Optimized Residential Loads Scheduling Based On Dynamic Pricing Of Electricity : A Simulation Study

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***Abstract* —This paper presents a simulation study which addresses Demand Side Management (DSM) via scheduling and optimization of a set of residential smart appliances under day-ahead variable pricing with the aim of minimizing the customer's energy bill. The appliances' operation and the overall model are subject to the manufacturer and user specific constraints formulated as a constrained linear programming problem. The overall model is simulated using MATLAB and SIMULINK / SimPowerSystems basic blocks. The results comparing Real Time Pricing (RTP) and the Fixed Time Tariff (FTT) demonstrate that optimal scheduling of the residential smart appliances can potentially result in energy cost savings. The extension of the model to incorporate renewable energy resources and storage system is also discussed.**

Keywords-*Demand Side Management; Optimization; Linear Programming; Real Time Pricing; Smart Appliances*

I. INTRODUCTION

In the emerging smart grid, residential energy users would be given the opportunity to schedule their loads to control their electricity consumption and reduce cost. Dynamic pricing is one way to engage users to shift their energy consumption from peak periods; this will subsequently reduce the grid capacity requirements and lead to significant savings. The rate of energy usage varies between the time of use and the consumption pattern. With the depleting resources and no large-scale of economically viable renewable energy resources, it is pertinent to optimize the use of electricity to minimize wastage. User modification of Energy management systems such as Advanced Metering Infrastructure (AMI) and Home Area Network (HAN) are currently used in most homes to manage the peak demand [1]. The real time price of the energy consumed by the household appliances is measured and analyzed by the AMI using an Automated Meter Reading (AMR) device. AMR Collects the meter measurement from the network and communicates to utility providers. The communication is through various mediums such as Fixed Radio frequency, Power Line carrier (PLC), wimax etc. This approach enables the user to decide on how best to utilize the energy infrastructure in order to save cost, thus giving birth to the concept of smart grid which engages the user participation in achieving demand response at the consumption level [2].

Studies indicate that load balancing of the residential loads have considerable implications in terms of savings to both the electricity consumers and the utility providers [3]. This can be accomplished by investing in additional renewable generation which can be utilized during peak periods while minimizing the usage of non-renewable generation. The advantage of using renewable is to embrace the low carbon economy in order to make the environment fit for the future generation. This contributes to the green house emission reduction target.

Previous research has been carried out on scheduling and optimization of residential load. The authors in [4] used Integer Linear Programming (ILP) to optimize DSM in the prospective smart grid. The ILP implementation was based on the discretized time slot of the simulated appliances. They argued that a better hourly load scheduling is achieved when multiple neighborhood participate in scheduling. In [5], minimization of electricity cost via scheduling of the smart home appliances using Mixed Integer Linear Programming (MILP) is proposed. The authors in [6] introduced a simulation model of a set of typical home appliances based on their load profiles. The unique signature of appliance in terms of the real and reactive power consumption was also considered. The time varying electricity tariff in the management of the power grid was discussed in [7]. However, there is a need for a decision support system to provide advice for customers based on the dynamic price of the electricity since the customers may not be willing to adapt to the tariff information.

In this paper, we present a basic simulation model of the smart home appliances. The smart home has an Intelligent Energy controller which schedules and optimizes the usage of the household electrical appliances. The energy controller operating in closed-loop monitors the load status and collects power consumption profiles from the household appliances. The aggregated power consumption is then used in the optimization algorithm to determine the best scheduling taking into account the devices operational constraints and user's preferences constraints.

The remainder of the paper is organized as follow: Section 11 describes the modeling of the residential load and the key components of the architecture of the energy management and control of the residential loads. Sections 111 describe the scheduling of smart home formulation problem. The model and the simulation results are presented in section IV. Section V concludes the paper.

II. MODELLING OF THE RESIDENTIAL LOADS

The simulation model developed in this work is depicted in Fig. 1. The key components in the model are:

- *Residential Appliances or Loads*: These are divided into two categories namely: Schedulable or controllable loads (Washing Machines, Tumble dryers & Dish washers) and non-schedulable loads (Electric Heater and Refrigerator). The appliances are modeled as a simple resistive loads with an ideal switch to control the on/off of the appliance or the operational phase of the appliance.
- *Energy Management Controller:* This block performs the load scheduling for the loads based on the results from the optimization and sends out instructions to the appliances to determine their operation time.
- *Real Time Pricing (RTP) and Fixed Tariff Pricing (FTP):* These signals generate the unit costs of electricity used in the model. RTP holds the day-ahead forecasted price of electricity while FTT represents a flat (constant) tariff. In the simulations, the RTP varies from 0.05 rates per unit during off-peak periods to 0.5 rates per unit during peak consumption period. The FTT is a fixed price all through the day. It does not vary per hour and is considered to be 0.22 rates per unit in the work. The pricing combines with the power measured from the individual loads to obtain the energy cost and the total energy cost of the appliances over the simulation period

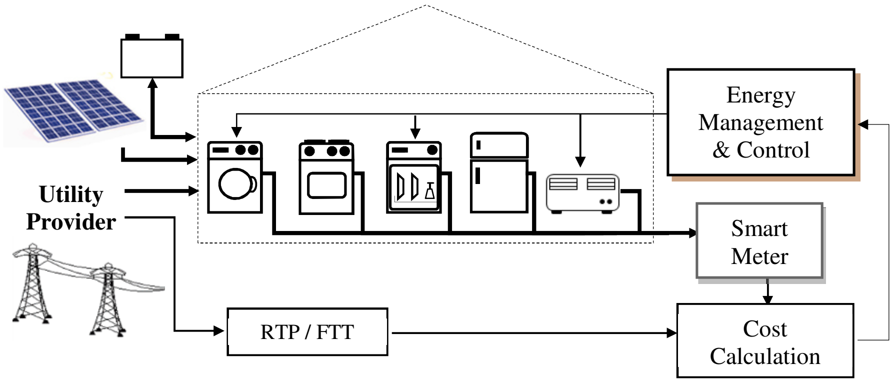

Fig. 1: Energy Management and Control of residential loads with dynamic pricing.

III. SCHEDULING OF THE RESIDENTIAL LOADS

Appliance scheduling involves the mathematical formulation of the objective function. In [5], the minimum electricity cost of the smart home appliance scheduling is based on MILP optimization technique. Using similar approach, the appliances are scheduled as a set of uninterruptible energy phases, each with specified time of operation and power consumption. As these energy phases are considered sequential with specific start time and duration, the next phase cannot begin until the previous phase is completed. In addition, a short delay is taken into account between the phases of a given appliance. This is subject to the physical (appliance-specific) and preference-based (user-specific) constraints.

The number of the appliances is denoted by $\boldsymbol{i}$ while the number of the energy phases for each appliance is denoted by $\boldsymbol{j}$. The execution period is discretized into uniform time slots ($\boldsymbol{t}$) of one minute per slot totaling 1440 minutes in 24 hours. The parameters of each appliance model are adjusted to reproduce typical energy consumption profiles. Each energy phase is considered as an energy block for scheduling and optimization. The aim of the Energy Management and Control block is to produce a set of optimized schedules of these appliances to achieve the minimum electricity cost given the above constraints.

A. Cost function

The objective function to be minimized is defined as:

$$J = \sum_t C_t \{\sum_i \ \sum_j P_{i,j}\} \qquad (1)$$

Where:
J = Total cost of energy consumed
C_t = Spot price of electricity
P = Power consumed
t = Time slot of the day
i = Number of appliances
j = Number of phases per appliance

At each time slot, the discretized power profiles denoted as $\boldsymbol{t}$ are calculated by the optimizer as a function of electricity cost and then implemented by the scheduler**.** $P_{t,i,j}$ represents the energy consumed by energy phase j of appliance i during the whole period of simulation for time slot t.

B. Constraints

The constraints as specified earlier are divided into two categories; device specific and user preference constraints. The latter is specified by the user who decides on the start and finish time of a particular appliance. Device specific constraints have both the energy and timing constraints. The energy constraints are as follows:

Energy phase constraint is imposed to ensure that the energy phases for multiple energy phase appliances fulfill their energy requirement. The constraint is imposed as:

$$\sum_t P_{t,i,j} = E_{i,j} \quad \forall\, i,j \qquad (2)$$

Where $E_{i,j}$ is the energy requirement for energy phase $\boldsymbol{j}$ in an appliance $\boldsymbol{i}$.

Peak power constraint is imposed to limit the maximum power consumption for all the appliances at any time slot $\boldsymbol{t}$. It is modeled as:

$$\sum_i \sum_j P_{t,i,j} \le PEAK_t \qquad (3)$$

Where $PEAK^k$ is the peak demand response signal provided by the utility power provider.

The timing constraints are:

Sequential processing constraint is imposed to make sure that an energy phase operation cannot start until the previous phases have finished. The constraint is described as follow:

$$x_{t,i,j} \le s_{t,i,(j-1)} \quad \forall i,t \quad \forall j = 2,3,\dots n \qquad (4)$$

Energy phase processing time limit constraint is imposed to model the limit of the energy processing time as follows:

$$a_{i,j} \le \sum_t x_{t,i,j} \le \bar{a}_{i,j} \;\; \forall\, i,j \qquad (5)$$

Where:
a = start time index of appliance
$\bar{a}_{i,j}$ = end time of processing of appliance operation

Between-phase delay constraint is imposed on an appliance with multiple operating phases. It imposes a specified amount of time delay at the end of one energy phase before the start of the next phase.

C. *Optimization Techniques*

The above optimization problem can be solved using CPLEX and the YALMIP interface to Matlab [8]. It can also be solved using branch -and -bound algorithm as well as cutting- plane method [9]. In this paper, the constrained minimization has been implemented using Matlab's Optimization Toolbox [10].

IV. SIMULATION RESULTS

The Simulink model of the power components is illustrated in Fig. 2. This model is linked to a Matlab script which runs the optimization and updates the control parameters in the Energy Management and Control block. The technical specifications of the appliances models are given in the Appendix.

Simulation results of the model before optimization and after scheduling & optimization are presented and discussed. A comparison between Real Time Pricing and the Fixed Time Tariff is also presented to show the savings in the cost of electricity when scheduling and optimization has been applied to the model. The spot price of electricity is stochastically assigned according to electricity demand data recorded from a residential area in the UK [11]. The RTP is not the measured data but is used in comparison to the statistical data for different utility providers in the North Yorkshire of England.

A. *simulation results before optimization and scheduling*

In the following case studies, simulations of the appliances are considered for a time horizon of 24 hours (1440) minutes using published spot price data [11]. Five smart appliances labeled A, B, C, D and E are modeled and simulated.

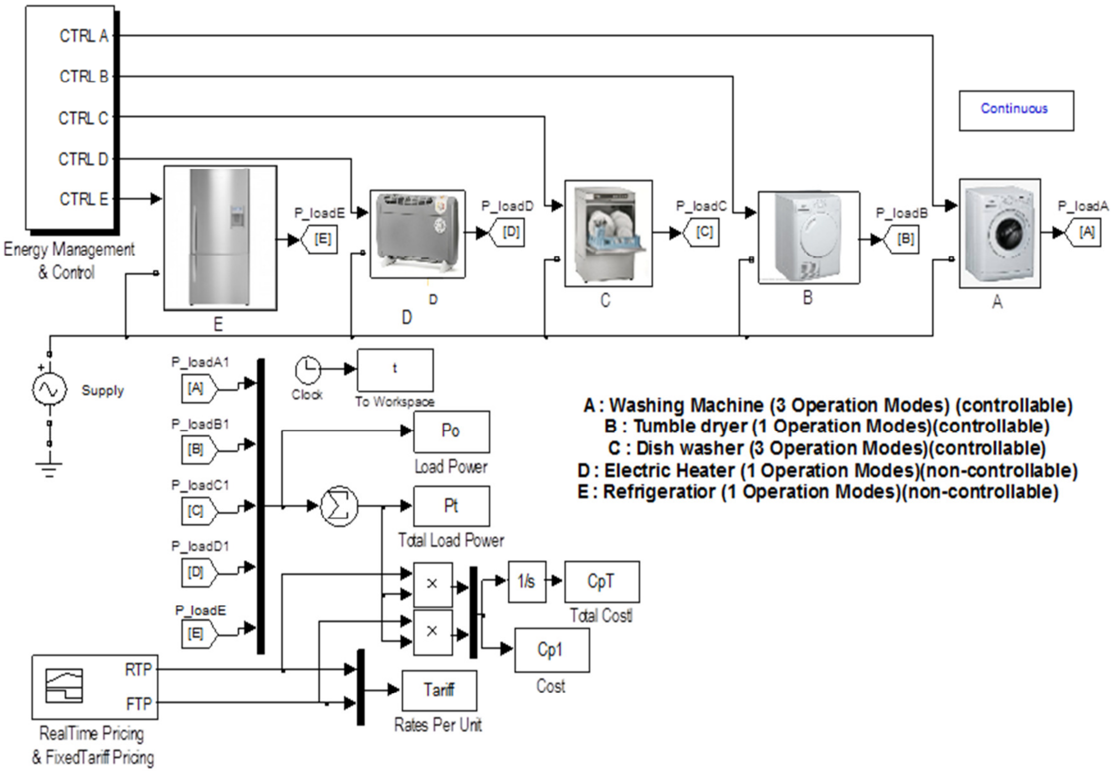

Fig. 2. Simulink model of the smart home appliances with the energy cost calculation..

There are three controllable smart appliances namely washing machine (A), tumble dryer (B) and dish washer (C) and two uncontrollable appliances which includes electric heater (D) and refrigerator (E). Appliances A and C are modeled as three energy phase devices while the rest are single energy phase devices. The controllable appliances are subject to the constraints defined in section III – B. The technical specifications of the appliances are given in Tables I, II & III (Appendix). The peak power is assumed to be 5500 Wh. Appliance (D) consumes 1270 W and its operation time is specified by the user. Device specific constraint is imposed to Appliance (C) to operate all day with intermittent on/offs and consumes a power of 110W. The power consumption profile of the smart appliances and the RTP signal before optimization and scheduling is shown in Fig. 3. This clearly shows that the appliances are operating during the peak period (i.e. when the price of electricity is high).

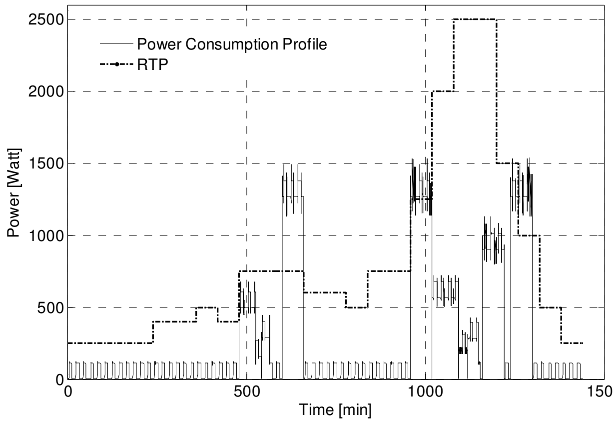

Fig. 3. The power consumption profile and the RTP before optimization and scheduling.

The effect can be seen in Fig. 4; the total cost of electricity over the simulation period show the RTP cost is 3.269 Pence/wh while the FTP cost is 2.827 Pence/wh. The RTP cost is greater as a result of the loads operating at the peak period.

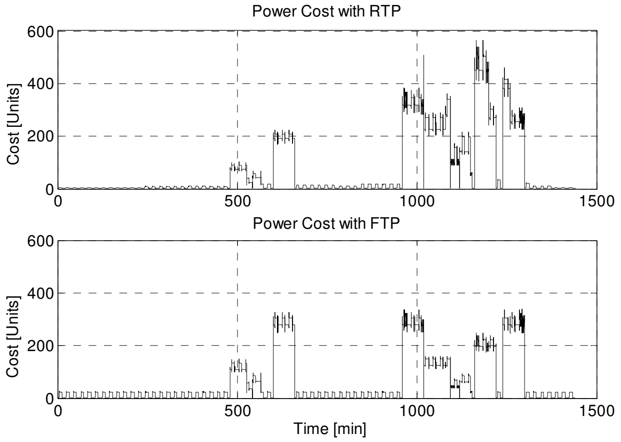

Fig. 4. The simulation results for individual appliance energy cost in RTP and FTP.

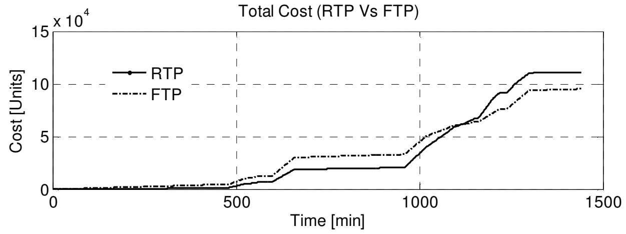

Fig. 5. The simulation results for total energy cost in RTP and FTP before scheduling and optimization.

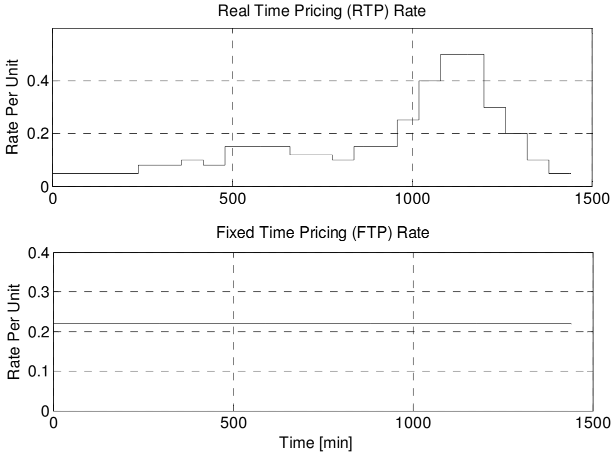

Fig. 6. Real Time Pricing and Fixed Time Tariff pricing used across a simulation period of 24 hours (1440 min).

B. *Simulation results after scheduling and optimization*

For this case study, the three controllable appliances (A, B and C) are scheduled and optimized. The scheduler assigns power to the appliances when the electricity consumption is low (off-peak period). The power consumption period and the RTP over the simulation period are shown in Fig7 below:

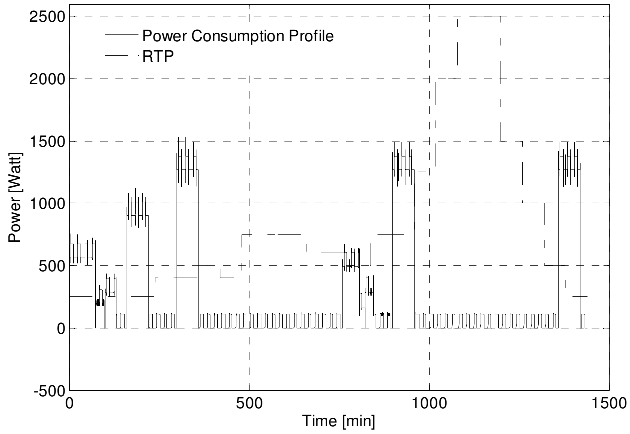

Fig. 7. The power consumption profile and the RTP after optimization and scheduling.

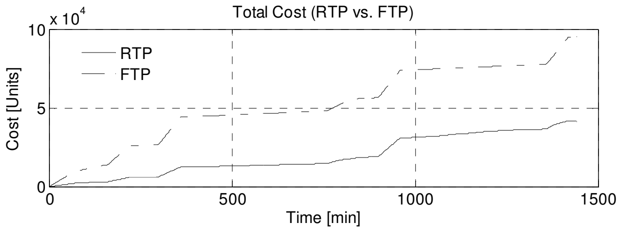

Fig. 8. The simulation results for total energy cost in RTP and FTP after scheduling and optimization.

To understand the cost saving achieved by the optimal scheduling of the appliances, the differeence in the energy cost for RTP is 2.05 Pence/wh while the FTP is 0.017 Pence/W-h.

V. DISCUSSIONS AND FUTURE WORK

In this paper, the model of the smart home appliances is designed for load balancing and optimization using the RTP and FTP for a typical household in the UK, The model demonstrates how optimal scheduling of residential electric loads can result in energy cost savings. The case studies are done to observe the cost of electricity consumed by the smart home appliances before optimization and after scheduling & optimization. Results for both dynamic and fixed price show a significant reduction in energy cost with the RTP being more cost effective as compared to FTP.

The model will be extended to incorporate solar panels and a storage device to supply power to the smart home loads along with the grid. The Energy Management and Control system will then be developed further to take into account these components into the optimization procedure and generate the best energy dispatch schedule among consumption, storage and import/export to the grid to achieve optimal cost benefit.

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Appendix

Technical specifications of the LG smart appliances

The sample smart home appliances with the energy phases, power rating and the energy consumption used in the modeling and simulation are shown in the table I, II and III respectively.

TABLE I

TECHNICAL SPECIFICATIONS OF DISH WASHER [12].

Appliance Energy phases	**Power (W-h)**	**Energy (kW)**	**Time (min)**
Pre-heating & washing	1133.3	1.263	72.3
Cooling & Maintenance	400	0.299	25.9
Rinsing & Spining	566.67	0.578	30.5

TABLE II

TECHNICAL SPECIFICATIONS OF DISH WASHER [12].

Appliance Energy phases	**Power (W-h)**	**Energy (kW)**	**Time (min)**
Drying	1800	2.17	60

TABLE III

TECHNICAL SPECIFICATIONS OF DISH WASHER [12].

Appliance Energy phases	**Power (W-h)**	**Energy (kW)**	**Time (min)**
Pre-wash & washing	1000.33	1.2	46
Cooling & Rinsing	320	0.48	15
Drain & Dry	579.67	0.72	24