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Optimization of Thermostatically Controlled Appliances to Minimize Energy Consumption Cost Based on Real-Time Pricing

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***Abstract*— An optimization model for residential users to minimize power consumption cost using real-time pricing is proposed in this paper. This model chooses the thermostatically controlled appliances (TCA) which consume the most power in the residential area. This scheme targets the residential area rather than the industrial area because the latter has interdependent tasks difficult to isolate. The proposed model automatically adjusts the TCA according to dynamic pricing and customer demand. Constrains like customer preferences, power consumption, dynamics of appliances, real-time pricing is taken into consideration. Simulation of the optimization scheme is done in the MATLAB platform. The model can successfully optimize the power consumption cost keeping customer comfort in mind.**

Keywords—Demand response (DR), Internet of things (IoT), Thermostatically controlled appliances (TCA), Time of use tariff, Home energy management system (HEMS), Demand Side Management (DSM)

I. INTRODUCTION

Recently, one of the most asked questions is how we can fulfill future energy demand. Electricity generation cost is increasing rapidly, burning fossil fuels destroying nature, and replacing fossil fuel with renewable energy is a long term process. Global energy demand and carbon emission from the power sector have grown by 2.9% and 2.7% respectively in 2018 [1]. Bangladesh has a national grid with an installed capacity of around 21,419 MW as of September 2019 and will need an estimated 34,000 MW of power by 2030 to sustain its economic growth of over 7 percent [1]. The burning of this large amount of fossil fuels can be reduced by efficient use of power and energy conservation which eventually bring down the fossil fuel burning [2]. It's easier to save electricity in residential areas rather than the industries as those require a specific amount of power supply to complete the tasks [3].

Many researchers working on the optimization of energy management [4]–[7]. Home Energy Management System (HEMS) in [8] schedule loads based on real-time pricing information and user-defined priority [2]. Optimal and automatic residential energy consumption scheduling framework in [9] attempts to achieve the desired trade-off between minimizing the electricity payment and minimizing the waiting time for the operation of each appliance in the household. The authors consider real-time pricing combined with inclining block rates. A significant number of researches have been carried out to bring TCAs under smart energy management systems [10]. Such as, a novel appliance commitment algorithm that schedules thermostatically controlled home appliances based on price and consumption forecasts considering users' comfort settings to meet an optimization objective such as minimum payment or maximum comfort [11]. A real-time price based optimal scheduling system for centralized air conditioning load is investigated in [12]. The work investigates reward-based TCLs scheduling. Several authors investigate the transactive control algorithm which is embedded in the EMS for a distribution network having both solar PV and battery energy storage [13]-[17]. The models collectively envision minimizing the power fluctuations while maintaining battery health specifically within SOC limits. The controller parameters in the model [18], which are membership functions and rules, are adjusted to optimize an ex-ante energy profile with a set of convenience constraints of the customers [19], [20]. To our best of knowledge, few works [21], [22] consider both energy-saving and customer comfort together in the energy management system model.

To fill this research gap, in this paper we developed an algorithm for not only Air Conditioners(AC) but also refrigerators and Deep Fridges. We have considered a different class of consumers reflecting their preferences. At this end, worthy to note, the TCAs consume more energy at the initial state than in stable conditions. We have focused on energy-saving initially for appliances; later, consumer comfort when the stable condition is reached is considered. So, both energy-saving and customer comfort is gone side by side. The total system is established on real-time pricing where the peak demand and price are well-considered. The consumers able to set their consumption cost limit, according to the prices of different periods hence save money and energy. A practical model is proposed based on the optimization algorithm where the consumers are actively participating. Nonetheless, it is automatic and consumer-friendly.

The rest of the paper is presented as follows.Section(II) discuss methodology having problem formulation and flow chart of the model. Section (III) is named as input parameters. Section (IV) focuses on the result analysis and section(V) is the conclusion.

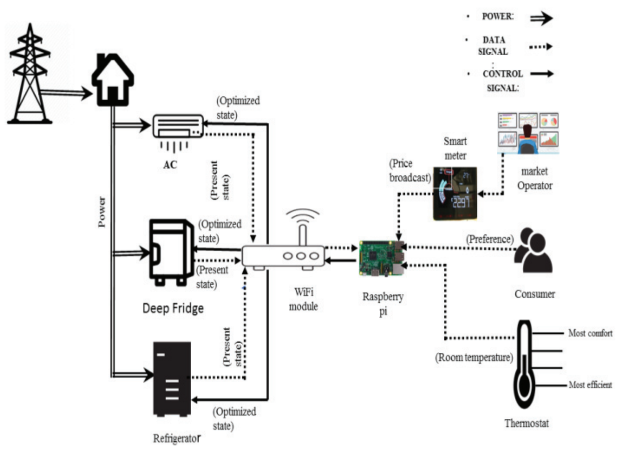

Fig. 1. Energy Management Model

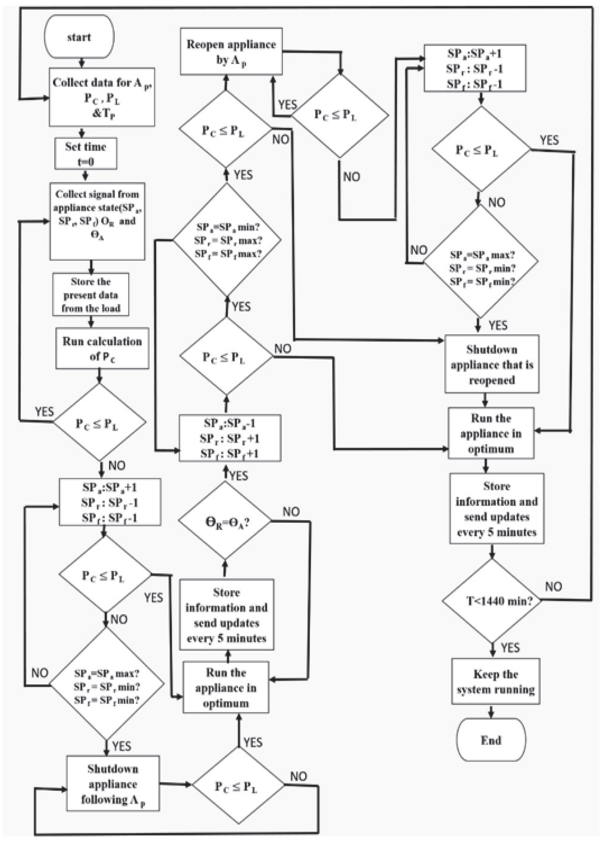

Fig. 2. Flow charts of the model used in optimization

II. Methodology

A. Formulation

Fig. 1 shows the proposed energy management system. In this model, power is being saved and consumption is being kept in the consumer-preferred limit simply by turning the appliances on/off or adjusting them to new set points.

In the model, a Raspberry Pi module works as the home operator, which is the hub of the control scheme. It constantly acquires information about appliances' state through the Wi-Fi module and tariff rate from market broadcasting through energy meter. According to the room temperature, consumption limit set by the consumer and appliance priority, the Pi calculates and finds the solution to achieve the optimized state. It then sends control signals to appliances through a Wi-Fi module. The appliances operation is adjusted automatically according to the control signals.

We turned this decision-making, problem into a linear optimization problem and its solutions indicate the number of appliances running and at what states they are running. TCAs are considered as variables and they have values of zero and one. Equation (1) shows the objective function of this linear optimization problem

$$\text{Max} \quad X_a + X_r + X_f \tag{1}$$

Equality Constraints are given in (2) - (4)

$$P = SP_a X_a + SP_r X_r + SP_f X_f \tag{2}$$

$$P_C = T_R \times P \tag{3}$$

$$P_C \le P_L \tag{4}$$

B. Flow chart of the model

Fig. 2 presents the flow chart of the optimization model. The variables used are defined as follows. Appliance priority expressed as A_P. The variable T_R is for tariff rate. P is power consumption at various Set Points(SP) presented as equation (2). Power consumption cost and power consumption limit are denoted by P_C and P_L. The C_h is for the class of the household. The T_p is for a period of the day. The Θ_R and Θ_A have respectively represented Room temperature and AC temperature.

Firstly, the model collects data of variables and appliance state. Secondly, it calculates P_C through equation(3), and if equation (4) satisfies the system continues to take data, and if not it changes to set points towards less power consumption. Thirdly, if Θ_R equals to Θ_A the home operator reverses the steps to approach consumer effort. Finally, If the running appliances reach the maximum comfort level meaning the last set points, the home operator will start opening the appliances one by one if one or more than one of them were shut down to achieve optimization. The home operator will store information and update the whole system every five minutes till $t \neq 1440$ minutes. After that, it will refresh the system and restart the system again.

III. Input Parameters

A. Number of appliances and customer classifications

Customers have been divided into 3 classes, namely as class A, B, C. Class A consumers have 5 AC,2 refrigerators, and deep fridges. Class B consumers have 3 AC,1 refrigerator, and a deep fridge. Class C consumers have 1 of every piece of equipment.

B. Tariff Profile

Here, for the simulation, we will use the "Time of Use" tariff scheme which splits a day among three-time slots namely as off-peak,mid-peak, and on-peak. Off-peak is from 7 pm to 7 am,mid-peak is from 7 am to 11 am and 5 pm to 7 pm,on-peak is from 11 am to 5 pm. Off-peak,mid-peak, and on-peak has a tariff rate of 6.5,9.4,13.4 cents per Kwh respectively.

C. Power ratings of appliances

For the simulation, we consider some assumption of power consumption by appliances around their power ratings at different setpoints based on two different conditions. Initial Condition (Room temperature>AC temperature). Stable Condition (Room temperature<=AC temperature).

At this end, the appliances set is referred as follows. The Air-conditioner set is defined as, $X_a = \{x_{a1}, x_{a2}, \ldots, x_{am}\}$. The m is index for their number. Refrigerators set, $X_r = \{x_{r1}, x_{r2}, \ldots, x_{isn}\}$. Deep fridges, $X_f = \{x_{f1}, x_{f2}, \ldots, x_{fp}\}$. The priority list is defined as well. For appliance Class A, at p = $\{x_{a5}, x_{a4}, x_{f2}, x_{r2}\}$. For Class B, it is $A_p = \{x_{a3}, x_{r2}\}$. Similarly, for appliances Class C, the $A_p = \{x_{a1}\}$.

The P_L of three households A,B,C are given as below respectively in cents.Firstly,at off-peak P_L is 50,22,16.Secondly,at mid-peak it is 60,30,16.Finally,at on-peak it is 55,35,5.

IV. Result Analysis

A. Case study

Here, let's see the optimization result at the initial state and stable state for each of the customer classes.

TABLE I. POWER CONSUMPTION COST FOR CLASS A (INITIAL STATE)

Period	Cost (cents)		
	With Optimization	Without Optimization	Full Load
Off-peak	43.94	52.65	52.65
Mid-peak	51.79	62.04	76.14
On-peak	54.81	68.34	108.54

TABLE II. POWER CONSUMPTION COST FOR CLASS A (STABLE STATE)

Period	Cost (cents)		
	With Optimization	Without Optimization	Full Load
Off-peak	26.65	26.91	26.91
Mid-peak	38.54	38.92	38.92
On-peak	54.94	55.48	55.48

TABLE III. POWER CONSUMPTION COST FOR CLASS B (INITIAL STATE)

Period	Cost (cents)		
	With Optimization	Without Optimization	Full Load
Off-peak	17.94	21.45	31.20
Mid-peak	25.95	31.02	45.12
On-peak	34.71	41.54	64.32

TABLE IV. POWER CONSUMPTION COST FOR CLASS B (STABLE STATE)

Period	Cost (cents)		
	With Optimization	Without Optimization	Full Load
Off-peak	15.60	15.93	15.93
Mid-peak	22.56	23.03	23.03
On-peak	29.21	41.54	41.54

TABLE V. POWER CONSUMPTION COST FOR CLASS C (INITIAL STATE)

Period	Cost (cents)		
	With Optimization	Without Optimization	Full Load
Off-peak	9.82	11.70	11.70
Mid-peak	14.20	16.92	16.92
On-peak	3.45	4.02	24.12

TABLE VI. POWER CONSUMPTION COST FOR CLASS C (STABLE STATE)

Period	Cost (cents)		
	With Optimization	Without Optimization	Full Load
Off-peak	5.85	6.18	6.18
Mid-peak	8.46	8.93	8.93
On-peak	2.01	2.68	12.73

Table I expresses that at initial state class A consumers have P_C of 108.54 cents at on-peak and full load while it is 55.48 at stable state as shown in Table II. As seen in Table III and Table IV, P_C for class B is 64.32 cents at initial state but it has a lesser value of 41.54 cents at stable state. Table V and Table VI show that the result is similar for class C because at the initial state P_C is 24.12 cents whereas at the stable state it is 12.73 cents.

B. Comparative analysis of energy-saving and cost minimization

TABLE VII. ENERGY SAVED BY OPTIMIZATION (INITIAL STATE)

Period	Energy saved (%)					
	Without optimization			Full Load		
	Class A	Class B	Class C	Class A	Class B	Class C
Off-peak	16.54	16.37	16.11	16.54	42.5	16.11
Mid-peak	16.51	16.37	16.11	31.98	42.5	16.11
On-peak	19.80	16.45	13.33	49.51	46.04	85.56

TABLE VIII. ENERGY SAVED BY OPTIMIZATION (STABLE STATE)

Period	Energy saved (%)					
	Without optimization			Full Load		
	Class A	Class B	Class C	Class A	Class B	Class C
Off-peak	0.97	2.04	5.26	16.54	2.04	0.97
Mid-peak	0.97	2.04	5.26	31.98	2.04	0.97
On-peak	0.97	11.02	25	49.51	11.02	0.97

TABLE IX. COST MINIMIZATION BY OPTIMIZATION (INITIAL STATE)

Period	Cost Minimization (cents)					
	Without optimization			Full Load		
	Class A	Class B	Class C	Class A	Class B	Class C
Off peak	8.71	3.51	1.88	8.71	13.26	1.88
Mid peak	10.25	5.07	2.72	24.35	19.17	2.72
On-peak	13.53	6.83	0.57	53.73	29.61	20.87

TABLE X. COST MINIMIZATION BY OPTIMIZATION (STABLE STATE)

Period	Cost Minimization (cents)					
	Without optimization			Full Load		
	Class A	Class B	Class C	Class A	Class B	Class C
Off-peak	0.26	0.33	0.33	0.26	0.33	0.33
Mid-peak	0.38	0.47	0.47	0.38	0.38	0.38
On-peak	0.54	12.33	0.67	0.54	12.33	10.73

Table VII, shows the appliances are in the initial state. According to the proposed optimization algorithm, the maximum power saved of class A, B, C appliances are 49.51%, 46.04%, 85.56% respectively compared to the full load. Table VIII shows that at a stable state this scheme saved up to 49.51%, 11.02%, 0.97% of maximum power. As seen in Table IX and Table X, at initial state money saved are 53.73 cents, 29.61 cents, 20.57 cents while at stable state these numbers are 0.54 cents, 12.33 cents,10.73 cents.

V. CONCLUSION

The model presented above encourages a consumer to adjust their load demand according to their comfort and behavioral fluctuation and focuses on the Real-Time Pricing and Customer Class. It has been shown that this load management model can save up to 49% of electricity during peak hours. If the proposed energy management scheduler can be implemented on a large scale, a country can save a hundred MW of power and moves towards more efficient load management. The saved power can be further used to electrify the unprivileged rural portion of the population that has no access to electricity.

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