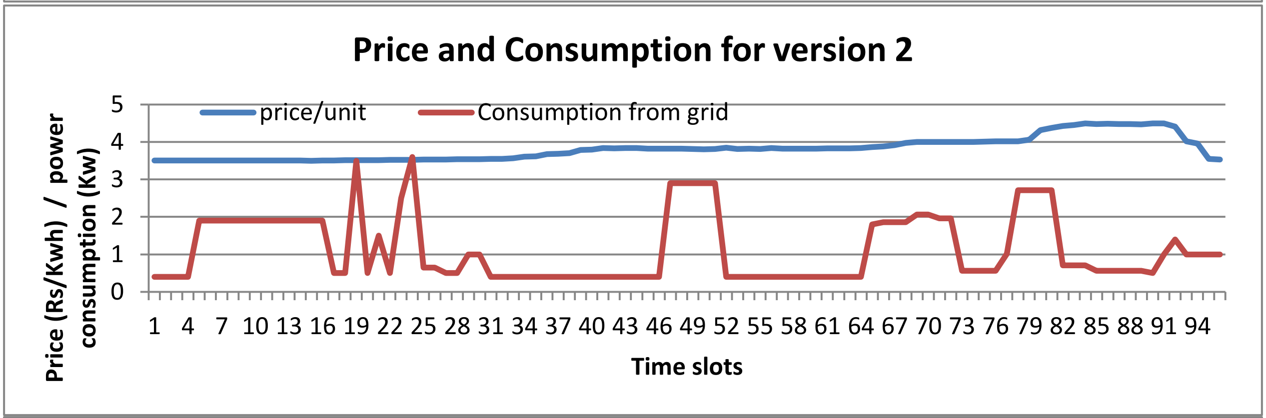
Fig. 3: The per unit price in the versions

	Version 5	Version 4	Version 3	Version 2	Version 1
price/time	1.9632	2.11283	2.12288	3.81715	4
price/unit	1.884019443	2.954967869	3.217849001	3.80229599	4

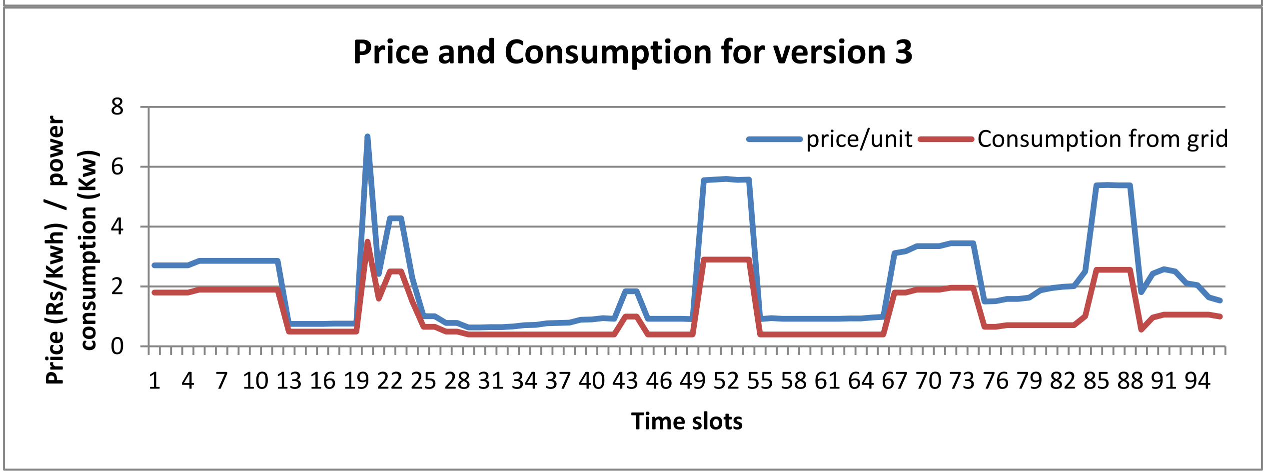
The Versions of the Model



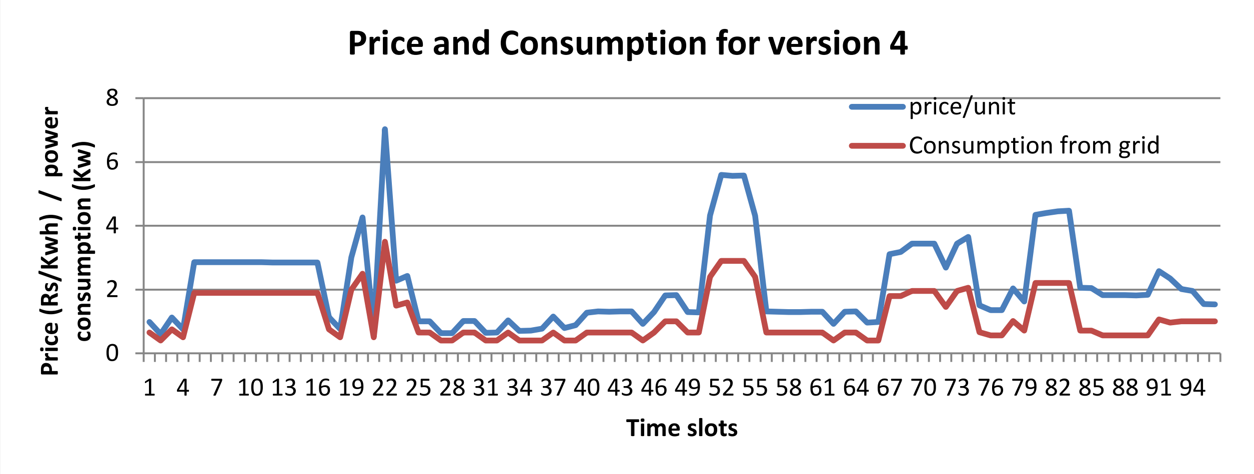
Price and Consumption for version 1
price/unit
Consumption from grid
Price (Rs/Kwh) / power consumption (Kw)
Time slots

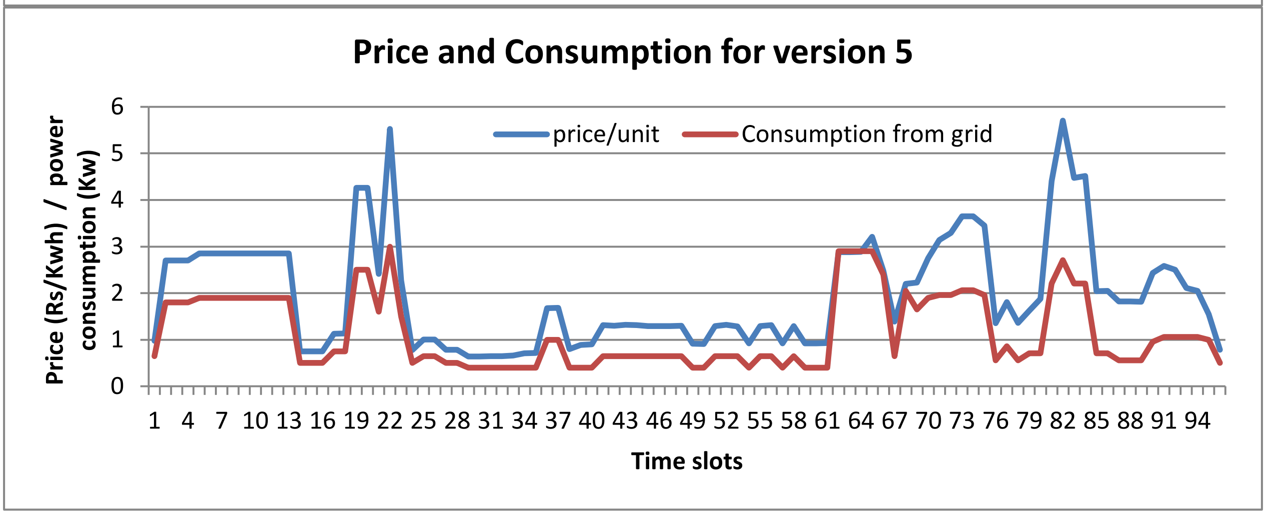


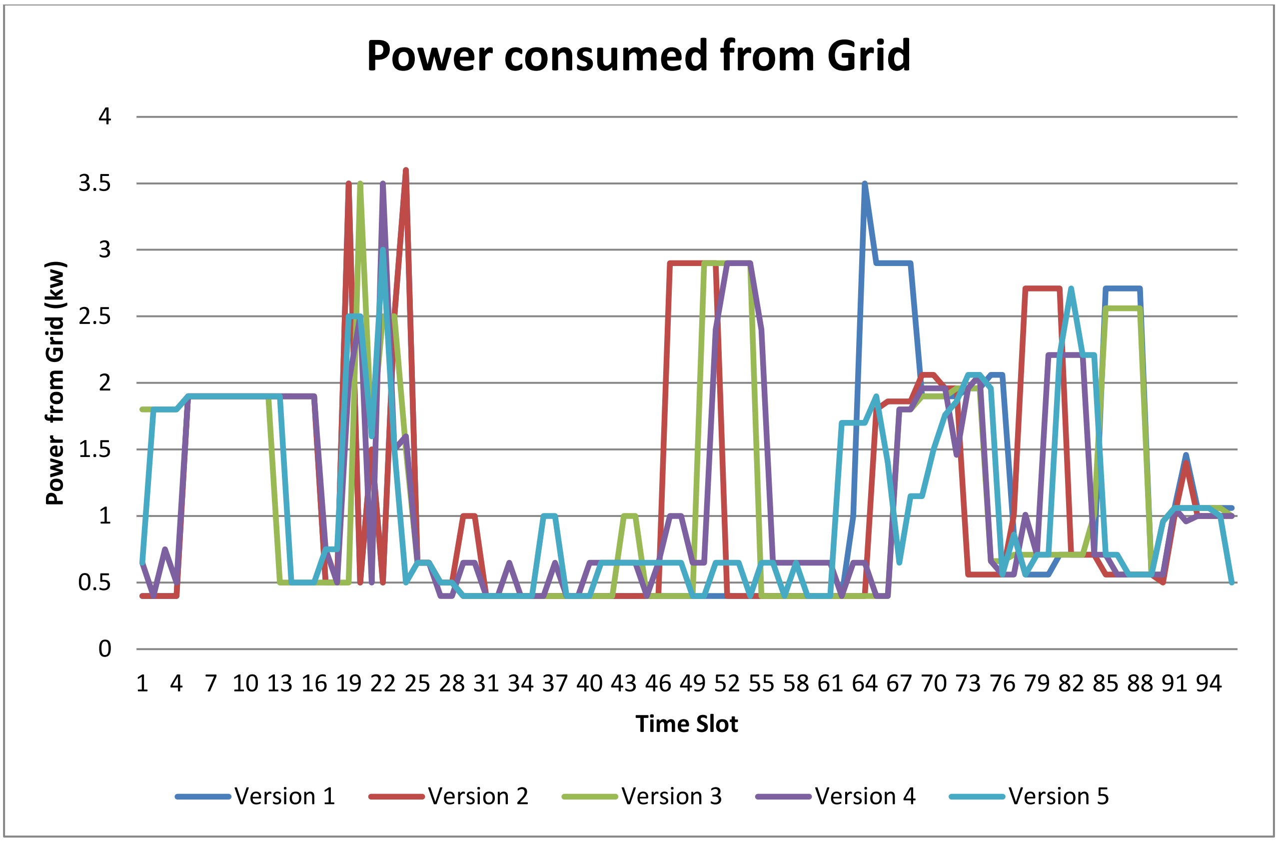
Price and Consumption for version 2
price/unit
Consumption from grid
Price (Rs/Kwh) / power consumption (Kw)
Time slots



Price and Consumption for version 3
price/unit
Consumption from grid
Price (Rs/Kwh) / power consumption (Kw)
Time slots


Price and Consumption for version 4
price/unit
Consumption from grid
Price (Rs/Kwh) / power consumption (Kw)
0
2
4
6
8
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49 52 55 58 61 64 67 70 73 76 79 82 85 88 91 94
Time slots


Price and Consumption for version 5
price/unit
Consumption from grid
Price (Rs/Kwh) / power consumption (Kw)
0
1
2
3
4
5
6
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49 52 55 58 61 64 67 70 73 76 79 82 85 88 91 94
Time slots



Results and Interpretations/Managerial Insights

The experiments highlight a number of inferences. The model is a Mixed Integer Linear Programming problem with high level of computational complexity. We have used the feasibility pump heuristics option of cplex to speed up the execution time. With the increase of the number of schedulable appliances or the increase of the time window of operation of the appliances, the model will become harder to solve.

The complexity of the model versions increase from version 1 to version 5. The addition of battery and renewable energy in the system increases the operation time significantly as can be seen in the plot of time of execution.

The expenditure incurred by the customer decreases with the advancement of the versions. The flat rate scheme offers a much higher expenditure than the dynamic versions. The consumption from grid slightly increases with the use of battery and decreases with the use of renewable energy. The price per unit of electricity also decreases with the inclusion of dynamic components in price and the addition of battery and renewable in the system. The results show that from the consumer's point of view, dynamic pricing which is dependent on grid demand and individual consumption is better than dynamic pricing that is dependent on grid demand alone which is in turn is better than flat pricing. The use of battery and renewable energy generation at home helps the consumer to further lower his/her electricity bill and flatten the individual load curve.

Conclusion and Extension

The model can be used for a broader range of situations including different price functions. This can help in developing the model for real time pricing and make it more realistic. Several consumer comfort issues and welfare issues can also be incorporated in the model to improve its applicability and realistic nature. The price function can be considered to be exponential or of any other form that matches most with reality. Different houses can be connected in the model to integrate the individual home appliance scheduler with other homes connected to a grid or microgrid.

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