Optimal power control strategy of a distributed energy system incorporating demand response

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***Abstract*—This paper presents an optimal power control scheduling of a distributed energy system in presence of demand response. The distributed energy system comprises of a solar photovoltaic (PV) module and a battery bank storage system. A non-convex mixed binary integer programming technique is used to model flexible and inflexible smart home appliances. Two scenarios are considered in the case study. The results show that efficient scheduling of smart home appliances combined with optimal control of distributed energy system can significantly reduce the total daily electricity cost by more than 50%. The optimal control of distributed energy system was also shown to have an effect on the scheduling of smart home appliances.**

***Keywords*— smart home appliance, distributed energy system, total daily electricity cost, demand response, optimal power control strategy.**

I INTRODUCTION

South Africa, like many other developing countries, is faced with critical shortage of power generation in its national power grid [1]. The main power utility, Eskom, is making efforts to maintain a balance in its power system grid by encouraging electricity customers to use electricity sparingly and efficiently. Recently, the power utility has increased its electricity tariffs in order to enforce efficient use of electricity by electricity consumers [2]. Residential customers' energy consumption levels constitute about 20% of the current country's total energy consumption [2]. The recent advance in smart home appliances and integration of distributed energy systems into the conventional power system grid have given residential customers opportunities to both reduce their electricity consumption and cost bill. Residential customers now have the opportunity to generate their own electricity and manage their home appliances in an efficient way. However, current demand response activities by most residential customers are mainly operated manually. The main problems with this type of demand response is that some residential customers may not have time to make load scheduling decisions and if the electricity tariff prices vary frequently, load scheduling may become too complex. Therefore, there is need to develop automated residential demand response strategies in order to fully gain the benefits of smart home appliances and distributed energy systems.

The participation of smart home appliances in demand response strategies have been modeled using different constraints [3,4]. Time dependent electricity tariff schemes necessitate the load control scheduling of smart home appliances depending on the responsiveness to price variation. Commonly, deterministic average non-varying energy consumption levels for complete operating cycle of home appliances are assumed [5]. However, it is not realistic to assume average values for complete operating cycle of home appliances such as dishwashers, water heaters, as this may lead to underestimation or overestimation of its energy consumption level. In this paper, smart home appliances with controllable hourly energy consumption levels under different customer time preference constraints are considered.

In some research studies, smart home appliance scheduling models without storage and/or distributed energy systems are presented [6]. On the other hand, application of distributed energy systems in residential customers is considered without smart home appliance scheduling [7,8,9]. The main disadvantage of decoupling smart home appliance scheduling models and distributed energy systems including energy storage systems, is that the cost saving opportunities that may exists between their interdependency is ignored. This paper formulates a practical optimal power control strategy for a residential customer with distributed energy system and smart home appliances. The contributions of this paper are:

- A case study with solar PV module and battery bank energy storage system is presented.
- Combined optimal power control strategy incorporating smart home appliance model is presented.
- Power controllable, time shiftable as well as customer time preferences of smart home appliances are considered in the case study.

II METHODOLOGY

The optimization problem is modeled using a non-convex mixed binary integer programming technique. The general formulation is expressed as Eq. 1 below [10].

$$\begin{aligned} min_{x,z} f(x,z) &= a^T x + b^T z \\ \text{subject to: } G(x,z) &= c \\ H(x,z) &\leq d \end{aligned} \quad (1)$$

where, x, are real values and, z, are binary values. *f(x,z),* is the objective function presented as a linear combination of variables. The objective function defines which particular assignment of feasible solution to the variables is optimal.

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G(x,z), and *H(x,z)* are the constraints, modeled as equalities and inequalities respectively. The constraints of the model are used to limit the solution of the model in a feasible region. The proposed modeling approach and constraints for smart home appliances and distributed energy system are outlined below.

A. Smart home appliance modeling

The smart home appliances considered in this paper are categorized into two main groups: flexible and inflexible home appliances. Flexible home appliances are those that can be scheduled to operate in several operational time intervals. Inflexible home appliances operate in fixed predetermined operating time intervals. The following subsections explain how the home appliances were modeled.

1) Inflexible home appliance modeling: Examples of inflexible home appliances are lighting devices, oven, refrigerators, television etc. These devices have fixed operating time intervals that are scheduled by the residential customer. If the time of operation of these home appliances is shifted, the residential customer may suffer significant costs. For example, a residential customer cannot afford to switch OFF the refrigerator because the stored food may spoil and cost more to replace than buying electricity that is supposed to be used to run the refrigerator for that time interval.

Let **A** denote a set of inflexible home appliances for a residential customer. Assume the hourly energy consumption of an inflexible home appliance, a, (a ∈ **A**), is given by E_a. If the inflexible home appliance is required to operate between a starting time, α_a, and end time, β_a, then the total energy requirement, E_D, for the inflexible home appliance is given as:

$$E_D = \sum_{t=\alpha}^{\beta} E_a^t \quad \forall\ t \in [\alpha, \beta] \tag{2}$$

It is also required that $E_a^t = 0$ for $t < \alpha$ and $t > \beta$. For example, if a television which consumes 7W per hour is switched ON between 1900hrs and 2100hrs, then the total energy requirement is given as:

$$\begin{aligned} E_D &= \sum_{t=17}^{19} E_a \\ &= 7 + 7 + 7 \\ &= 21Wh \end{aligned}$$

In some cases, inflexible home appliances can have controllable hourly energy consumption with total daily energy consumption, E_D, fixed or predetermined. This type of inflexible home appliances can participate in demand response program by adjusting its hourly energy consumption level in response to electricity price signals. Assume the controllable hourly energy consumption of an inflexible home appliance, *a,* is bounded between a maximum energy consumption level, E_a^{max} and minimum energy consumption level, E_a^{min}. The hourly energy consumption of the inflexible home appliance must satisfy constraint (3) below.

$$\begin{aligned} E_D = \sum_{t=\alpha}^{\beta} E_a^t \qquad \forall\, t \in [\alpha, \beta] \\ E_a^{min} \le E_a^t \le E_a^{max} \end{aligned} \tag{3}$$

For example, an electric vehicle is required to charge when a residential customer has gone to sleep at $\alpha = 2100$hrs and stop charging at $\beta = 0900$hrs in the morning. The electric vehicle hourly energy consumption can be controlled between $E_a^{min} = 100$Wh and $E_a^{max} = 1500$Wh. If the daily energy consumption of the electric vehicle is $E_D = 5$kWh, the actual energy consumed by the electric vehicle at each given hour should satisfy constraint (3), i.e.,

$$\begin{aligned} E_D &= \sum_{t=\alpha}^{\beta} E_a^t \\ 5000 &= \sum_{t=1}^{9} E_a^t + \sum_{t=21}^{24} E_a^t \\ & \forall\, t \in [21,9],\quad 100 \le E_a^t \le 1500 \end{aligned}$$

2) Flexible home appliance modeling

Examples of flexible home appliances are washing machine, swimming pool water pump, etc. The participation of flexible home appliances in demand response programs can be achieved by shifting the operational times within predetermined operational intervals and/or adjusting the hourly energy consumption of the respective home appliance.

Let **B** denote a set of flexible home appliances of a residential customer. Assume the hourly energy consumption of a flexible home appliance, b, is given by, E_b, (b ∈ **B**). Let X_b denotes the fundamental load demand pattern of a flexible home appliance as $[E_b^1, E_b^2, \ldots, E_b^t, \ldots, E_b^T]$. To arrange all possible operational times of the flexible home appliance, a circulant matrix of the fundamental load demand pattern, X_b, is used. The circulant matrix, X_b^C, is given as:

$$X_b^C = \begin{pmatrix} E_b^1 & E_b^T & \cdots & E_b^2 \\ E_b^2 & E_b^1 & \cdots & E_b^3 \\ \cdot & \cdot & \ddots & \cdot \\ \vdots & \vdots & \ddots & \vdots \\ E_b^T & E_b^{T-1} & \cdots & E_b^1 \end{pmatrix}$$

In order to select one of the optional operation times of the flexible home appliance for optimization, a binary switching vector, S_b, is used. The binary switching vector is defined as $S_b = [s_b^1, s_b^2, \ldots, s_b^t, \ldots, s_b^T]$, where $s_b^t \in [0,1]\ \forall\ t \in [1,2,\ldots,T]$. The binary digits 1 and 0 means the flexible home appliance is switched ON and OFF respectively. The binary switching vector, S_b, has only one non-zero element. The position of the non-zero element in the binary switching vector indicates the position or the starting time when the flexible home appliance is switched ON. For a flexible home appliance, $b \in$ **B**, this constraint can be written as Eq. 4 below:

$$\sum_{t=1}^{T} S_b^t = 1 \tag{4}$$

Using the binary switching vector, S_b, the flexible home appliance demand pattern, x_b is calculated as in Eq. 5 below:

$$x_b = S_b \times X_b^C \tag{5}$$

For simplicity, let us take an example of a flexible home appliance with hourly energy consumption $E_b^t = 100\text{Wh}$ and an operational interval of $T = 6$ hours. If the fundamental load demand pattern of the flexible home appliance during the 6 hours is given as: $X_b = [100\ 100\ 0\ 0\ 0\ 0]$, then the flexible home appliance can operate in 6 different optional operational times, i.e., [100 100 0 0 0 0], [0 100 100 0 0 0], [0 0 100 100 0 0], [0 0 0 100 100 0], [0 0 0 0 100 100] and [100 0 0 0 0 100]. This can be achieved easily by circular shifting the fundamental load demand vector of the flexible home appliance. The circulant matrix can be expressed as:

$$\mathbf{X}_b^C = \begin{pmatrix} 100 & 100 & 0 & 0 & 0 & 0 \\ 0 & 100 & 100 & 0 & 0 & 0 \\ 0 & 0 & 100 & 100 & 0 & 0 \\ 0 & 0 & 0 & 100 & 100 & 0 \\ 0 & 0 & 0 & 0 & 100 & 100 \\ 100 & 0 & 0 & 0 & 0 & 100 \end{pmatrix}.$$

In order to select one of the optional operation times of the flexible home appliance, a binary switching vector, S_b, is used. In this example, to select the operational time when the flexible home appliance is switched ON at the third hour, the third element of the binary switching vector must be set to binary digit 1, i.e, $S_b = [0\ 0\ 1\ 0\ 0\ 0]$. The flexible home appliance load demand pattern, x_b, is calculated as:

$$\begin{aligned} x_b &= (\ S_b\ ) \begin{pmatrix} 100 & 100 & 0 & 0 & 0 & 0 \\ 0 & 100 & 100 & 0 & 0 & 0 \\ 0 & 0 & 100 & 100 & 0 & 0 \\ 0 & 0 & 0 & 100 & 100 & 0 \\ 0 & 0 & 0 & 0 & 100 & 100 \\ 100 & 0 & 0 & 0 & 0 & 100 \end{pmatrix} \\ &= (\ 0\ \ 0\ \ 100\ \ 100\ \ 0\ \ 0\ ) \end{aligned}$$

$$\Rightarrow x_b = [0\ 0\ 100\ 100\ 0\ 0]$$

Similarly, to select the first, second, fourth, fifth or sixth optional operational time of the flexible home appliance, the first, second, fourth, fifth or sixth element of the binary switching vector, S_b, is set to binary digit 1 respectively.

In some cases, the hourly energy consumption of the flexible home appliance, E_b, is bounded between maximum hourly energy consumption level, E_b^{max}, and minimum hourly energy consumption level, E_b^{min}. If the total daily energy requirement, E_D, of the flexible home appliance, b, is known, the flexible home appliance load demand pattern, x_b, is calculated as follows:

$$x_b = (S_b)(X_b^C) \qquad \forall\, E_b^{min} \le E_b^t \le E_b^{max} \tag{6}$$

Similarly, the binary switching vector, S_b, is used to choose the flexible home appliance load demand pattern as described earlier.

The smart home appliance data used in this case study is presented in Table I below.

B. Distributed energy system modeling

Figure 1 shows the distributed energy system used in this paper. The distributed energy system comprises of a solar PV module, inverter, charging controller and a battery bank storage system. The residential customer gets electricity energy from the solar PV module through the inverter for his/her total home appliance load demand. When the total home appliance load demand is greater than the energy produced by the solar PV module, the battery bank storage system can discharge its stored energy in order to complement the solar PV module. If the energy is still not enough to supply the total home appliance load demand, the electric grid is connected to supply the surplus energy requirement.

The hourly state of charge (SOC), $P_B(t)$, of battery bank storage system is constrained between its maximum capacity, P_B^{max} and minimum capacity, P_B^{min}, i.e.

$$P_B^{min} \le P_B(t) \le P_B^{max} \tag{7}$$

The minimum capacity is set in order to protect the battery bank from over-draining and damaging the battery cells. It is defined in terms of depth of discharge (DOD), that is, the allowable charge the battery bank storage system can discharge and is given as a percentage, i.e.

$$P_B^{min} = P_B^{max}(1 - DOD) \tag{8}$$

The manufacturer gives the DOD that is allowable for the battery, beyond which the life span of the battery can be shortened. The most common DOD value for different long life batteries is 50% [5] and it is adopted in this paper. At any given hour, t, the state of charge (SOC) of the battery is defined as:

$$P_B(t) = P_B(t-1) + \eta_C P_C(t) + \eta_D P_D(t) \tag{9}$$

If the battery bank storage system has operated for a time

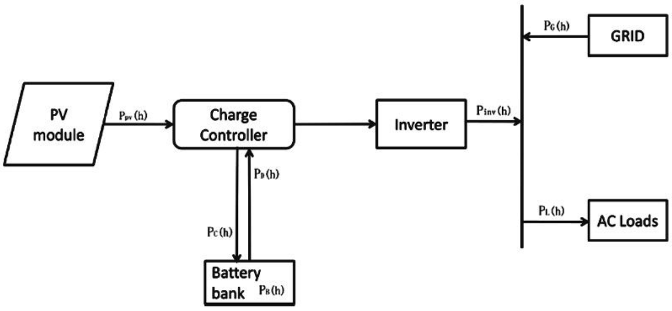

Fig. 11. Power flow for the solar PV – Battery bank energy system

RESIDENTIAL CUSTOMER HOME APPLIANCE LOADS

Appliance	**Type**	$E_a(Wh)$	$\alpha(h)$	$\beta(h)$	$Z(h)$
Inflexible					
Refrigerator	Non-	540	1	24	24
Ceiling fan (4)	Non-shiftable	280	23	8	10
			18	20	3
		140	9	17	9
Cooker	Non-shiftable	750	8	8	1
			13	13	1
			20	20	1
Lights (5)	Non-shiftable	36	8	12	5
			15	17	3
		72	13	14	2
			18	18	1
		180	19	23	5
Television	Non-shiftable	7	23	11	13
			15	18	4
		70	12	14	3
			19	22	4
PC	Non-shiftable	9	23	20	22
		50	21	22	2
Hand iron	Non-	250	7	7	1
Flexible					
Air Conditioner	Non-shiftable (Customer	Hourly energy consumption = 1kWh	12	16	5
			20	22	3
Water boiler	Power shiftable (Customer preference)	Hourly energy consumption = 0 - 1kWh	3	8	-
		Total energy	9	16	-
EV	Power shiftable (Customer preference)	Hourly energy consumption = 0.1kWh - 1.5kWh	21	9	-
Washing machine	Time Shiftable	1st hour = 1.2kWh	1	24	once a day
Water pump	Time	Hourly energy	1	24	every

interval, $t = 1$ to τ, then the SOC of the battery bank storage system is given by Eq. 10:

$$P_B(t) = P_B(0) + \eta_C \sum_{t=1}^{\tau} P_C(t) - \eta_D \sum_{t=1}^{\tau} P_D(t) \tag{10}$$

where $P_B(0)$ is the initial SOC of the battery bank storage system, η_C and η_D are the charging and discharge efficiencies of the battery bank storage system, $\eta_C \sum_{t=1}^{\tau} P_C(t)$ is the total energy transferred to the battery bank storage system during the given time interval and $\eta_D \sum_{t=1}^{\tau} P_D(t)$ is the total energy transferred from the battery bank storage system during the given time interval. To ensure that the battery bank storage system does not charge and discharge at the same time, at any given hour, *t*, the discharge energy, $P_D t)$, and charging energy, $P_C(t)$, are related as Eq. 11 below.

$$P_C(t) * P_D(t) = 0 \tag{11}$$

From Figure 1, the energy from the grid, $P_G(t)$ is defined as:

$$P_G(t) = P_L(t) - P_{INV}(t) \tag{12}$$

In most cases, due to high demand of energy in the system network the power utility normally set the maximum power demand, P_G^{max}, of the power system network. This is normally done to avoid peak loading in the system network during periods when the price of electricity is low. This constraint can be written as in Eq. 13.

$$0 \leq P_G(t) \leq P_G^{max} \tag{13}$$

In this case study, the power system network maximum demand is set as $P_G^{max} = 3200\text{W}$ per each hour of the day. The objective of the residential customer is to minimise the use of electricity import from grid by efficiently scheduling smart home appliances, use of solar PV module and battery bank storage system. The power output of the inverter, $P_{INV}(t)$, and total home appliance load $P_L(t)$, at any given time, *t*, are defined by Eqs. 14 and 15 respectively.

$$P_{INV}(t) = \eta_{CC} * \eta_{INV} * P_{PV}(t) - \eta_{CC} * P_C(t) + \eta_{CC} * \eta_{INV} * P_D(t) \tag{14}$$

$$P_L(t) = \sum_{t \in T} E_a(t) + \sum_{t \in T} E_b(t) \quad \forall\, t \in [1,2,\dots,T] \tag{15}$$

Eq. 14 represents the balance of energy between the energy produced from the solar PV module, $\eta_{CC} * \eta_{INV} * P_{PV}(t)$, the charging energy, $\eta_{CC} * P_C(t)$, and discharge energy, $\eta_{CC} * \eta_{INV} * P_D(t)$, of the battery bank storage system. Eq. 15 is the total home appliance load demand of both flexible home appliances, $\sum_{t \in T} E_a(t)$, and inflexible home appliances, $\sum_{t \in T} E_b(t)$. Table II below shows the distributed energy system components data used in this case study.

C. Optimal power control strategy modeling

The optimal power control strategy of the distributed energy system is achieved by minimizing the total daily electricity cost of the residential customer. The residential customer is assumed not to incur any cost by operating the solar PV module and battery bank storage system. The only cost the residential customer incurs is as a result of import of power from the grid.

SOLAR PV MODULE AND BATTERY BANK ENERGY STORAGE SYSTEM PARAMETERS

Parameter description	**Quantity**	**Units**
Battery Bank		
Nominal capacity P_B^{max}	10.3	kWh
Charge efficiency η_C	98	%
Discharge efficiency η_D	98	%
Depth of Discharge (DOD)	50	%
Solar PV energy system		
Nominal design capacity P_{PV}^{max}	3.395	kWp
Inverter efficiency η_{INV}	98	%
Charge controller efficiency η_{CC}	98	%

TIME VARYING ELECTRICITY PRICE RATES FOR RESIDENTIAL CUSTOMERS

Time (hr)	1	2	3	4	5	6	7	8	9	10	11	12
TOU prices (RSA/kWh)	40.88	40.88	40.88	40.88	40.88	64.13	92.93	92.93	92.93	64.13	64.13	64.13
Time (hr)	13	14	15	16	17	18	19	20	21	22	23	24
TOU prices (RSA/kWh)	64.13	64.13	64.13	64.13	64.13	92.93	92.93	64.13	64.13	40.88	40.88	40.88

Assume the power import from the grid has an electricity price vector, ρ, denoting the time varying electricity price rates for the day, i.e.,

$$\rho = [\rho(1), \rho(2), \ldots, \rho(t), \ldots, \rho(24)], \qquad \rho \geq 0 \tag{16}$$

The residential customer minimizes the total daily electricity cost by scheduling the smart home appliances in response to the time varying electricity price rates during the day and efficient use of the distributed energy system. The time varying electricity pricing rates used in this case study are obtained from Eskom's 2015/16 Tariff book [2]. Table III shows the TOU electricity tariff data used and the electricity tariff prices are given in South African rands (RSA).

a) Scenario 1: Power import from grid only

In this scenario, the residential customer gets electricity from the grid only and the scenario is used as a base case for the research study. The total hourly electricity cost, $EL_C(t)$, at any given hour, *t*, is calculated as:

$$EL_C(t) = \rho(t)\left[\sum_{a\in\mathbf{A}} L_a(t) + \sum_{b\in\mathbf{B}} L_b(t)\right] \tag{17}$$

The total daily electricity cost, EL_{DC}, for the residential customer is given by:

$$EL_{DC} = \sum_{t=1}^{24}\left(\rho(t)\left[\sum_{a\in\mathbf{A}} L_a(t) + \sum_{b\in\mathbf{B}} L_b(t)\right]\right) \tag{18}$$

The DR strategy of the residential customer is to minimize the total daily electricity cost without changing the total daily electricity consumption of the smart home appliances. The DR strategy in this scenario is achieved by efficient scheduling of smart home appliances with respect to their constraints, i.e.,

$$DR_{min} = min\left[\sum_{t=1}^{24}\left(\rho(t)\left[\sum_{a\in\mathbf{A}} L_a(t) + \sum_{b\in\mathbf{B}} L_b(t)\right]\right)\right] \tag{19}$$
$$\text{subject to constraints } (2) - (6)$$

b) Scenario 2: Solar PV module and Battery bank storage system connected (Figure 1)

In this scenario, the total hourly electricity cost incurred by the residential customer at any given hour, *t*, is given by:

$$EL_C(t) = \rho(t) * P_G(t) \tag{20}$$

The total daily electricity cost, EL_{DC}, for the residential customer is given by:

$$EL_{DC} = \sum_{t=1}^{24} \rho(t) P_G(t) \tag{21}$$

The DR strategy of the residential customer is to minimize the total daily electricity cost, EL_{DC}, by efficiently schedule the smart home appliances in respect to efficient use of the solar PV module and battery bank storage system. The DR minimization objective is defined as Eq. 22 below.

$$DR_{min} = min\left[\sum_{t=1}^{24} \rho(t) P_G(t)\right] \tag{22}$$
$$\text{subject to constraints } (2) - (15)$$

VII. RESULTS AND DISCUSSION

The total daily electricity costs for scenario 1 and 2 are RSA2325.10 and RSA998.86 respectively. This represents a 57% decrease in total daily electricity cost with respect to scenario 1. It therefore shows the electricity cost saving opportunity that distributed energy systems offer to many residential customers. Figure 2 below shows the total home appliance load demand pattern for both scenarios. It can be clearly seen from the graph that flexible and power controllable home appliances were shifted as a result of the distributed energy system. The increase in total home appliance load demand for Scenario 2 occurs at t_{01}, t_{10} and t_{22}.

Figure 3 shows the power import from the grid for both scenarios. As expected, the power import for Scenario 1 is the same as the total home appliance load demand pattern. However, for Scenario 2, the power import from the grid is greatly reduced because of the presence of solar PV module and battery bank storage system. It is clearly seen that during the day when the solar PV module power output is high, the solar PV module is able to supply the total home appliance load demand between t_{09} to t_{17}. In the early morning of the day between t_{01} to t_{04}, the battery bank storage system is able to supply all the total appliance load demand.

Figures 4 and 5 show the scheduling of flexible and power controllable home appliances in both scenarios. By comparison of both scenarios, it can be seen that the water pump operation

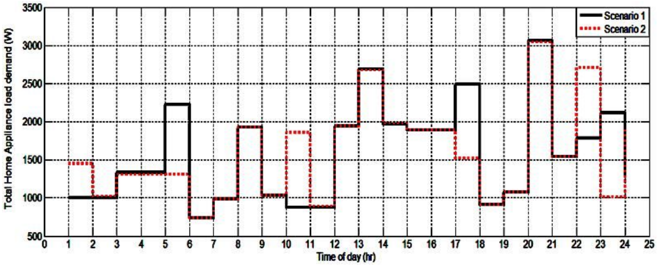

Fig. 12. Total home appliance load demand pattern for both scenarios

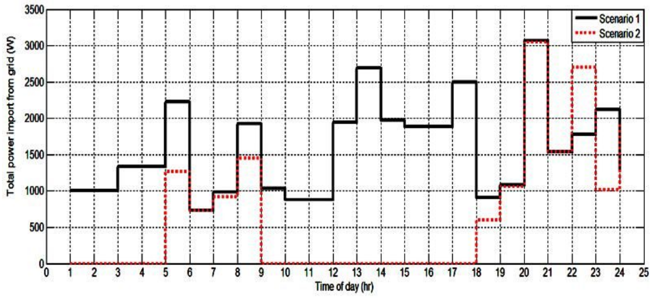

Fig. 13. Total power import from grid for both scenarios

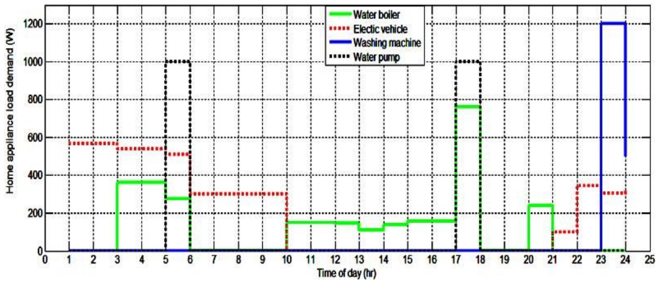

Fig. 14. Home appliance load demand for scenario 1

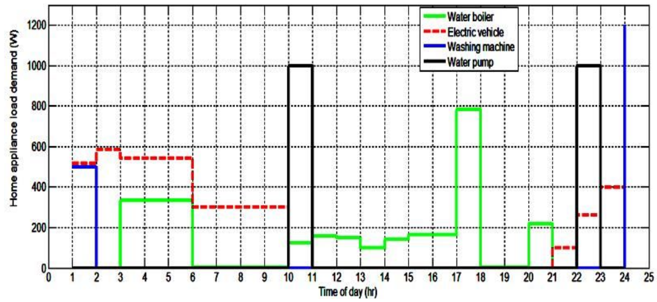

Fig. 15. Home appliance load demand for scenario 2

times were shifted from t_{05} and t_{17} to t_{10} and t_{22} for Scenario 1 and 2 respectively.

The washing machine also shifted from t_{23} and t_{24} to t_{24} and t_{01} for Scenario 1 and 2 respectively. This operational time shifting of home appliances for Scenario 2 increased the total appliance load demand at the respective times of day as shown in Figure 2. Although there is no clear difference in the operation of power controllable home appliances, however, slight differences in energy consumption levels of the home appliances can be noted at t_{05}, t_{10} and t_{17} for water boiler and at t_{01}, t_{02}, t_{05}, t_{22} and t_{23} for electric vehicle.

VIII. CONCLUSSION

This paper presents an optimal power control strategy of a distributed energy system in presence of demand response. The smart home appliances are modeled using a mixed binary integer programming technique. The DR strategy minimizes the total daily electricity cost of the residential customer without affecting the total daily electricity consumption of the smart home appliances. The results show that the solar PV module and battery bank storage system can significantly reduce the total daily electricity cost of the residential customer. Approximately 57% reduction of total daily electricity cost is achieved when solar PV module and battery storage system is connected. The distributed energy system also has an effect on scheduling of the smart home appliances. Future work is going to focus on developing optimal control strategies for coordinated multi-energy hub systems.

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