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An Optimal Energy Optimization Strategy for Smart Grid Integrated with Renewable Energy Sources and Demand Response Programs

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Abstract: An energy optimization strategy is proposed to minimize operation cost and carbon emission with and without demand response programs (DRPs) in the smart grid (SG) integrated with renewable energy sources (RESs). To achieve optimized results, probability density function (PDF) is proposed to predict the behavior of wind and solar energy sources. To overcome uncertainty in power produced by wind and solar RESs, DRPs are proposed with the involvement of residential, commercial, and industrial consumers. In this model, to execute DRPs, we introduced incentive-based payment as price offered packages. Simulations are divided into three steps for optimization of operation cost and carbon emission: (i) solving optimization problem using multi-objective genetic algorithm (MOGA), (ii) optimization of operating cost and carbon emission without DRPs, and (iii) optimization of operating cost and carbon emission with DRPs. To endorse the applicability of the proposed optimization model based on MOGA, a smart sample grid is employed serving residential, commercial, and industrial consumers. In addition, the proposed optimization model based on MOGA is compared to the existing model based on multi-objective particle swarm optimization (MOPSO) algorithm in terms of operation cost and carbon emission. The proposed optimization model based on MOGA outperforms the existing model based on the MOPSO algorithm in terms of operation cost and carbon emission. Experimental results show that the operation cost and carbon emission are reduced by 24% and 28% through MOGA with and without the participation of DRPs, respectively.

Keywords: multi-objective energy optimization; smart grid; renewable energy sources; wind; photovoltaic; demand response programs

1. Introduction

Energy optimization is an indispensable task in energy management of the smart grid (SG) [1,2]. Optimal energy optimization is possible only by actively engaging consumers in demand response programs (DRPs) offered by electric utility companies (ECUs) [3]. DRPs enable the ECUs to shift a load of consumers from on-peak to off-peak hours by giving economic incentive to the consumers [4]. A market overview model consisting of 10 chapters is presented [5] for economic cost reduction, which consists of market forecasting, market management, and market monitoring to schedule energy, ancillary services, and transmission. Moreover, DRPs provide ease and flexibility to consumers to actively participate in the electricity market for energy optimization.

Energy demand is rising, and conventual energy sources are limited and depleting gradually. Therefore, renewable energy is a hot topic for researchers due to high energy potential and continually replenished nature. According to [6], the increase in population results in an increase in energy demand, and it is predicted that demand will increase to 50% or more at the end of 2030. Renewable energy is free of economic cost and emission. It is most suitable to use. Thus, in [7], energy optimization of a model considering RESs is discussed due to the low price and environment-friendly advantages of RESs. The integration of RESs was studied recently in [8], which provides a massive comfort to SG technology in terms of cost. There is always a variation issue in RESs, to overcome these issues, and an energy optimization model was proposed, which consists of a mathematical tool PDF discussed in [9], to model solar and wind sources. Intermittent behaviour of wind and solar energy is modelled in [10] by using PDF and Rayleigh distribution; in this case, the proposed method was a tree optimization. Intermittency in RESs is one of the significant issues, RESs integration is discussed [11] by taking a survey of models all around the world. The author concluded that communication system, specifically two-way communication plays a significant role in the energy optimization of the SG.

An article [12] was discussed to reduce economic cost and carbon emission simultaneously as a multi-objective function. The proposed model was accurate in all perspectives as implemented on SCADA software and also the hardware of the proposed model was tested; in addition, the economic cost and carbon emission are successfully reduced through a dynamic programming-based algorithm. In this research, the author avoids the use of solar energy. A central controller is designed for a micro-grid to improve the efficiency of the micro-grid and predict the performance of a dynamic system [13]. The implementation of this model shows that, when a micro-generator is less than seven, the proposed model is not working properly. In this paper, the author used an economic model predictive control (EMPC) method to reduce economic cost. The traditional grid is not applicable for energy optimization due to lake of communication infrastructure. The SG has advanced metering and bi-directional communication infrastructures, which enables RESs accommodation and active participation of consumers in DRPs to ensure low operation cost and gives carbon emission [14]. In addition, SG enables us to perform optimization from all perspectives like energy, cost, carbon emission, and maintaining a balance between demand and supply. The DRPs in SG reduce cost and provide relief to the end-users; similarly, DRPs are used to overcome uncertainty in RESs. Implementation of DRPs for operating cost minimization and efficiency improvement is discussed in [15]. The proposed energy optimization model based on teaching and learning-based optimization (TLBO) and shuffle frog leaping (SFL) techniques is tested on four types of residential consumers in the centre of Tehran in Iran. The focus of the authors is only on residential load, and no value is assigned to commercial and industrial consumers. A model predictive control (MPC) based work is presented for sharing distributed energy resources (DERs) in micro-grids in order to optimize the available energy [16]. The implementation of this model reduces the economic cost. A fuzzy logic controller based model is studied in [17] to reduce economic costs. In this model, the aim is to manage the charging and discharging rate of an energy storage system to minimize consumers' operational cost. For RES forecasting, the authors used a new method to take the difference between the current REEs and load rather than forecasting approach to predict RESs.

Similarly, an energy optimization model for the residential load is presented in [18]. The authors perform optimization of economic cost function by managing the operation of appliances in the low generation and on-peak period using a robust optimization algorithm. The authors compared the proposed model based on a math-heuristic optimization algorithm with the existing one, which was based on a mixed-integer nonlinear (MILP) method and achieved better results than the current model. However, the carbon emission is not discussed, which is a very critical future challenge. In [19], the authors addressed both operating cost and carbon emission using a mixed-integer nonlinear programming (MINLP) technique of a microgrid including microturbine, fuel cell, battery, and utility as a back-up source. The proposed model based on MINLP results is compared to the genetic algorithm (GA) and particle swarm optimization (PSO) algorithm based models in terms of operation cost and emission. However, the uncertainty accompanied by RESs is catered either by DRPs or PDF/CDF. Economic cost and peak to average ratio (PAR) are reduced by using two heuristic based demand side management techniques [20], a bacterial Foraging Optimization Algorithm (BFOA) and a Flower Pollination Algorithm (FPA). In order to optimize the results of both proposed techniques, a novel heuristic algorithm is introduced. Demand side management (DSM) is a very important aspect in the energy management system (EMS). Economic cost is reduced by shifting load from peak to off-peak hours; moreover, peak to average ratio (PAR) is also minimized in the proposed model by using the concept of DSM to control the load at user end [21]. In order to implement DSM, BFOA and FPA are proposed. Home appliances are scheduled in such a way to minimize economic cost, PAR, and provide user comfort to consumers while using the home energy management system (HEMS) concept [22]. In this research, the authors used GA, FPA, and the combination (hybrid) of these two techniques, the genetic-flower pollination algorithm (GFPA). Similarly, HEMS focuses on scheduling home appliances in such a way to reduce the peak load, as a result, it reduces electricity cost, PAR, optimizes user comfort as well as the time of execution [23]. The time of use (TOU) concept was used to obtain the required results; moreover, the proposed techniques are GA, biogeography-based optimization (BBO). For EMS, it is important to create a balance between energy consumption and user comfort. This paper proposes three techniques GA, Pigeon Inspired Optimization (PIO), and hybrid of GA and PIO techniques to distribute appliances in off-peak time and reduce load at peak time to optimize electricity cost and PAR [24]. In this research [25], few methods are used for energy optimization, such as TOU to reduce economic cost by shifting load from peak to off peak hours, real time pricing (RTP), and DRPs. The proposed model is beneficial for both electricity market and consumers. The multi-agents network can provide ease and reduce economic cost. In this study [26], a nano-biased system engages multi-agents that consist of residential, commercial, and industrial consumers. The operational cost is reduced by using the concept of real time tariff while purchasing/sell electricity. Moreover, incentive-based packages are provided to the different consumers. The proposed model is designed with machine learning and reinforcement intelligence.

In this work, an optimal energy optimization strategy is developed to optimize the operation of SG integrated with RESs in terms of operation cost and carbon emission. In addition, the concept of incentive-based DRPs is introduced as price offer packages to overcome the uncertainty factor in power generation by RESs like solar and wind. In this method, end-users can select an offered price package to participate in energy optimization. In this model, the Rayleigh PDF is proposed to model variation in energy generation caused by RESs like solar and wind. Units, distributed generations (DGs), fuel cell (FC), wind turbine (WT) and battery are intended to provide relief to SG. Residential, commercial and industrial consumers are considered the end-users in the proposed model. The multi-objective problem is solved through a programming technique, multi-objective genetic algorithm (MOGA), taking Pareto fronts into account for achieving the desired optimization results. In brief, the main contributions of this paper are as follows:

- The uncertainty in renewable energy generation like solar and wind is covered by DRP implementation by considering operation cost and carbon emission as multi-objective functions.
- Incentive-based DRPs introduced to encourage end-users, commercial, residential and industrial sectors to participate in energy optimization actively.
- Probability density function is proposed to predict wind and solar RES behaviour.
- The multi-objective optimization problem of operating cost and carbon emission is solved through a multi-objective genetic algorithm (MOGA).

The remaining sections of this work are organized as: the problem statement is discussed in Section 2, objective function is introduced in Section 3, the proposed system model is discussed in Section 4, the proposed technique is presented in Section 5, simulation results and discussion are illustrated in Section 6, followed by the conclusions in Section 7.

2. Problem Statement

In this paper, an energy management system model is proposed to optimize operational cost and pollution emission with and without the implementation DRPs in SG. Due to the stochastic behaviour of RESs, the prediction of wind and solar are not possible; in order to solve this issue, PDF is proposed. Moreover, there is always uncertainty in RESs; in order to resolve this problem in wind and solar, an incentive based DRPs are proposed. However, the balance between generation and consumption is a very important factor; the proposed model discussed these frameworks while applying demand response programs in the smart grid.

3. Objective Function

The two main objectives of the proposed energy optimization model are operation cost and carbon emission reduction.

3.1. Operation Cost

The operational cost is divided into two categories, certain operational costs which include start up and running cost of DGs, reserve costs of DGs and the power costs provide or taken to/from utility, and uncertain operational cost by taking the probability of the proposed scenarios (probs) in time slot t = 1 to T and kth scenarios, which is affected by uncertainty in the wind and solar parameters in each case. The uncertain operational cost function normally includes the reduction in load and expected energy not served (EENS) for consumers at the user end. The operation cost objective function is defined as follows:

$$\begin{aligned} MinF_1(X) &= \sum_{t=1}^{T} f^{\cos t}(t) \\ &= \sum_{t=1}^{T} C_{op}(t) + \sum_{t=1}^{T}\sum_{k=1}^{K} probs \times UC_{op} \end{aligned} \tag{1}$$

where C_{op} and UC_{op} are certain and uncertain cost of operation, respectively, and arranged according to the proposed scenario, *probs* is the probability of the proposed scenarios k, and t is the time period starts from t = 1 to T. A certain operation cost function is given below:

$$\begin{aligned} C_{op} = &\sum_{j=1}^{N_{DG}} \left[W_j(t)\sigma_j(t)Y_j(t) + R_j(t)\left|Y_j(t) - Y_j(t-1)\right| + \mathrm{R}_e C_j{}^{DGs}(t) \right] \\ &+ \sum_{k=1}^{K} \mathrm{R}_e C_k{}^{DRPs}(t) Y_{Buy}(t) W_{Grid-Buy}(t)\sigma_{Grid-buy}(t) - Y_{Sell}(t) W_{Grid-Sell}(t)\sigma_{Grid-Sell}(t) \end{aligned} \tag{2}$$

where $W_j(t)$ and $\sigma_j(t)$ show output power and offered price for different units, $Y_i(t)$ indicates on, off mode of the jth DGs in time slot t. $R_j(t)$ indicates running and shutdown costs for different units in time period t. $\mathrm{R}_e C_j{}^{DGs}(t)$ and $\mathrm{R}_e C_k{}^{DRPs}(t)$ are the reserve cost of DGs and DRPs in time slot t, $W_{Grid-Buy}(t)$, and $W_{Grid-sell}(t)$ shows energy exchange with a utility in time period t. Similarly, the uncertain operating cost function is defined as:

$$UC_{op} = \sum_{i=1}^{N_{DG}} RC_{i,s}{}^{DG}(t) + \sum_{k=1}^{K} RC_{k,s}{}^{DR}(t) + ENSs(t) \tag{3}$$

where $RC_{i,s}{}^{DG}(t)$, $RC_{k,s}{}^{DR}(t)$ shows the running cost of DGs, DRPs in time slot t and ENSs(t) is the expected energy not served in time period t, which is also categorized in uncertain operating costs, respectively.

3.2. Carbon Emission

The carbon emission produced by DGs and grid during the energy generation is minimized through the following equation:

$$\begin{aligned} MinF_2(X) &= \sum_{t=1} f^{CE}(t) \\ &= \sum_{t=1} CE^{DGs}(t) + \sum_{t=1} CE^{Grid}(t) \end{aligned} \tag{4}$$

where $CE^{DGs}(t)$ and $CE^{Grid}(t)$ are carbon emission produced by DGs and Grid in time period t, respectively. The carbon emission produced by DGs is defined by the following equation:

$$CE^{DGs}(t) = \sum_{k=1}^{N_{DGs}} Emission_{CO_2}{}^{DGs}(j) \times Po^{DGs}(t) \tag{5}$$

where $Emission_{CO_2}{}^{DGs}(t)$ is the carbon dioxide emission produced by jth DGs in time slot t; these carbon emissions produced during power generation and $Po^{DGs}(t)$ is the output power produced by DGs in time slot t. The carbon emission generated by grid is calculated as follows:

$$CE^{Grid}(t) = Emission_{CO_2}{}^{Grid} \times Po^{Grid}(t) \tag{6}$$

where $Emission_{CO_2}{}^{Grid}$ is carbon emissions produced by grid during power generation and $Po^{Grid}(t)$ is the output power produced by grid in time period t, respectively.

4. System Model

A programming-based energy optimization model is proposed to minimize operating cost and carbon emission with and without DRPs implementation in SG integrated with RESs. The proposed model consists of wind energy system, solar energy system, hybrid energy system, and demand response programs, which is shown in Figure 1. The detailed description is as follows:

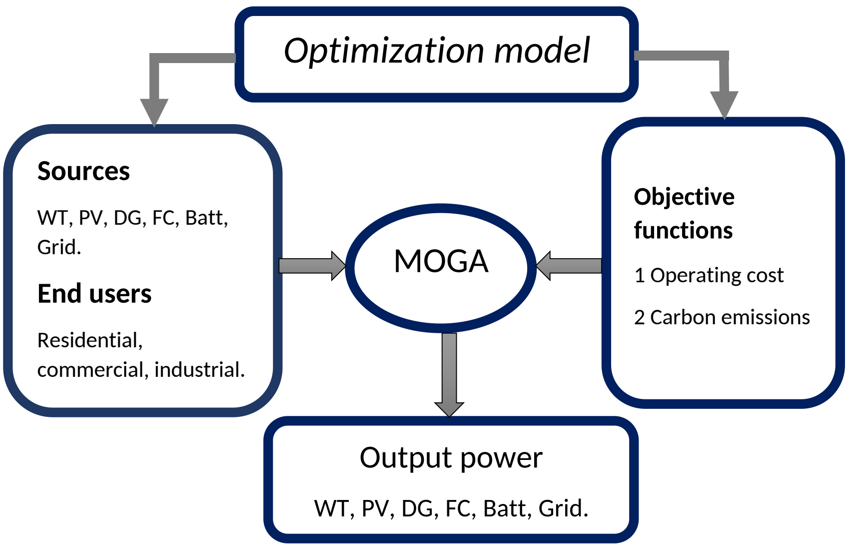

Figure 1. Proposed multi-objective energy optimization model.

4.1. Wind Based Renewable Energy Generating System

The wind turbine produces electrical energy from the potential of wind. With the demand of energy increasing day by day, RE is suitable to use because of low cost and emission. The online web site data for wind is predicted through Rayleigh distribution [27] is proposed for modeling wind energy. The PDF function is as follows:

$$F_E(S_{wind}) = 1 - \exp\left[-\left(\frac{Swind}{\beta\omega}\right)^2\right] \tag{7}$$

where S_{wind} is speed of wind and and $\beta\omega$ is the scale parameter. The function for output power of wind energy system is as follows:

$$P(S_{wind}) = \begin{cases} 0 S_{wind} < S_{c\_i} \\ P_{rated}\frac{(S_{wind}-S_{c\_i})}{(2S_r - S_{c\_i})} S_{c\_i} \leq S_{wind} < S_r \\ P_{rated} S_r \leq S_{wind} < S_{c\_o} \\ 0 S_{wind} \geq S_{c\_o} \end{cases} \tag{8}$$

where $P_{rated}, S_{wind}, S_{c\_i}, S_r \; and \; S_{c\_o}$ are turbine rated power, wind speed, cut-in speed, rated speed, and cut-off speed, respectively. The wind turbine in this study is used as the vertical axis wind turbine [28], where P_{rated} = 18kw, S_{c_i} = 4 m/s, S_{c_o} = 20 m/s, S_r = 19 m/s.

4.2. Solar Energy System

The solar generator converts solar energy into electrical energy. To model the behaviour of solar irradiance, a mathematical tool PDF is proposed [29]. The solar irradiance modeling through PDF is shown in Equation (9):

$$F_{beta} = \begin{cases} \frac{\Gamma(\delta+\gamma)}{\Gamma(\delta)\Gamma(\gamma)}(s\_i)^{\delta-1}(1-s\_i)^{\gamma-1} \\ 0 \; otherwise \end{cases}$$
$$where \; 0 \leq s\_i \geq 1, \delta \geq 0, \gamma \geq 0 \tag{9}$$

where s_i shows solar radiation coming from the sun, δ and γ are the parameters of beta PDF, which is calculated from solar radiation. Beta PDF parameters can be calculated from solar radiation data as follows:

$$\delta = \psi\left(\frac{\psi(1+\psi)}{\sigma 2} - 1\right), \tag{10}$$

$$\gamma = 1 - \psi\left(\frac{\psi(1+\psi)}{\sigma 2} - 1\right). \tag{11}$$

The output power depends on the amount of solar irradiance. The following equation is used to convert solar radiation into solar energy [30]:

$$W_{p\_v}(s\_i) = A \times \eta \times s\_i \tag{12}$$

where A shows the effective area of the PV array, $W_{p\_v}(s\_i)$ shows total output energy of the PV system in kW, η shows efficiency of PV energy system and s_i indicates solar radiation which comes from the sun in kW/m^2.

4.3. Hybrid Energy System

The hybrid energy system is the combination of output power of the solar and wind energy system:

$$P_{hyb} = P_{wind} + P_{photovoltaics} \tag{13}$$

where P_{hyb}, P_{wind}, and $P_{photovoltaics}$ is total output power, wind power and solar power, respectively. It seems to be difficult to use PDF in a mathematical way because the process is so lengthy; therefore, authors used Monte Carlo simulation for solving this problem [31]. This technique is used to forecast different models and is beneficial while making decisions. In general, this method is used to predict such models which can not be predicted easily.

4.4. Incentive-Based DRPs

In this study, the consumers are residential, commercial and industrial which are taking part in DRPs. In Equations (14)–(16), constraints show that energy reduction by each consumer at each hour should be less than or equal to the total amount of energy offered to each consumer. The following equations are used to model the behaviour of different types of consumers:

$$\mathrm{Res}(res, t) = R_C(res, t) \times \sigma_{r,t}, R_C(res, t) \leq R_C{}^{max} \tag{14}$$

$$Com(c, t) = C_C(com, t) \times \sigma_{com,t}, C_C(com, t) \leq C_C{}^{max} \tag{15}$$

$$Ind(i, t) = I_C(ind, t) \times \sigma_{ind,t}, I_C(ind, t) \leq I_C{}^{max} \tag{16}$$

where *Res(r,t)*, *Com(c,t)* and *Ind(i,t)* show cost due to load minimization by each consumers in time t, *res*, *com* and *ind* are industrial, residential and commercial consumers, respectively. $R_C(res, t)$, $C_C(com, t)$, $I_C(ind, t)$ are load minimization according to the plans by each consumers. $R_C{}^{max}$, $C_C{}^{max}$ and $I_C{}^{max}$ are max minimization of load in time t. $\sigma_{r,t}$, $\sigma_{c,t}$ and $\sigma_{i,t}$ are incentive based payments, respectively.

5. Proposed Multi-Objective Genetic Algorithm

In this study, the MOGA technique is proposed for operating cost and Carbon emission reduction. The MOGA algorithm used the position and velocity of the particle and used Pareto-fronts for positioning best possible results [32,33]. MOGA uses the non-dominated classification of the GA population, also maintaining diversity in non-dominated solutions. The nearest solutions to Pareto-front are ranked equal to 1, and the ranked equal to 1 solutions are pick-up solutions. Similarly, the other solutions than the ranked one solution are ranked accordingly, based on its location. The equation for finding rank as follows:

$$R_j = 1 + N_j \tag{17}$$

where R_j and N_j show the rank of solutions and the number of solutions which dominate j, respectively. If a large number of solutions dominates, its mean rank is higher. To combine more than one objective, the equation is as follows:

$$F(Y) = m_1 \cdot F_1(Y) + \cdots + m_i \cdot F_i(Y) + \cdots + m_N f_N(Y) \tag{18}$$

where Y, $F(Y)$, and $F_i(Y)$ are string of the rank, fitness function and j-th objective function, respectively, m_i represents the variable weight for $F_i(Y)$ and N indicates objectives function. MOGA steps are:

step 1: Assigning rank according to R_j.
step 2: Using a linear mapping function (LMF) to assign row fitness to each solution. Linear mapping functions will assign the row fitness and also assign the row fitness function for the worst solutions.
step 3: Calculating the average of row fitness values for each rank solutions. If the rank is one, then check the number of solutions having rank 1, and take the average of row fitness value of these solutions.
step 4: Applying crossover to each of the assigned values to produce a new string.
step 5: Applying to mutate.
step 6: The algorithm returns to step number 1, if satisfying conditions are not valid.

Now, here we discussed how to assign fitness values to MOGA.
MOGA fitness assignment: Assign fitness values are calculated as follows:

step 1: Choose σ share, which is a constant variable and denotes how much distance is considered between two solutions. If σ share has a lower value, then we say that the solutions are near.
step 2: Compute the number of solutions N_j and rank of solution R_j as shown in Equation (19).
step 3: If $j \propto N$, $j = j + 1$ back to step 1. Otherwise, go to step 4.
step 4: Identify max rank R_j.

The assigned fitness value is called average fitness value, and given as follows:

$$F_j = N_j - \sum_{j=1}^{R_j+1} \mu(j) - 0.5[\mu(R_j) - 1] \tag{19}$$

Equation (20) will give average fitness to each solution j. Where N_j is total number of solutions, μ_j is number of solutions of the rank R_j and $\mu(R_j)$ are the number of solutions in the current rank. For every solution in the rank, we have to calculate the niche count [34], which is calculated as follows:

$$Nc_j = \sum_{i=1}^{\mu(R_j)} sh(dji) \tag{20}$$

where j and i are two different solutions which must be in the same rank, and $sh(dji)$ is a share fitness value. The Pareto-fronts determine the best possible solutions [35]. The proposed technique implementation is shown in Algorithm 1.

Algorithm 1 MOGA code.

```
procedure
    Inputs:Population size, max iteration, Boundary conditions, Crossover, mutation;
    Output: Minimization of operational cost and Carbon emissions using RE;
    Initialization:
    Nj= No of solutions assigned;
    Rj= Rank of solutions;
    Sigma share= A constant which determines distance between two solutions;
    Step1: Assigning Rank Rk=s, where s=1,2,3,........................n;
    Step2: Using LMF to assign row fitness to each solution to number of best and worst solutions;
    Implementation:
    Step3: Choose solutions having rank 1;
    Step4: Calculate the average of row fitness value for each rank solutions;
    Step5: Assigning fitness to each rank;
    step6: Applying mutate;
    Fitness assignment to MOGA;
    Choose σ share;
    Compute Rj and Nj using Equation (19);
    while iter <Maximum iterations do
        for Rj=1 do
            using equation Rj=1+Nj, then how many solutions for rank 1?;
            Take average of row fitness value of these solutions, These are assigned fitness values;
            if j∝N, j=j+1 then
                back to step 1;
                otherwise, Go to step 4;
            End If
            if Rj= other then 1 then
                move to step 1;
            End If
            Apply crossover to each assigned values to produce new string;
            if conditions satisfied then
                pareto ranks are checked;
                then Apply mutate;
            End If
        End For
        for Rj=1 do
            for i = 1 do
                Getting desired pareto-fronts ranks;
                Algorithm will back to step 1 if the following conditions are not satisfied;
            End For
        End For
    End While
End Procedure
```

6. Simulation Results and Discussion

A programming-based energy optimization model is proposed to reduce operational cost and carbon emission with and without DRPs in SG using RESs. To predict the behavior of RESs, wind, and solar energy, a mathematical tool PDF is proposed. Monte Carlo simulation is proposed for PDF implementation because PDF is difficult to use in a mathematical way. DRPs are proposed to overcome the uncertainty factor in renewable energy generation like solar and wind. To implement DRPs in SG, we recommend an incentive-based payment method as price offered packages. In this method, industrial, residential, and commercial consumers can participate in DRPs by taking an offered package at a time. The proposed model consists of different participants, such as sources and end-users and objective functions, operating cost, and carbon emission, which are shown in Figure 1. The data for wind energy generation are taken from [36,37]. The behavior of wind speed is shown in Figure 2. The solar energy system used in the proposed model has the following specifications: 25 kW SOLAREX MSX type, compose d of solar array 10 × 2.5 kW with h = 18.6% and s = 10 m^2 [38]. The average solar irradiance profile utilized by the solar energy system is shown in Figure 3.

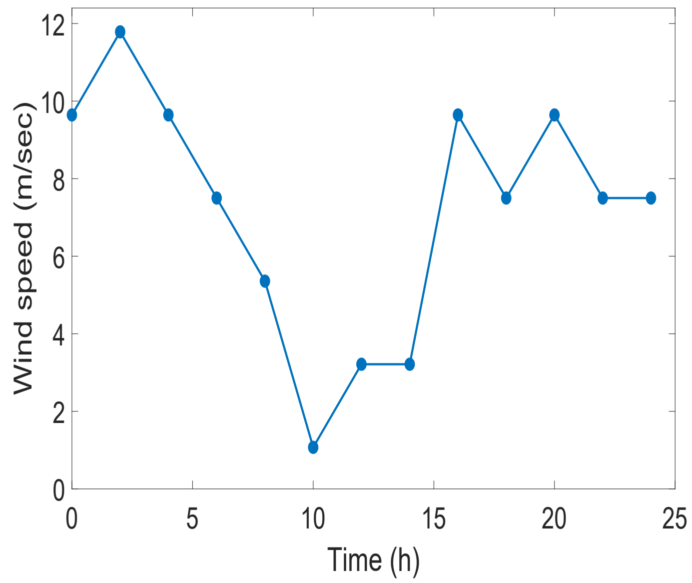

Figure 2. Hourly wind speed curve.

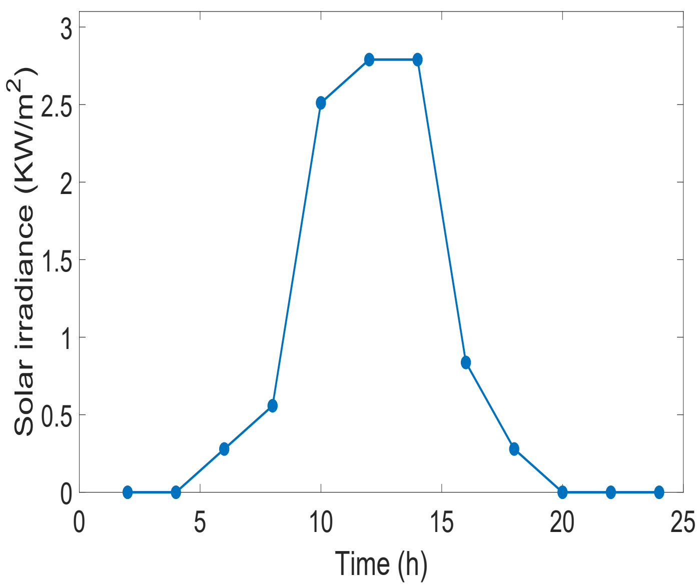

Figure 3. Hourly solar irradiance curve.

A battery used in this study, having high and low charges 10% and 100% with efficiency 94% [39,40]. Residential, commercial and industrial consumers' daily load demand profile is illustrated in Figure 4 [41].

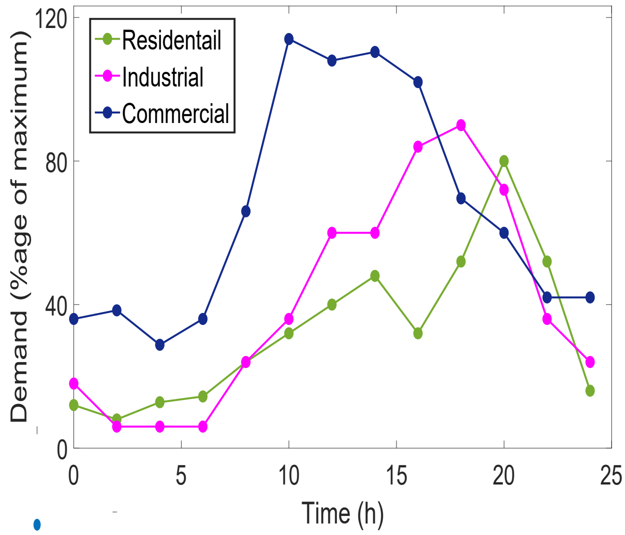

Figure 4. Daily load curves for different consumers like industrial, residential and commercial.

Figure 5 shows that DRPs optimize operation cost and carbon emission by actively engaging consumers in the electricity market to efficiently utilize RESs (Wind/Solar) and shift their load from on-peak hours to off-peak hours. The consumers' participation in DRPs reduce the burden on ECUs in terms of not turning peak power plants. The system operator reduces unscheduled power generation and is capable of managing demand with scheduled power generating units. The results before and after DRPs implementation are shown in Figure 5. To implement the proposed scenarios, we divided the proposed study into three steps.

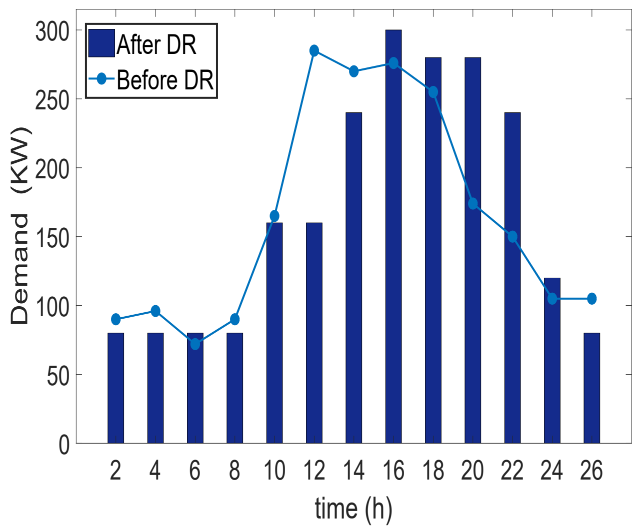

Figure 5. Load demand with and without involvement of demand response programs.

Step 1: Operation cost and carbon emission minimization with DRPs.

Step 2: Operation cost and carbon emission minimization without DRPs

Step 3: The MOGA technique is proposed to solve the problem by taking operation cost and carbon emission as multi-objective functions.

All the units are taking part in the SG operation to provide relief to SG. In this study, the multi-objective problem is solved by taking operational cost and carbon emission as objective functions and are implemented in MATLAB 2017b.

Step 1: Operation cost and carbon emission minimization with DRPs.

In this step, the cost of operation and carbon emissions are separately reduced without the involvement of DRPs. Table 1 results indicate that, in working hours, the emissions produced by sources are high. In this case, the utility takes energy from SG. While taking carbon emission function into account, both wind and solar energy produce low emissions during power production. In this case, the power reaches the maximum level. Wind and solar energy have high operating costs, and this scenario is only suitable for carbon emission function.

The results of Figure 6a,b show the simultaneous reduction of cost of operation and Carbon emission with and without the implementation of DRPs. The cost of operation and Carbon emission can be reduced by 24.5% and 28%, respectively. Figure 7a,b indicates wind and solar power generation while taking cost of operation and Carbon emission reduction and simultaneous reduction of wind and solar function with and without DRPs.

Step 2: Operation cost and carbon emission without DRPs.

In this step, the cost of operation and carbon emission are separately reduced with the involvement of DRPs. The cost of operation and carbon emission are separately reduced successfully, and the results are shown in Tables 2 and 3, respectively. Comparing Tables 1–4 shows that, when DRPs are implemented, the wind and power generation are reduced from 9.72 kW to 8.12 kW and from 5.54 kW to 4 kW, respectively. The optimization model proposed that the DRPs are taken with incentive-based payments. In the case of using DRPs with incentive-based payments, it converts loads from on-peak to off-peak hours and helps in operating cost reduction. When load shifts from peak to off-peak hours the cost of operation starts to reduce in this period.

Step 3: Solving multi-objective energy optimization problem using a MOGA technique by taking Pareto optimal fronts into account.

In this step, the simultaneous minimization of multi-objective functions, cost of operation, and carbon emission with and without DRPs takes place and is based on the MOGA technique. Both functions start to reduce simultaneously and result in the best possible solution by using a Pareto optimal path. Figure 6a,b show that operation cost and carbon emission are plotted on the x-axis and y-axis, respectively. Moving from an initial point towards the finishing point along the Pareto path represents a change in operation behavior from low operation cost and high emission to high operation cost and low emission, respectively. The optimize operation point is obtained via a fuzzy mechanism of MOGA.

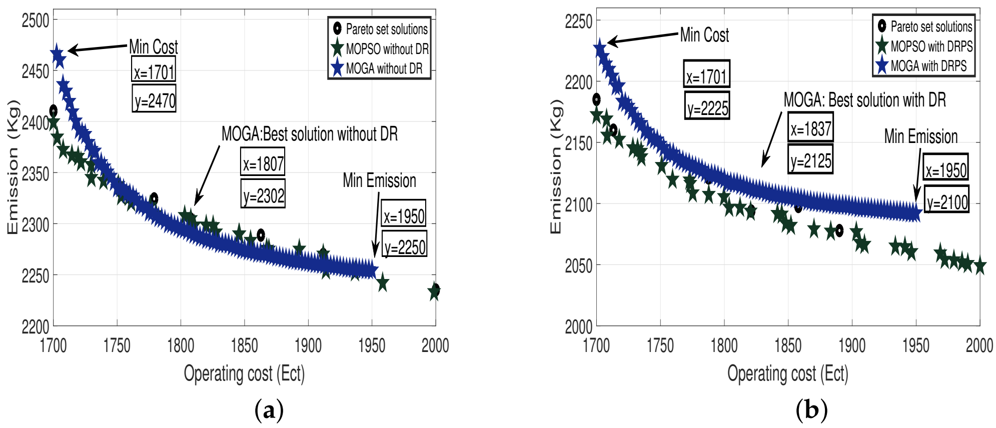

Figure 6. Multi-objective energy optimization of the proposed MOGA and existing MOPSO algorithm using Pareto-fronts criterion for operation cost and carbon emission optimization (**a**) without DRPs; (**b**) with DRPs

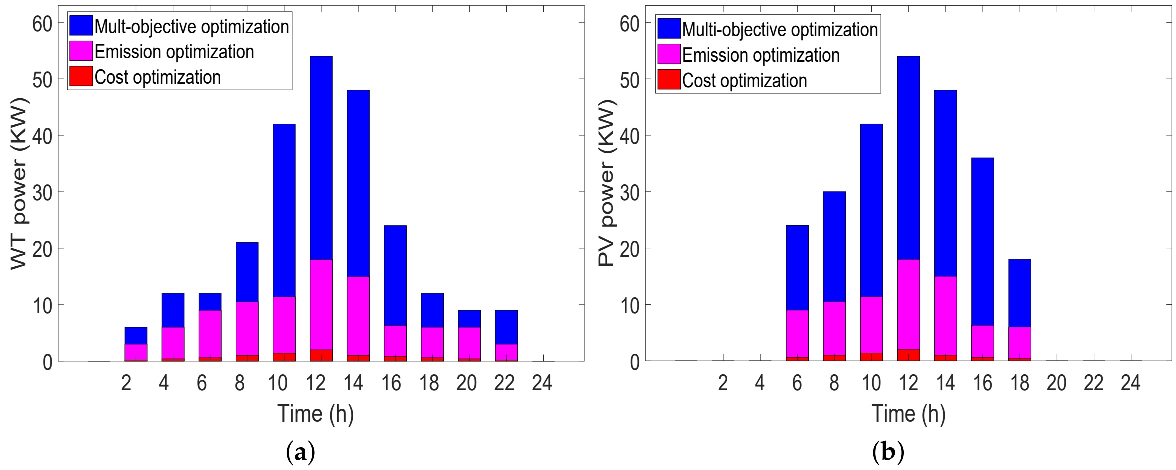

Figure 7. Renewable energy sources generation. (**a**) wind energy system; (**b**) solar energy system

Figure 7a,b results show that maximum solar and wind energy production are utilized considering carbon emission and operation cost to establish a balance between them by simultaneous optimization.

Table 1. Carbon emission optimization different energy generating units without DRPs.

Hours	Distributed Generations (kW)	Fuel Cell (kW)	Wind Turbine (kW)	Solar Array (kW)	Battery (kW)	Utility (kW)
1	39.64	30.91	1.92	0.00	31.08	−30.00
2	32.00	25.00	0.78	0.00	29.58	−26.56
3	32.00	27.17	1.98	0.00	30.95	−25.54
4	32.05	30.55	0.98	0.00	30.56	−23.33
5	32.00	28.00	1.95	0.00	31.98	−26.91
6	32.00	32.00	0.99	0.00	31.01	−26.28
7	35.27	30.68	1.90	0.00	30.35	−24.26
8	52.71	30.00	1.95	0.27	29.25	0.00
9	49.52	31.56	1.93	4.12	30.00	−9.00
10	115.04	30.00	1.89	12.00	31.95	−8.00
11	127.77	30.99	10.75	13.81	30.44	−30.00
12	152.40	30.99	11.41	25.00	30.00	−30.00
13	143.10	30.98	4.95	21.65	29.25	−26.96
14	165.92	32.00	2.94	8.42	29.98	−20.84
15	176.90	32.00	1.98	4.19	30.05	−10.91
16	171.37	30.09	1.99	0.93	31.80	−15.00
17	160.97	28.93	1.99	0.50	31.00	−21.22
18	154.91	31.00	1.98	0.00	31.06	−26.00
19	117.21	29.81	1.90	0.00	31.40	28.87
20	110.76	29.98	1.98	0.00	25.86	27.35
21	99.16	31.00	1.80	0.00	31.80	21.92
22	74.69	31.00	1.88	0.00	31.10	28.23
23	46.10	30.98	1.11	21.65	29.25	−25.96
24	40.99	29.00	0.75	8.32	29.98	−20.83

Table 2. Operating cost optimization of different energy generating units with DRPs.

Hours	Distributed Generations (kW)	Fuel Cell (kW)	Wind Turbine (kW)	Solar Array (kW)	Battery (kW)	Utility (kW)
1	33.64	7.18	0.38	0.00	0.68	30.00
2	34.00	12.00	0.28	0.00	−16.51	26.57
3	30.00	12.31	0.38	0.00	−19.97	29.47
4	30.15	20.5	0.71	0.00	−29.57	29.13
5	30.00	4.000	0.58	0.00	−29.99	3.81
6	30.00	7.000	0.14	0.00	−21.30	16.28
7	31.77	25.67	0.50	0.00	−29.73	28.22
8	35.71	28.000	0.05	0.25	−3.525	2.00
9	80.56	21.456	0.60	0.12	−20.00	−32.00
10	161.60	16.000	0.80	0.00	26.75	−32.00
11	233.37	5.99	0.75	0.51	28.44	−32.00
12	203.64	14.98	0.10	0.00	18.00	−30.00
13	260.21	26.98	0.91	0.65	−1.25	−30.66
14	223.99	4.00	0.34	0.42	−4.88	−34.83
15	214.90	22.00	0.90	0.19	−7.05	−32.71
16	171.36	23.09	0.38	0.38	−3.90	−32.00
17	125.09	26.93	1.79	0.55	11.00	7.52
18	44.01	28.00	0.68	0.00	5.07	29.00
19	52.25	28.12	1.11	0.00	30.34	31.79
20	90.26	24.98	1.01	0.00	27.88	31.35
21	129.16	22.00	0.22	0.00	25.80	−29.72
22	100.69	18.00	0.35	0.00	30.81	29.33
23	29.21	26.98	0.65	0.51	−1.24	−30.66
24	28.99	29.00	0.35	0.21	−4.98	−34.43

Table 3. Carbon emission optimization of different energy generating units with DRPs.

Hours	Distributed Generations (kW)	Fuel Cell (kW)	Wind Turbine (kW)	Solar Array (kW)	Battery (kW)	Utility (kW)
1	29.00	10.98	0.08	0.00	26.08	−30.000
2	29.00	23.00	0.28	0.00	28.18	−24.567
3	30.00	26.17	0.00	0.00	29.75	−27.547
4	30.15	2.65	0.00	0.00	19.76	−29.133
5	30.00	3.00	2.78	0.00	30.88	−31.981
6	29.00	26.00	0.98	0.00	5.31	−29.288
7	31.77	26.68	1.01	0.00	21.75	−28.262
8	30.77	29.00	0.05	0.00	29.25	−29.000
9	34.56	24.46	2.30	3.11	29.00	−28.00
10	37.64	28.00	7.09	7.00	23.75	−20.00
11	78.75	26.99	9.77	9.51	26.44	20.00
12	105.60	30.99	3.40	11.10	21.60	15.00
13	40.21	30.88	2.15	21.65	29.45	29.96
14	128.99	29.00	1.35	23.32	27.98	1.83
15	124.98	28.00	2.80	7.89	23.25	15.71
16	70.37	30.19	1.74	5.98	29.80	29.00
17	57.07	29.53	1.93	0.50	28.60	3.22
18	65.01	30.00	1.85	0.00	30.07	22.00
19	100.15	30.30	0.00	30.30	23.79	−19.66
20	95.26	28.96	1.30	0.00	26.86	18.75
21	56.16	28.00	1.20	0.00	27.80	27.72
22	35.99	30.00	1.55	0.00	26.80	15.33
23	50.10	29.98	2.91	21.65	29.45	16.96
24	30.92	29.00	1.34	23.32	27.98	−11.43

Table 4. Operation cost optimization of different energy generating units without DRPs.

Hours	Distributed Generations (kW)	Fuel Cell (kW)	Wind Turbine (kW)	Solar Array (kW)	Battery (kW)	Utility (kW)
1	30.43	8.98	0.48	0.00	12.78	30.00
2	33.00	29.00	0.48	0.00	−16.51	27.57
3	37.00	20.31	0.28	0.00	−16.97	23.57
4	39.66	25.65	0.81	0.00	−29.57	30.13
5	33.00	14.70	0.78	0.00	−26.99	27.91
6	31.00	24.91	0.00	−21.30	−10.28	23.00
7	32.12	26.67	0.50	0.00	−19.73	23.22
8	34.61	25.00	0.305	0.27	−0.55	23.00
9	106.66	3.46	0.30	0.12	30.00	-32.00
10	243.60	19.00	0.09	0.00	−13.95	−32.00
11	215.77	5.99	0.75	0.81	18.44	−32.00
12	291.64	6.98	0.10	0.00	−26.00	−30.00
13	277.21	9.98	0.95	0.95	−25.25	−30.96
14	223.99	25.00	5.00	0.345	22.32	−30.88
15	218.90	29.00	0.98	0.89	32.20	−27.91
16	228.36	7.09	0.78	0.38	30.00	−27.00
17	117.09	27.93	1.99	0.50	31.00	27.22
18	95.01	30.00	0.98	0.00	31.07	29.00
19	107.25	32.82	1.31	0.00	30.34	31.79
20	125.76	31.96	1.31	0.00	27.88	31.35
21	157.11	29.00	0.32	0.00	30.80	−29.72
22	89.69	25.00	0.55	0.00	30.81	29.33
23	56.21	26.98	0.95	0.65	30.24	−30.66
24	33.99	25.00	0.35	0.32	29.98	26.83

7. Conclusions

A programming-based energy optimization model is proposed to optimize operation cost and carbon emission with and without the involvement of DRPs in SG with integrated RESs like solar and wind. The incentive-based DRPs in SG as price offered packages is introduced to overcome the uncertainty factor in renewable energy generation like solar and wind. Moreover, to achieve optimized results, a PDF is intended to predict the behaviour of solar and wind RESs. Simulations are conducted in three steps: (i) multi-objective energy optimization problem of operation cost and carbon emission is solved using MOGA, (ii) operation cost and carbon emission optimization without DRPs, and (ii) operation cost and carbon emission optimization with DRPs. The proposed model is tested on a smart sample grid serving consumers of residential, commercial, and industrial sectors. The proposed energy optimization model based on MOGA outperforms the existing models in terms of operation cost and carbon emission. Experimental results show that the operation cost and carbon emission with and without DRPs are reduced by 24% and 28% using the proposed technique MOGA, respectively.

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References

1. Rahman, S. An efficient load model for analyzing demand side management impacts. *IEEE Trans. Power Syst.* **1993**, 8, 1219–1226. [CrossRef]

2. Cohen, A.I.; Wang, C.C. An optimization method for load management scheduling. *IEEE Trans. Power Syst.* **1988**, *3*, 612–618. [CrossRef]
3. Palensky, P.; Dietrich, D. Demand side management: Demand response, intelligent energy systems, and smart loads. *IEEE Trans. Ind. Inform.* **2011**, *7*, 381–388. [CrossRef]
4. Renzhi, L.; Hong, S.H. Incentive-based demand response for smart grid with reinforcement learning and deep neural network. *Appl. Energy* **2019**, *236*, 937–949.
5. Shahidehpour, M.; Yamin, H.; Li, Z. *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*; John Wiley and Sons: Hoboken, NJ, USA, 2003.
6. Shuba, E.S.; Kifle, D. Microalgae to biofuels: 'Promising'alternative and renewable energy, review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 743–755. [CrossRef]
7. Reinhard, P.; Rusdianasari, R.; Eviliana, E. Renewable Energy: Advantages and Disadvantages. In Proceedings of the Forum in Research, Science, and Technology (FIRST) 2016, Politeknik Negeri Sriwijaya, Palembang, Indonesia, 18–19 October 2016.
8. Rehmani, M.H.; Reisslein, M.; Rachedi, A.; Erol-Kantarci, M.; Radenkovic, M. Integrating renewable energy resources into the smart grid: Recent developments in information and communication technologies. *IEEE Trans. Ind. Inform.* **2018**, *14*, 2814–2825. [CrossRef]
9. Domenico, M.; Oliveti, G.; Labonia, E. Estimation of wind speed probability density function using a mixture of two truncated normal distributions. *Renew. Energy* **2018**, *115*, 1260–1280.
10. Ran, X.; Shihong, M. Three-phase probabilistic load flow for power system with correlated wind, photovoltaic and load. *Iet Gener. Transm. Distrib.* **2016**, *10*, 3093–3101. [CrossRef]
11. Hafeez, G.; Alimgeer, K.S.; Wadud, Z.; Khan, I.; Usman, M.; Qazi, A.B.; Khan, F.A. An Innovative Optimization Strategy for Efficient Energy Management with Day-ahead Demand Response Signal and Energy Consumption Forecasting in Smart Grid using Artificial Neural Network. *IEEE Access* **2020**, *8*, 84415–84433. [CrossRef]
12. Kanchev, H.; Colas, F.; Lazarov, V.; Francois, B. Emission reduction and economical optimization of an urban microgrid operation including dispatched PV-based active generators. *IEEE Trans. Sustain. Energy* **2014**, *5*, 1397–1405. [CrossRef]
13. Tedesco, F.; Mariam, L.; Basu, M.; Casavola, A.; Conlon, M.F. Economic model predictive control-based strategies for cost-effective supervision of community microgrids considering battery lifetime. *IEEE J. Emerg. Sel. Top. Power Electron.* **2015**, *3*, 1067–1077. [CrossRef]
14. Kakran, S.; Chanana, S. Smart operations of smart grids integrated with distributed generation: A review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 524–535. [CrossRef]
15. Derakhshan, G.; Shayanfar, H.A.; Kazemi, A. The optimization of demand response programs in smart grids. *Energy Policy* **2016**, *94*, 295–306. [CrossRef]
16. Parisio, A.; Wiezorek, C.; Kyntäjä, T.; Elo, J.; Strunz, K.; Johansson, K.H. Cooperative MPC-based energy management for networked microgrids. *IEEE Trans. Smart Grid* **2017**, *8*, 3066–3074. [CrossRef]
17. Teo, T.T.; Logenthiran, T.; Woo, W.L.; Abidi, K. Intelligent Controller for Energy Storage System in Grid-Connected Microgrid. *IEEE Trans. Syst. Man Cybern. Syst.* **2018**. [CrossRef]
18. Melhem, F.Y.; Grunder, O.; Hammoudan, Z.; Moubayed, N. Energy management in electrical smart grid environment using robust optimization algorithm. *IEEE Trans. Ind. Appl.* **2018**, *54*, 2714–2726. [CrossRef]
19. Kamboj, A.; Chanana, S. Optimization of cost and emission in a Renewable Energy micro-grid. In Proceedings of the 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, 4–6 July 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
20. Hafeez, G. Energy Efficient Integration of Renewable Energy Sources in the Smart Grid for Demand Side Management. Master's Thesis, COMSATS University Islamabad, Islamabad, Pakistan, 2017.
21. Khan, T.A.; Ullah, K.; Hafeez, G.; Khan, I.; Khalid, A.; Shafiq, Z.; Usman, M.; Qazi, A.B. Closed-Loop Elastic Demand Control under Dynamic Pricing Program in Smart Microgrid Using Super Twisting Sliding Mode Controller. *Sensors* **2020**, *20*, 4376. [CrossRef]
22. Pedram, S.; Mohsenian-Rad, H.; Schober, R.; Wong, V.W.S. Advanced demand side management for the future smart grid using mechanism design. *IEEE Trans. Smart Grid* **2012**, *3*, 1170–1180.
23. Imran, A.; Hafeez, G.; Khan, I.; Usman, M.; Shafiq, Z.; Qazi, A.B.; Khalid, A.; Thoben, K.D. Heuristic-Based Programable Controller for Efficient Energy Management Under Renewable Energy Sources and Energy Storage System in Smart Grid. *IEEE Access* **2020**, *8*, 139587–139608. [CrossRef]

24. Abdul-Rahman, A.; Zualkernan, I.A.; Rashid, M.; Gupta, R.; Alikarar, M. A smart home energy management system using IoT and big data analytics approach. *IEEE Trans. Consum. Electron.* **2017**, *63*, 426–434.
25. Linas, G.; Gamage, K.A.A. Demand side management in smart grid: A review and proposals for future direction. *Sustain. Cities Soc.* **2014**, *11*, 22–30.
26. Saifuddin, M.R.B.M.; Logenthiran, T.; Naayagi, R.T.; Woo, W.L. A nano-biased energy management using reinforced learning multi-agent on layered coalition model: Consumer sovereignty. *IEEE Access* **2019**, *7*, 52542–52564. [CrossRef]
27. Rahimi, E.; Rabiee, A.; Aghaei, J.; Muttaqi, K.M.; Nezhad, A.E. On the management of wind power intermittency. *Renew. Sustain. Energy Rev.* **2013**, *28*, 643–653. [CrossRef]
28. Seki, K.; Shimizu, Y.; Kato, Y. Vertical Axis Wind Turbine. U.S. Patent 4,247,253, 27 January 1981.
29. Ettoumi, F.Y.; Mefti, A.; Adane, A.; Bouroubi, M.Y. Statistical analysis of solar measurements in Algeria using beta distributions. *Renew. Energy* **2002**, *26*, 47–67. [CrossRef]
30. Deshmukh, M.K.; Deshmukh, S.S. Modeling of hybrid renewable energy systems. *Renew. Sustain. Energy Rev.* **2008**, *12*, 235–249. [CrossRef]
31. Tina, G.; Gagliano, S.; Raiti, S. Hybrid solar/wind power system probabilistic modelling for long-term performance assessment. *Sol. Energy* **2006**, *80*, 578–588. [CrossRef]
32. Murata, T.; Ishibuchi, H.; Sanchis, J.; Blasco, X. MOGA: Multi-objective genetic algorithms. In *IEEE International Conference on Evolutionary Computation*; IEEE: Piscataway, NJ, USA, 1995; Volume 1, pp. 289–294.
33. Herrero, J.M.; Manuel Martínez, J.S.; Blasco, X. Well-Distributed Pareto Front by Using the $\epsilon\nearrow$—*MOGA* Evolutionary Algorithm. In Proceedings of the International Work-Conference on Artificial Neural Networks, San Sebastián, Spain, 20–22 June 2007; Springer: Berlin/Heidelberg, Germany, 2007; pp. 292–299.
34. Miller, B.L.; Shaw, M.J. Genetic algorithms with dynamic niche sharing for multimodal function optimization. In *Proceedings of IEEE International Conference on Evolutionary Computation*; IEEE: Piscataway, NJ, USA, 1996; pp. 786–791.
35. Yang, J.; Ji, Z.; Liu, S.; Jia, Q. Multi-objective optimization based on pareto optimum in secondary cooling and EMS of continuous casting. In *2016 International Conference on Advanced Robotics and Mechatronics (ICARM)*; IEEE: Piscataway, NJ, USA, 2016; pp. 283–287.
36. Available online: https://wind.willyweather.com.au/ (accessed on 15 September 2019).
37. Reconstruction and Short-term Forecast of the Solar Irradiance. Available online: https://www.lpc2e.cnrs.fr/en/scientific-activities/plasmas-spatiaux/projects/other-projects-anr-europe-etc/fp7-soteria/ (accessed on 20 October 2019).
38. The Solar Power Group Company. Available online: https://www.enfsolar.com/directory/installer/67081/the-solar-power-group (accessed on 1 November 2019).
39. Chen, C.; Duan, S.; Cai, T.; Liu, B.; Hu, G. Smart energy management system for optimal microgrid economic operation. *IET Renew. Power Gener.* **2011**, *5*, 258–267. [CrossRef]
40. Mirzaei, M.J.; Kazemi, A.; Homaee, O. RETRACTED: Real-world based approach for optimal management of electric vehicles in an intelligent parking lot considering simultaneous satisfaction of vehicle owners and parking operator. *Energy* **2014**, *76*, 345–356. [CrossRef]
41. Luo, C.; Ukil, A. Modeling and validation of electrical load profiling in residential buildings in Singapore. *IEEE Trans. Power Syst.* **2014**, *30*, 2800–2809.