Environmental and Climate Technologies
2020, vol. 24, no. 1, pp. 580–603
https://doi.org/10.2478/rtuect-2020-0036
https://content.sciendo.com

Optimal Scheduling of Residential Electricity Demand Based on the Power Management of Hybrid Energy Resources

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***Abstract* – The present study sought to address the scheduling of the grid-connected hybrid energy resources under uncertainty of renewable sources, and load in the residential sector. After introducing hybrid resources, scheduling model was implemented through a power management algorithm in an attempt to optimize resource cost, emissions, and energy not supplied (ENS). The stated problem consists of two decision-making layers with different weight coefficients based on the prioritization of each objective function. The proposed algorithm is selected for energy optimal management based on technical constraints of the dispatchable and non-dispatchable resources, uncertainty parameters and day ahead real time pricing (RTP). Furthermore, the impact of demand response programs (DRP) on the given algorithm was investigated using load shedding and load shifting techniques. Finally, the results obtained led to the optimization of the functions in all decision-making layers with different modes of operation.**

***Keywords* – Day ahead real time pricing (RTP); demand response programs (DRP); Power management algorithm; two decision-making layers.**

Nomenclature

$P_{N.PV}$	Rated power of the PV
R_S	Solar irradiance
R_{ST}	Solar radiation in the standard conditions
R_N	A certain radiation point
$P_{N.WT}$	Rated power of the WT
V	Wind speed
V_{Ci}	Wind turbine cut-in speed
V_R	Wind turbine rated speed
V_{Co}	Wind turbine cut-out speed
α, β, γ	Fuel cost factors of DG
P_{DG}	Output power of DG
C_{DG}^{SU}	Start-up Cost of DG
C_{BB}	Cost of BB

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$P_{BB}^{dis}, P_{BB}^{ch}$	Discharge power and charge power of BB
η_{dis}, η_{ch}	Discharge and charge efficiency of BB
C_{BB}^{CA}	Capital cost of BB
$C_{BB}^{O\&M}$	Operation and maintenance cost of BB
N_C	Number of discharge and charge cycles
N_B	Number of batteries
V_B	Voltage of a battery
Q_B	Capacity of a battery
L_{BB}	Lifetime of BB
χ_g^b, χ_g^s	Cost of purchased and sold power factors
P_g^b, P_g^s	Purchased power and sold power
C_g^b, C_g^s	Cost of purchased power and Cost of sold power
μ, λ, ρ	Emission factors of DG
σ_g	Emission factor of grid
P_{LS}	Load shedding power
P_L	Power load of household appliances
$VOLL$	Value of lost load
u	Binary variable
MUT, MDT	Minimum uptime and minimum downtime of DG
R_D, R_U	Ramp up and ramp down limit of DG
$P_{L.a}^S$	Power load of movable household appliances
$P_{L.IN}^S$	Power load of interruptible household appliances
$P_{L.a}^{S.0}$	Power load of movable household appliances before DRP

1. INTRODUCTION

Recently, the usage of renewable energy resources in the distribution grids to supply the residential energy demands has considerably increased in various countries. Taking into account the environmental and economic issues, renewable energy resources can be considered an effective source of power in distribution grids. One of the most prominent applications of the hybrid energy resources is using on-site portable generators to meet residential energy demands [1]. These generators can meet the energy demands with the minimum emissions and at the least cost through optimal scheduling. Research indicates that the main part of the energy consumption is dedicated to the household sector [2]. Accordingly, the attention of many researchers has been drawn to the energy management in the household sector, thereby plenty of research has been conducted in this field. The stated researches generally cover three main areas, namely increasing the productivity of the household appliances, scheduling the household appliances usage, and augmenting the penetration of renewable resources [3]. Moreover, given the recent advances in telecommunication technology and the emergence of smart measurement devices and automatic control equipment, growing interest has been focused on the smart grids application in residential areas [4].

The consumption pattern and time is determined so that the consumers reduce the power consumption at peak hours and shift it to non-peak hours. Intelligent consumption management or demand response may afford consumers economic benefits. Time of use (TOU) program operates such that similar economic benefits are also provided for power suppliers [3], [4].

Power generators are designed to meet consumer demand at peak hours. However, typically, they cannot save energy. They have excess capacity for all off-peak hours, which has high maintenance costs for the suppliers. Thus, if the peak hour demand declines, the power suppliers can save their capital, which helps not to construct power plants for the peak hours and leads to discounts on the prices [5].

Until a few years ago, power networks were assumed to meet the power needs of modest and small consumers, and there have been power plants built around communities and local energy consumers. Such water and power networks have been designed for the end-users, and then their peak consumption along with efficiency was calculated once a month. This one-way interaction resulted in difficult conditions for the network to be controlled by the 21st century ever-changing and ever-increasing demands for energy. On the other hand, with the emersion of intelligent networks, interactive communications can be made between the supplier and the customers, where power generation and consumption information can easily be exchanged. In such an environment, not only can the network be more efficient, reliable, safe, and green but also newer technologies such as solar and wind energy generation can help the integration and reliability of the network [6]–[8]. With active participation of end-users as the aware consumers and improving communications between them and services, the intelligent network is used instead of the outdated network infrastructure. Above all, by using communication means, such as Home Area Networks (HANs), there is the possibility of connecting different smart devices and measurement units to Energy Management System (EMS), so that manage internal device functionalities in a cost-efficient manner [9]. Given the residential Energy Management System (EMS), many pieces of research have recently been conducted, and their findings have been published in different papers. A residential EMS has been proposed for network support programs and Distributed Energy Resource (DER) management with respect to the minimum operation cost [10]. Thus, the single-purpose energy management algorithm has been specified for home demand planning concerning the minimum power price. Work plans and internal energy management were developed for a residential building considering different technical and operational aspects. Moreover, this was investigated by different methods, taking into account the domain-time simulation with dynamic thermal-electrical limitations, price flexibility variation, and incentive-based response actions. As we see in the literature, extensive studies exist in the field of energy management in intelligent residential networks considering relevant objectives and limitations. Demand Side Management (DSM) is a fascinating approach in intelligent network management that is employed by a means to minimize energy consumption in the demand side [11]. DSM scheme involves energy saving, consumption shift, and response demand plans. In DR plans, the consumers are motivated to participate in the power market actively and directly communicate with the network. The consumers are expected to change their energy consumption pattern as a response to the power price variation; thus, they could decrease their electricity bills. In the conducted studies, it was indicated that a considerable part of the energy price for the consumers is obtained from DR plans. Direct Load Control (DLC) and Time of Use (TOU) are two common methods in DSM that have been proposed by different suppliers. In DLC, the service providers have direct control on the replacement and deactivation of the consumer loads. At the same time, in RTP, water and power have a time-dependent pricing scheme; the load curve of the system, therefore, is almost divided during the high demand period equal to the increase in the price [9], [10]. Given the increased demand and reduced common energy resources, the energy is continuously increasing in price. Hence, after-sales services concerning Renewable Energy Resources (RER) are established as an alternative solution to respond to the demand. However, the unpredictability in generating energy from RERs due to the alternating nature of RER directs the devices to additional operational challenges. In addition to the renewable energy generation systems on a large scale, the residential consumers are also encouraged by the governments to meet the solar or small-wind-turbine energy generation systems, either partly or completely. Such a renewable generation in small scale helps to reduce power credits when renewable power generation is higher [13], [14]. New resources are expected to affect the energy price dynamism. Moreover, in recent days, residential buildings have been becoming more accurate by extensively using intelligent devices and integrating Information and Communication Technology. To achieve the maximum use of RERs at home along with the maximum TOU benefits, use of smart appliances requires a right time. As a result, the need for timing the load for each residential building in an intelligent network environment is inevitable [15].

Smart household appliances enable the optimal scheduling of the appliances, such that the use of some appliances can be shifted from peak to mid-peak or off-peak hours [16], [18]. In [19]–[21], for example, household peak load reduction and load shifting through optimization algorithms were investigated. The scheduling optimization of the smart household appliances for emissions minimization and economic use of smart household appliances was studied in [22], [23]. Taking into consideration the consumer performance, smart household appliances scheduling was addressed in [24], and the software infrastructure was developed to this end. In [25], electricity cost minimization was tackled by considering electric vehicles and hybrid energy resources for smart household energy management. Hybrid resources optimization and residential energy management through the weighted sum method (WSM) were examined in [26]–[28]. Some studies, for example, [29]–[33], also dealt with multi-objective functions for minimizing the operating cost and emissions in a hybrid energy system regardless of the reliability indices.

Therefore, scheduling of the electric power generating units may require an economic-environmental model to describe the relationship between the costs and capacity of power generation. As it is a non-linear model, effective optimization methods are needed to reduce the costs. Table 1 shows a comparison between this paper scheduling models with those reported in the literature.

In this paper, the use of a power management algorithm is considered as a smart strategy to optimize energy. The objective functions are based on the minimization of equipment operating costs, emissions, and ENS. Also, the interaction between home automation technologies and consumer behaviour is taken into account. The consumer can also use movable and adjustable household appliances to reduce the operating costs and power consumption at peak hours.

TABLE 1. COMPARISON OF SCHEDULING MODELS REPRESENTED IN THIS PAPER AND IN LITERATURE

Reference	Objective functions	Uncertainties	Implementing Load shedding by	Load-Shift Model	Solving Method and Implementation Approach
[16]	Reliability Environment economy	Load, WT, PV	Total Loads	Price, Encourage and RTP-Based	Weighted Sum
[17]	Reliability environment	Load, WT	Total Loads	Price-Based	Weighted Sum
[18]	Reliability	PV, WT	Total Loads	Price and Encourage-Based	Weighted Sum and non-linear
[19]	Reliability Economy	Load, WT, PV	Total Loads	Price-Based	Non-linear
[20]	Reliability Economy	PV, WT	Total Loads	Price and Encourage-Based	Weighted Sum and non-linear
[21]	Reliability Environment	Load, PV, WT	Total Loads	Price-Based	Weighted Sum
[22]	Reliability	Load, WT	Total Loads	Encourage-Based	Weighted Sum and non-linear
[23]	Reliability Economy	PV, WT	-	Price-Based	Non-linear an SFL
[24]	Reliability Economy Environment	Load, PV	-	Price and Encourage-Based	Weighted Sum and non-linear
[25]	Reliability Economy	Load, WT, PV	Total Loads	Price-Based	Weighted Sum
[26]	Economy	Load	-	-	Random
[27]	Environment Economy	Load	-	-	Weighted Sum
[28]	Environment Economy	PV, WT	-	Price-Based	Weighted Sum and Monte Carlo
[29]	Environment Economy	Load, WT	-	Price and Encourage-Based	Weighted Sum
[30]	Reliability Economy	Load, PV, WT	-	Price, Encourage, and RTP-Based	PSO
[31]	Reliability Environment	Load, WT, PV	-	Price and Encourage-	SFL, TLBO
[32]	Economy Reliability	PV, WT	Total Loads	Price-Based	Epsilon-Constraint and Weighted Sum
[33]	Reliability	Load, WT, PV	-	Price and Encourage-Based	Random

The innovations undertaken in the present study are briefly presented as follows:

– Proposing a multi-objective function based on the power management algorithm and the WSM by considering different layers of decision-making.
– Investigating the impact of DRP on each objective function through power management algorithm in different cases under uncertainty of renewable source and loads.
– Recommending ENS as an objective function for managing the consumers' power consumption behaviours in an effort to reduce emissions and operating costs.

– Suggesting the implementation of load shedding program for interruptible loads.

The rest of the paper is organized as follows. Section 2 presents the deterministic model and the configuration of the hybrid energy system. Section 3 is dedicated to scenario generation. Section 4 is dedicated to the introduction of the proposed objective functions and constraints. Section 5 describes DRP modelling and constraints. The power management algorithm and optimization method are proposed in section 6. Section 7 investigates the numerical simulation and the results analysis. Finally, the conclusions are presented in section 8.

2. DETERMINISTIC MODEL

The configuration of the proposed system is demonstrated in Fig. 1. In this hybrid system, resources can be classified under three units according to the type of generation: 1) dispatchable units, such as diesel generator (DG), 2) non-dispatchable units, such as photovoltaic (PV) systems and wind turbines (WT), and 3) power reserve units, such as battery bank (BB) and loads. The modelling of each aforementioned equipment is explained in the following sub-sections.

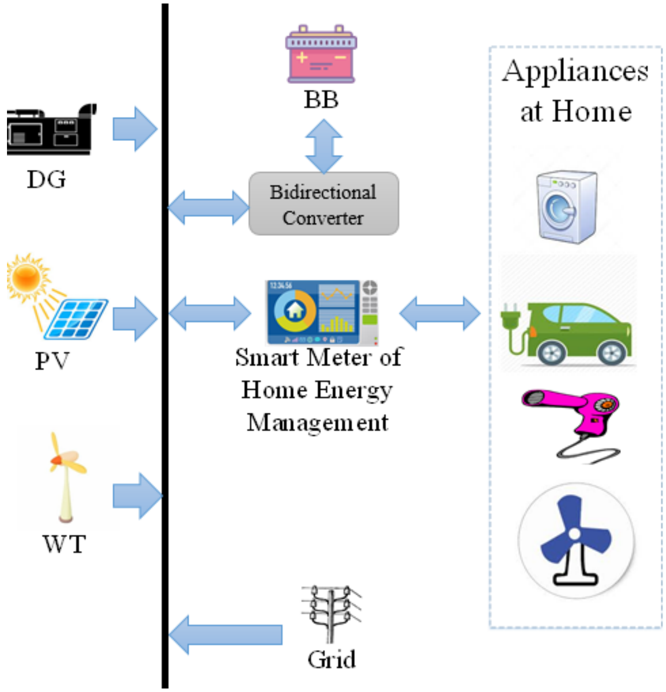


Fig. 1. The configuration of the proposed hybrid energy system.

2.1. PV Modelling

PV system output is variable and typically dependent on the solar irradiance. The solar irradiance distribution in a specific place typically follows a two-dimensional distribution which can be perceived as a linear combination of two non-generative distribution functions.

As it is provided below, the same Probability Density Function (PDF) beta is used for each of the following items [34]:

$$\rho^{PV} = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{\alpha-1}(1-s)^{\beta-1} & 0 \le s \le 1, \alpha \ge 0, \beta \ge 0 \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

where s represents the solar irradiance (kW/m^2). The α and β are parameters of the Beta distribution function.

The output power of PV can be calculated under the standard test condition Eq. (2) [34].

$$P_{PV}(t) = \begin{cases} P_{PV}^{N}\left(\dfrac{{R_S}^2}{R_{ST}R_N}\right) & \text{if} \quad 0 \le R_S \le R_N \\ P_{PV}^{N}\left(\dfrac{R_S}{R_{ST}}\right) & if \quad R_N \le R_S \le R_{ST} \\ P_{PV}^{N} & \text{if} \quad R_{ST} \le R_S \end{cases} \tag{2}$$

2.2. WT Modelling

PDF Rayleigh is typically used as a suitable model of wind velocity expression. It is a specific case of PDF Weibull, is as follows [34]:

$$\rho^{WT}(v) = \begin{cases} \dfrac{k}{c} \times \left(\dfrac{v}{c}\right)^{k-1} \times e^{-\left(\frac{v}{c}\right)^k} & v \ge 0 \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$

where $\rho^{WT}(v)$, c and v are Rayleigh PDF, scale index and wind speed, respectively.

The output power of WT, which is proportional to the wind speed in each hour, is expressed as below [34]:

$$P_{WT}(t) = \begin{cases} 0 & \text{if} \quad V_i \le V \le V_O \\ P_{WT}^{N}\left(\dfrac{V-V_O}{V_R-V_O}\right) & \text{if} \quad V_O \le V \le V_R \\ P_{WT}^{N} & \text{if} \quad V_R \le V \le V_i \end{cases} \tag{4}$$

2.3. Load Modelling

In this paper, the load demand forecast error based on normal distribution function is assumed and by ρ_d is specified by the region under the Gaussian distribution curve between the upper and lower limits in the i-th interval in each time. Therefore, forecast error is presented by standard deviation (σ) for normal PDF and net forecast demand (d_f) is given as follows [35]:

$$\rho^{D} = \frac{1}{\sigma \times \sqrt{2\pi}} \int_{l_i}^{u_i} e^{\frac{-\left(x-d_f\right)^2}{\sigma^2 \times 2}} \mathrm{d}x, \tag{5}$$

where u_i and l_i are, the upper and lower bounds of the demand at each interval, respectively.

2.4. DG Modelling

The function cost of the power generated by DG is proportional to the output power and power generated by DG is depended on fuel cost, and it is stated as Eq. (6).

$$C_{DG}(t) = \sum \alpha P_{DG}(t)^2 + \beta P_{DG}(t) + \gamma \tag{6}$$

2.5. BB Modelling

The cost function of BB considering the variables such as charge-discharge power is expressed as:

$$C_{BB}(t) = \sum L_{BB} \times (P_{BB}^{dis}(t) / \eta_{dis} - P_{BB}^{ch}(t) \times \eta_{ch}), \tag{7}$$

where [36]:

$$L_{BB} = \left(\frac{C_{BB}^{CA} + C_{BB}^{O\&M}}{N_C \times N_B \times V_B \times Q_B} \right). \tag{8}$$

The charge-discharge power of BB has direct and unidirectional effect on the BB lifetime, which by Eq. (8) is given.

2.6. Grid Modelling

Given the price of purchasing power from the electricity grid as well as RTP tariffs, the grid model can be stated as Eq. (9) and Eq. (10).

$$C_g^b(t) = \chi_g^b(t) \times P_g^b(t) \tag{9}$$

$$C_g^s(t) = \chi_g^s(t) \times P_g^s(t) \tag{10}$$

The buying and selling power from electricity grid in each hour are variable and based on RTP tariffs by consumers can be consumed.

3. SCENARIO GENERATION

According to the given explanations, in uncertainty modelling, random variable of the probability distribution is applied using a limited set of scenarios. One probability of event is obtained in each scenario. In this paper, Monte Carlo simulation (MCS) is used to scenario generation process. Thus, scenario generation process of solar, wind and load demand can be expressed as follows [37]:

$$\rho(s) = \rho^{PV}(s) \times \rho^{WT}(s) \times \rho^{D}(s)\,, \tag{11}$$

$$\sum_{s=1}^{S} \rho^{PV}(s) \times \rho^{WT}(s) \times \rho^{D}(s) = 1\,, \tag{12}$$

where ρ^{PV}, ρ^{WT} and ρ^{D} are probability of solar generation, wind generation and load demand in scenario s, respectively. The probability of solar generation, wind generation and load demand in each time are variable.

3.1. Scenario Reduction

Uncertainty typically occurs as a result of random and non-controllable events mostly happen due to the unknown probability distribution. The calculation of uncertainty through mathematical modelling may lead to a difference between the measured and estimated values, which can be a matter of utmost importance in economic and environmental issues. In this paper, day-ahead forecasting was used to predict electricity power price and load demand. Furthermore, beta and Weibull distribution function was used due to the uncertainty in the estimated values of solar radiation and wind speed, respectively.

Due to the increasing number of scenarios by applying the scenario generation method, number of the scenarios can be easily reduced by scenario reduction methods. The process of the scenario reduction methods removes similar scenarios and very low probability of event. In this paper, backward method is employed to scenario reduction. The process of scenario reduction in backward method includes following steps [37].

1. Provide the probability distance with the cardinality of $DT\ (\xi_s, \xi_{s'})$ including the distance between pairs of created scenarios.
2. Compute the probability distances of all scenario pairs as Eq. (13).

$$DT_t = \sqrt{\sum_{s=1}^{N_S} (\rho_s^i - \rho_s^j)^2} \tag{13}$$

3. Minimum distances are select as DT_i = arg min DT_t.
4. If cardinality of DT is adequate, go to step 2. If cardinality of DT is not adequate, then continue.
5. Obtain accurate size of the reduced scenario set based on repeat steps 2–4.

4. OBJECTIVE FUNCTIONS

In this paper, three objectives are minimized and classified into: 1) The operation cost; 2) Emission polluting; 3) Energy not supplied (ENS).

4.1. The Operation Cost Modelling

The operation cost of DG, including fuel and start-up costs by first and second term of (14) are calculated, respectively. Third term of (14) is operation cost of BB system, and operation cost of buying and selling from electricity grid by fourth and fifth terms of (14) are given, respectively. It should be noted that, operation costs of the equipment and electricity grid in section 2 are explained.

$$j_1 = \sum_{s=1}^{S} \rho_s \sum_{i=1}^{t} C_{DG}(t,S) + C_{DG}^{SU} + C_{BB}(t,S) + \sum_{i=1}^{t} C_g^b(t,S) - C_g^s(t,S) \tag{14}$$

4.2. The Emission Polluting Modelling

The second objective function is emissions polluting considering the amount of emissions generated by DG and electricity grid. This function is expressed as Eqs (15)–(17).

$$j_2 = \sum_{s=1}^{S} \rho_s \sum_{i=1}^{t} E_{DG}(t,S) + \sum_{i=1}^{t} E_g(t,S), \tag{15}$$

where [38]:

$$E_{DG}(t) = \sum \mu P_{DG}(t)^2 + \lambda P_{DG}(t) + \rho, \tag{16}$$

$$E_g(t) = \sigma_g(t) \times P_g^b(t). \tag{17}$$

The first term of (15) is emission generated by DG, that by (16) is modelled, and emission of electricity grid by second term of (15) is given, and by (17) can be calculated.

4.3. The ENS Modelling

The third objective function is the cost of ENS which is related to the unmet demand. This function is stated as Eq. (18).

$$j_3 = \sum_{s=1}^{S} \rho_s \sum_{i=1}^{t} ENS(t,S) \times VOLL \tag{18}$$

The ENS can be expressed in two models:

$$P_{LS}(t) = \begin{cases} 0 \quad \text{if,} \quad P_L(t) - \sum_{i=1}^{t} \left(P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + \dfrac{P_{BB}^{dis}(t)}{\eta_{dis}} + P_g^b(t) \right) + \eta_{ch} \times P_{BB}^{ch} \le 0 \\ P_L(t) - \sum_{i=1}^{t} \left(P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + \dfrac{P_{BB}^{dis}(t)}{\eta_{dis}} + P_g^b(t) \right) + \eta_{ch} \times P_{BB}^{ch} \quad \text{otherwise} \end{cases} \tag{19}$$

The Value of Lost Load (VOLL) depends on multiple factors, including the type of load and duration of outage. The ENS can be investigated from two perspectives: (1) load shedding and (2) increased power generated by resources. The latter fails to be considered in the present study due to the limits imposed upon resources. Further explanations in this regard will be presented in the following sections.

4.4. Constraints

The optimal scheduling is managed by several constraints presented next.

4.4.1. Power Balance Constraint

The power balance constraint covers power generated and consumed by respective units. This constraint is expressed as Eqs (20)–(22).

$$\begin{aligned}&\sum_{i=1}^{t} P_{PV}(t) + P_{WT}(t) + P_{DG}(t)\times u_{DG}(t) + P_g^b(t)\times u_g^b(t) + P_{LS}(t)\times u_{LS} + P_{BB}^{dis}(t)\times u_{BB}^{dis}(t)\\ &= \sum_{i=1}^{t} P_L(t) + P_{BB}^{ch}(t)\times u_{BB}^{ch}(t) + P_g^s(t)\times u_g^s(t)\end{aligned}\quad ,(20)$$

where:

$$u_g^b(t) + u_g^s(t) \le 1, \tag{21}$$

$$u_{BB}^{dis}(t) + u_{BB}^{ch}(t) \le 1. \tag{22}$$

Equations (15) and (16) are binary variables and used to restrict the electric power sold to or purchased from the grid, as well as to regulate the charge/discharge action of the BB.

4.4.2. Power Limits Constraint

The generation power of each resource such as DGs, BB system and as well as electricity grid should have a certain limit to enable continuous optimal scheduling in the system.

$$0 \le P_{DG}(t) \le P_{DG}^{\max} \tag{23}$$

$$0 \le P_{BB}^{dis}(t) \le P_{BB}^{dis,\max} \tag{24}$$

$$0 \le P_{BB}^{ch}(t) \le P_{BB}^{ch,\max} \tag{25}$$

$$0 \le P_g^b(t) \le P_g^{b,\max} \tag{26}$$

$$0 \le P_g^s(t) \le P_g^{s,\max} \tag{27}$$

4.4.3. Technical Constraints

The equipment used in the hybrid system also has technical constraints such as maximum and minimum uptime, downtime, ramp down and up limit of DG by Eqs (28)–(30) are given, respectively. Moreover, BB determines the power supply by considering the state of charge (SoC), which by Eq. (31) limit of SoC is given, and Eq. (32) is SoC model.

$$\sum_{i=1}^{t} u_{DG}(t+1) \ge MUT \tag{28}$$

$$\sum_{i=1}^{t} 1 - u_{DG}(t+1) \ge MDT \tag{29}$$

$$R_D \le P_{DG}(t) - P_{DG}(t-1) \le R_U \tag{30}$$

$$SOC^{\min} \le SOC(t) \le SOC^{\max}, \tag{31}$$

where [25]:

$$SOC(t) = SOC(t-\Delta t) - \frac{(P_{BB}^{dis}(t)/\eta_{B}^{dis}) + (P_{BB}^{ch}(t) \times \eta_{BB}^{ch})}{N_B V_B Q_B} \quad . \tag{32}$$

5. ELECTRICAL LOAD AND DEMAND RESPONSE PROGRAM

Household electrical appliances can be divided into three categories according to the type of load:

1) non-movable loads, e.g., critical lighting, refrigerator (RE), air conditioning (AC);
2) movable loads, e.g., dryer (DY), washing machine (WM), and electric vehicles (EV); and
3) interruptible loads, e.g., air conditioning (AC), optional lighting, and dryer (DY) [39].

Therefore, to implement Demand response programs (DRP), household appliances scheduling is required to be examined from the facet of consumption characteristic at operating time. DRP implementation in the present paper is conducted using load shedding and load shifting techniques. Accordingly, the implementation of DRP is specific to movable and interruptible loads. DRP modelling is described in the following [40]:

- For each load, the power consumption limit must be considered. The reason for applying this constraint is to introduce the nominal power of the electrical appliances at operating time as well as the threshold of the curtailed power in interruptible loads;

$$0 \le P_{L,a}^{S}(t) \le P_{L,a}^{S,\max} \tag{33}$$

$$0 \le P_{LS}(t) \le P_{L,IN}^{\max} \tag{34}$$

- Implementation of the consumer model tends to change the pattern of consumption; This model is applied by enabling movable-load device adjustment by the consumer, as modelled in Eqs (35)–(36);

$$P_{L,a}^{S}(t) = \left(\sum_{i=1}^{t} \xi \times P_{L,a}^{S,0\max}(t), t \right) \tag{35}$$

$$\sum P_{L,a}^{S,0} = \sum P_{L,a}^{S} \tag{36}$$

- In Eq. (35), the value of ξ is in the interval [0, 1], which can be adjusted by the consumer, i.e., the consumer can adjust its consumption at any time according to the consumption pattern. A point that deserves mentioning is that the total movable load before and after the DRP implementation must be equal, as formulated in Eq. (36). The movable-load based on diverse RTP traffics in each time can be employed by consumer in low price traffic in day ahead scheduling.

6. INVESTIGATION OF THE OPTIMIZATION MODEL AND THE PROBLEM-SOLVING METHOD

Given the optimization problem-solving method, objective functions must be defined as one objective function. Considering that the problem at issue includes three objectives (optimization of operating cost, emissions, and ENS), WSM and uncertainty parameters of wind speed, solar radiation, load, and RTP changes in the energy market are considered to fulfil the stated objectives. In this paper, the optimization model is implemented as follows:

- Forecast of the uncertain parameters;
- Establishing an algorithm for energy optimization.

Therefore, the objective functions for solving the optimization problem can be written as:

$$\min\left(w_1 j_1 + w_2 j_2 + w_3 j_3\right), \tag{37}$$

subject to constraints Eqs (19)–(37), here, w_1, w_2, *and* w_3 are weight coefficients in the interval [0, 1], and their sum is equal to 1. The objective functions are considered according to the constraints. The power management algorithm for the hybrid system at each time step is presented in Fig. 2. In this algorithm, at first, the power generation capacity of the non-dispatchable energy sources (PV and WT) is calculated, and then this generating power is compared with the power consumption, and then the following states are obtained:

- The generating capacity of the non-dispatchable sources is equal to the power consumption. Hence, thanks to the power balance, the algorithm runs at the next time step.
- The generating capacity of the non-dispatchable sources is less than the consumption power, hence consumers use the batteries depending on the SOC. In this case, the maximum discharged power of the batteries at this time step is compared with the remaining consumption power. If the power balance is still maintained, the algorithm runs at the next step. Otherwise, DG or grid is used based on the tariffs in the electricity market for peak, mid-peak, and off-peak periods chosen by the consumer. In this case, following power balancing, the Energy Management Center (EMC) is used to monitor the consumer performance respecting emissions generation. Comparing the cost of emissions and that of operation, EMC may impose limits on the consumer (limits are applied with weight coefficients). Then, if the consumer fails to react to the given limits, the load shedding program is implemented. Indeed, EMC must pay penalties associated with greenhouse gas emissions. In this case, the objective functions are prioritized based on the importance of the problem, and then weights are tuned so that sum total of weights equals 1. On the other hand, the cost of DG fuel and the cost of electricity purchased from the grid can be of priority objectives. This issue will be further discussed in the simulation section. The power management algorithm based on consumer decision and EMC decision are divided. In consumer decision, consumer is attempted for minimization of generation costs such as RTP, fuel cost and etc. But, in EMC decision, EMC is provided energy optimal management for reducing emission polluting in consumer decision.

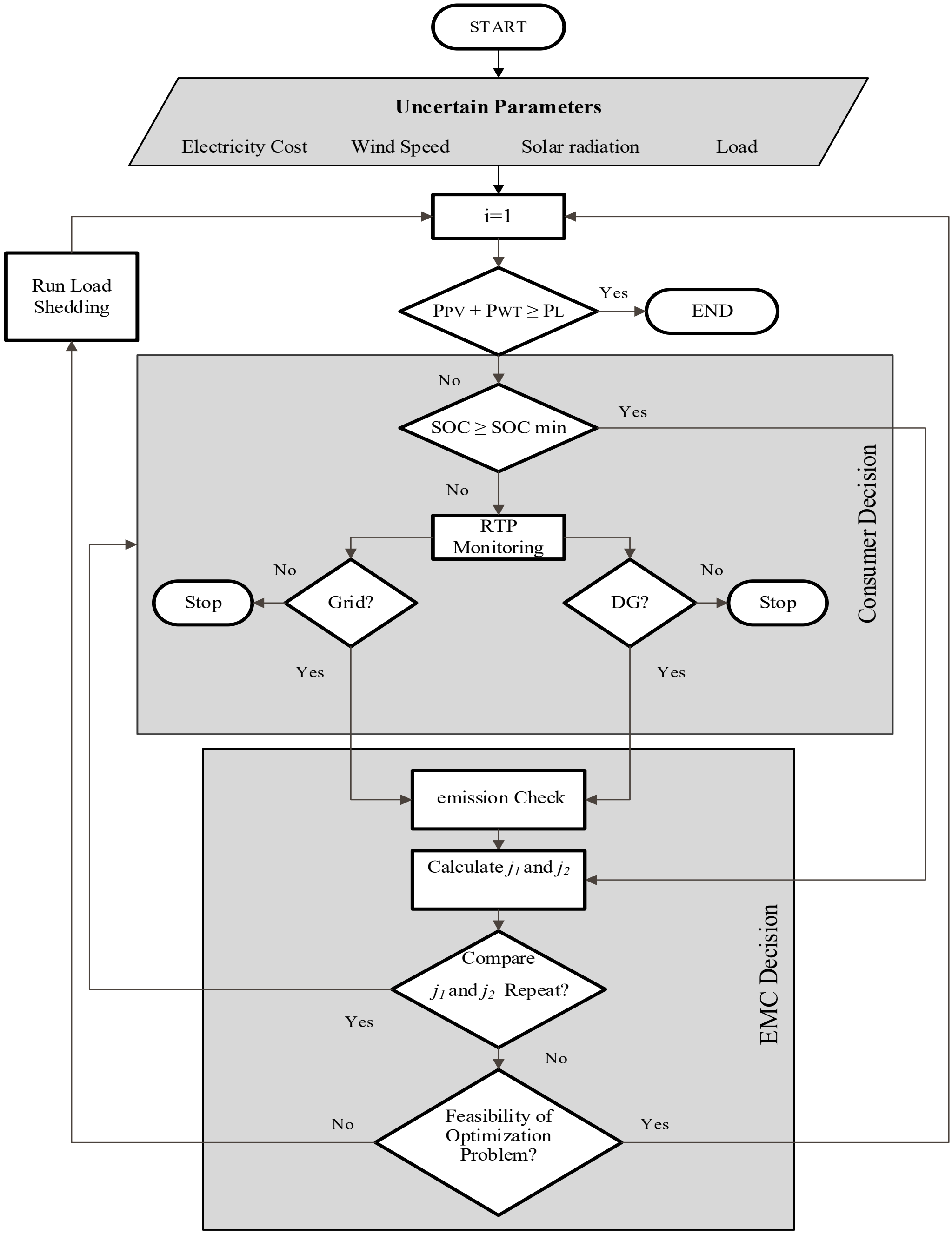


Fig. 2. Power management algorithm based on decision-making layers.

7. NUMERICAL SIMULATION AND RESULTS ANALYSIS

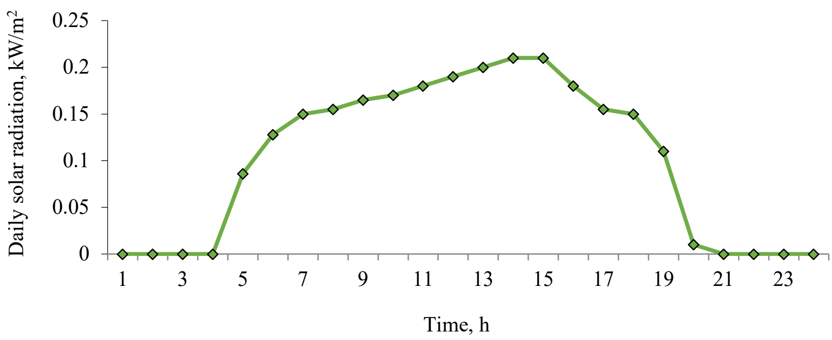
Given the components used in the hybrid energy system and the control components of the system, input data is required to be provided. Fig. 3 depicts the estimated value of solar radiation and wind speed. Table 2 and Table 3 present data associated with WT and PV. Power demand of household appliances is demonstrated in Fig. 4. Economic and technical data related to DG and BB are presented in Tables 4 and 5. The modelling is considered for single house in Tehran city based on RTP traffics in Iran, which Fig. 5. demonstrates the electricity purchase price from the grid at the hours under study. Energy supply tariffs according to the RTP are categorized for hours as off-peak (7–24), mid-peak (8–17), and peak (18–23).

TABLE 2. WT DATA

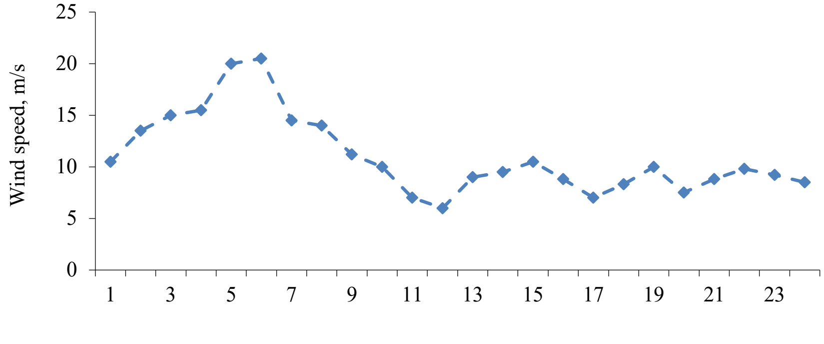
Parameters	Values	Units
$P_{N,WT}$	2	kW
V_{Ci}	2	m/s
V_R	15	m/s
V_{Co}	25	m/s

TABLE 3. PV DATA

Parameters	Values	Units
$P_{N,PV}$	0.26	kW
R_N	0.15	kW/m^2
R_{ST}	1	kW/m^2



(a)



(b)

Fig.3. (a) Estimated daily solar radiation and (b) estimated wind speed in hours under study.

The environmental pollution refers to carbon dioxide (CO_2) and nitrogen oxides (NO_x) emissions from DG and grid. In this regard, the cost function for the emissions is a penalty applied for producing per kilo of the mentioned gases. $\mu = 0.5$, $\rho = 1$, and $\sigma = 5$ are considered as the emission coefficients.

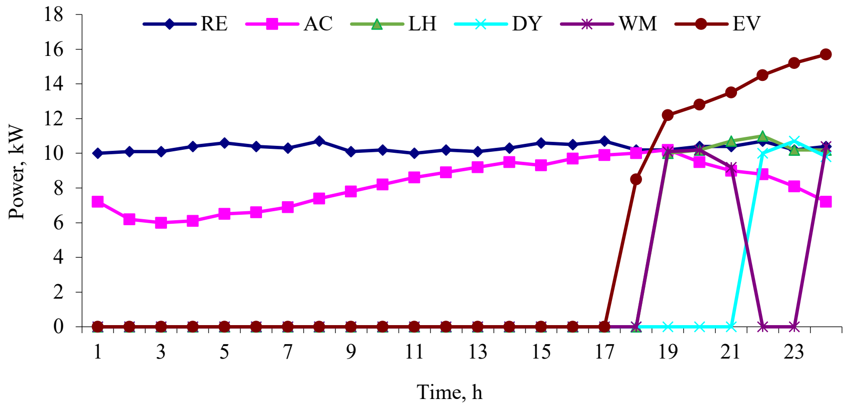


Fig. 4. Consumer energy demand profile based on the day-ahead prediction.

A point that should be clarified is that the price of selling electricity to the grid is considered 0.01 $/kW, and the VOLL is set at 5 $/kWh.

The simulation was implemented with the Intel (R) Core [(TM)] i5 2.5 GHz processor and 6 GB RAM and GAMS software. Also, to evaluate the proposed algorithm, different modes of operation are chosen in light of the decisions. Table 6 presents the weight coefficients in two operation cases.

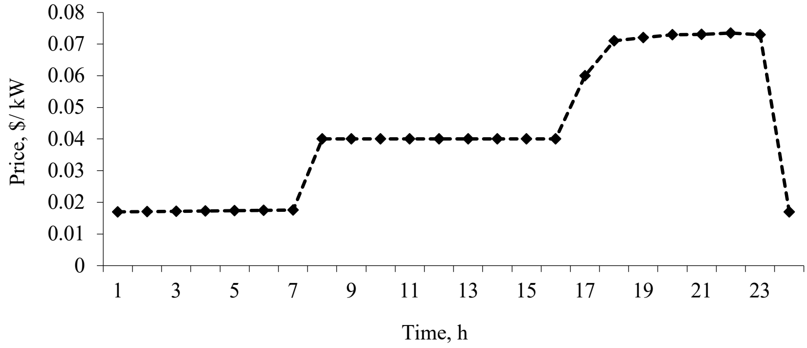


Fig. 5. RTP rate according to the market tariffs.

TABLE 4. DG DATA

Parameter	Values	Units
α	0.018	$/kW^2
β	1.2	$/kW
γ	0	$
C_{DG}^{SU}	0.01	$
R_D	2	kW/h
R_U	4	kW/h
$P_{DG}^{\max}$	35	kW
MUT	4	hr
MDT	2	hr

TABLE 5. BB DATA

Parameter	Values	Units
C_{BB}^{CA}	150	$
$C_{BB}^{O\&M}$	0.5	$
N_B	6	Number
V_B	12	Volt
N_C	500	Cycle
SOC_{min}	30	%
Q_B	100	Ahr
$P_B^{ch,max}$	5	kW
$P_B^{dis,max}$	5	kW
η_{dis}	85	%
η_{ch}	90	%

The weights selection in case 1 is based on consumer decision, and EMC has a limited role in power generating and consumption management. In case 2, EMC has more authority over energy management. Indeed, selecting a weighted coefficient with a greater value in each function may minimize that objective function and optimize the costs associated with that decision-making layer. In case 1, for instance, the consumer is mostly focused on minimizing the costs of power purchased from the grid, DG fuel, and ENS, but less attention is dedicated to the environmental pollution issues. Contrariwise, the objective function associated with the emissions is more important in case 2.

TABLE 6. WEIGHT COEFFICIENTS FOR TWO OPERATING MODES

Operation Mode	w_1	w_2	w_3
Case 1	0.6	0.1	0.3
Case 2	0.1	0.6	0.3

7.1. Results Analysis

The generating power of the hybrid system to supply power in light of the weighted coefficients in cases 1 and 2 is shown in Fig. 6 and Fig. 7, respectively. The variables include the power of DG (P_{DG}), grid power (P_{grid}), power of battery bank (P_{BB}), load shedding power (P_{LS}), PV power (P_{PV}), and WT power (P_{WT}) are calculated based on changing in consumption pattern by moveable-loads and interruptible loads. As demonstrated in Fig. 6, the power is purchased from the grid by the consumer in mid-peak and off-peak hours. However, at peak times, due to the increased RTP rates by the grid, the consumer has to respond part of this power demand through DG.

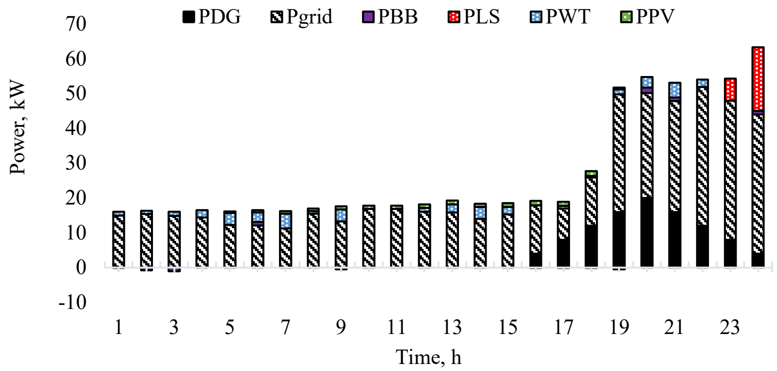


Fig. 6. The optimized output power of the hybrid system in case 1.

On the other hand, in an attempt to reduce emissions, load shedding is instituted at hours 23 and 24, due to the higher demand during peak hours and considering the increased power purchased from the grid and DG. load shedding at mentioned hours is respectively 6.2 kW and 18.3 kW. BB generates 2.5, 2, and 2 kW power supplies at hours 20, 21 and 24, respectively. However, in case 2, because of the high value of the grid emission factor, DG is used to meet load demand. Hence, at 17, 4.9 kW power is sold to the grid. Also, in peak hours due to the power limitation of DG and increased fuel consumption, the grid is used instead (Fig. 7).

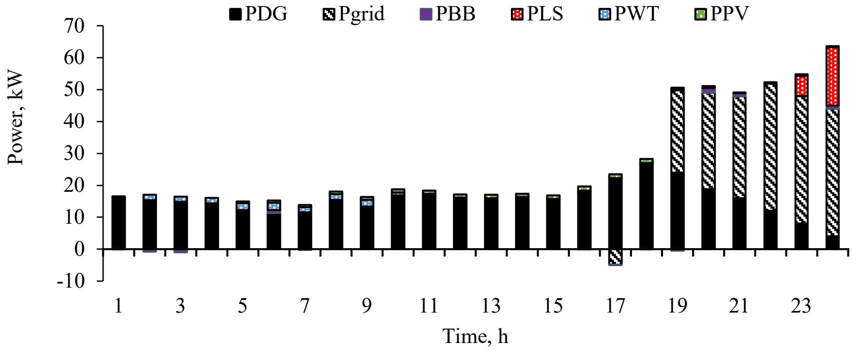


Fig. 7. The optimized output power of the hybrid system in case 2.

Given the results depicted in Fig. 6 and Fig. 7, resource generation management for two operating modes is examined. As it is observed, due to the reduced generation of non-dispatchable electricity sources and BB to meet electricity demands, the use of DG and grid has increased. The efficient performance of the proposed algorithm in case 1 is due to the reduced fuel cost of the DG compared to case 2. However, in the latter, the grid is used less by the consumer as a result of increased weighted coefficients associated with emissions.

7.2. Impact of Movable Loads on Optimal Scheduling

In this subsection, the impacts of the movable loads on the optimization of the power generated by resources are investigated using the proposed algorithm. The respective loads are classified into two types according to the consumption characteristic, namely adjustable loads and non-adjustable loads. Adjustable loads, e.g., DY and WM, refer to loads in which the power consumption limit can be adjusted by the consumer [30]. For example, a consumer can use WM and DY with a lower power consumption, albeit for a longer time. The implementation of such kind of DRP not only shifts demand to off-peak hours but also reduces the outage as well. Non-adjustable load (e.g., EV), on the other, has a specific charge profile, and the consumer fails to play a role in reducing or increasing its amplitude.

Considering Eq. (35) and Eq. (36), the value of ξ for WM and DY is chosen 0.5 and 0.7, respectively. Load shifting times for WM and DY are considered from 24 to 1 and 6 to 10, respectively. The value of ξ for EV is considered 1, and the load shifting times are considered 24 to 5. Fig. 8 depicts the power consumption profile of the household appliances after load shifting.

As shown in demand curve, load shifting in the time interval under study leads to reduced demand during peak periods, as presented in Fig. 9 (case 1) and Fig. 10 (case 2). In Fig. 9, the ENS value after load shifting is less than the value observed before shifting, power purchased from the grid also increased in the hours under study.

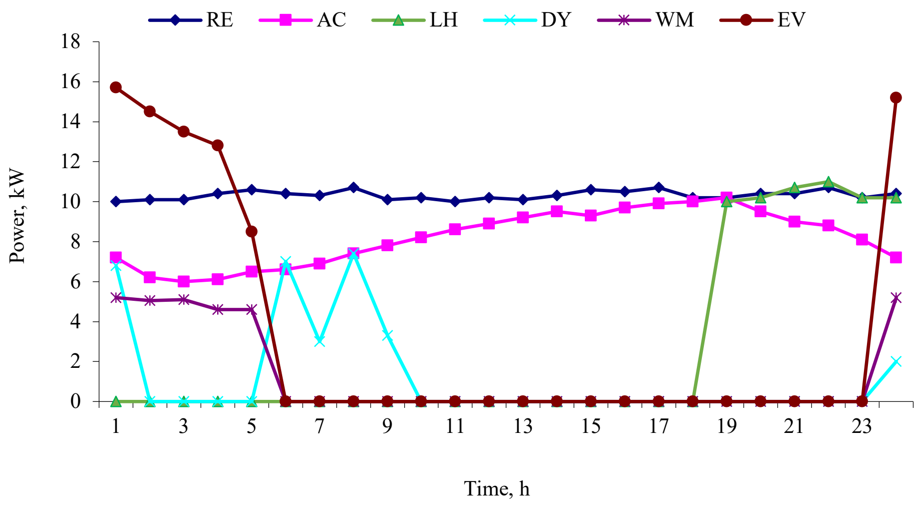


Fig. 8. Power consumption profile after movable loads shifting.

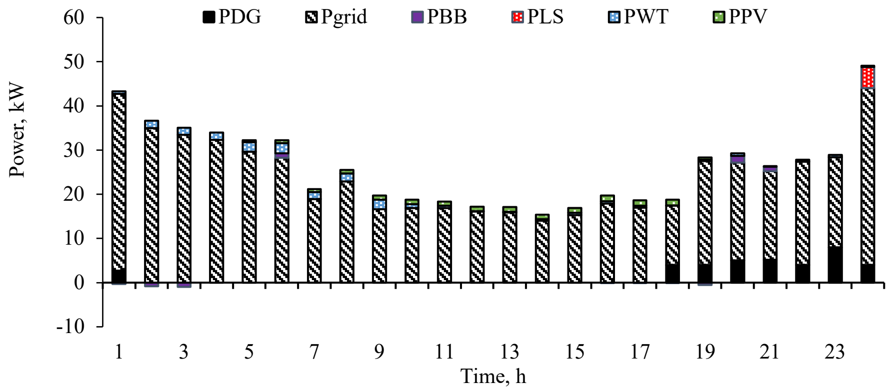


Fig. 9. The optimized output power of the hybrid system in case 1 after movable load shifting.

In Fig. 10, DG provides demand with maximum capacity. However, the grid is also used, and load shedding is applied at peak hours. Table 7 presents the results of operating modes based on the weighted coefficients for each of the objective functions.

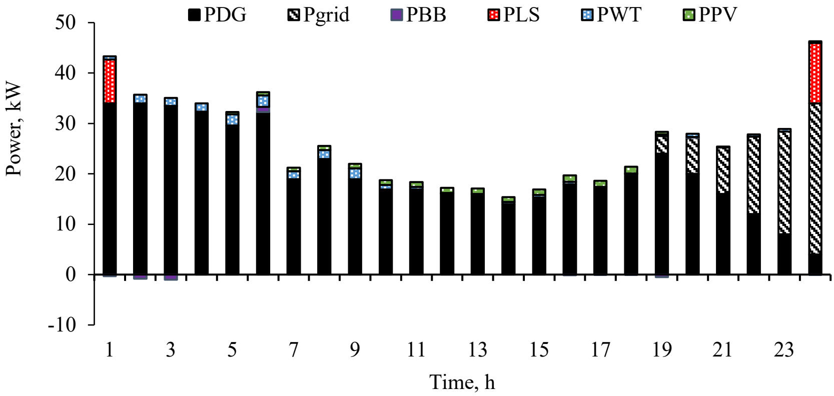


Fig. 10. The optimized output power of the hybrid system in case 2 after movable loads shifting

TABLE 7. THE ESTIMATED OBJECTIVE FUNCTIONS IN CASES 1 AND 2 BEFORE AND AFTER LOAD-SHIFTING

Obj. f. / Case	**Before load shift**			**After load shift**		
	j_1, $	j_2, $	j_3, $	j_1, $	j_2, $	j_3, $
1	366.66	2487.74	122.95	130.91	2874.94	23.95
2	490.33	1452.39	122.95	400.12	972.8	103.45

8. CONCLUSION

The present paper investigated short-term energy management of a smart house in consideration of RTP tariffs under uncertainty of renewable sources and loads. The proposed algorithm consisted of two decision-maker layers in energy consumption management, emissions control, and reliability testing based on the uncertainty parameters. Furthermore, different operating modes were considered with respect to weight coefficients to show the performance of the algorithm. As revealed by the results yielded, implementation of load shifting led to reduced amplitude of the movable loads and demand shifting from peak to mid- or off-peak periods. The simulation results for case 1 indicated that the operating cost and ENS reliability index were optimized following DRP implementation. Therefore, excessive electricity purchase from the grid resulted in an increase in emissions. In case 2, on the contrary, a significant reduction was observed in the environmental emissions following DRP implementation. Therefore, it can be concluded that DRP implementation using the proposed algorithm had an effective role in optimizing the objective functions at issue. Eventually, the proposed power management algorithm provided a framework for optimal scheduling of energy demand and optimal utilization of the extant resources.

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