Price Based Demand Response for Optimal Frequency Stabilization in ORC Solar Thermal Based Isolated Hybrid Microgrid under Salp Swarm Technique

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Abstract: Smart grid technology enables active participation of the consumers to reschedule their energy consumption through demand response (DR). The price-based program in demand response indirectly induces consumers to dynamically vary their energy use patterns following different electricity prices. In this paper, a real-time price (RTP)-based demand response scheme is proposed for thermostatically controllable loads (TCLs) that contribute to a large portion of residential loads, such as air conditioners, refrigerators and heaters. Wind turbine generator (WTG) systems, solar thermal power systems (STPSs), diesel engine generators (DEGs), fuel cells (FCs) and aqua electrolyzers (AEs) are employed in a hybrid microgrid system to investigate the contribution of price-based demand response (PBDR) in frequency control. Simulation results show that the load frequency control scheme with dynamic PBDR improves the system’s stability and encourages economic operation of the system at both the consumer and generation level. Performance comparison of the genetic algorithm (GA) and salp swarm algorithm (SSA)-based controllers (proportional-integral (PI) or proportional integral derivative (PID)) is performed, and the hybrid energy system model with demand response shows the supremacy of SSA in terms of minimization of peak load and enhanced frequency stabilization of the system.

Keywords: ORC solar thermal power system; thermostatically controllable loads (TCLs); price-based demand response (PBDR); real-time pricing (RTP); load frequency control; genetic algorithm; salp swarm algorithm (SSA)

1. Introduction

The demand for electricity consumption is growing day by day, in line with consumer activities. The expansion of generation capacity with traditional energy sources leads to negative effects on the environment and, subsequently, increases the operational cost. Therefore, the introduction of smart microgrid technologies, such as renewable energy sources (RESs) and demand response management (DSM), enables environmentally friendly solutions.

Smart microgrids with digital technological strategies and the utilization of generation of power from RESs, such as wind turbine generators (WTGs) and solar power, are able to generate and distribute [1] electricity as optimally, echo-friendly and user-friendly in a smart manner. Since wind power generation (WTG) is fluctuating in nature, the diesel and wind energy combination [2,3] is utilized
in hybrid systems. The integration of a solar thermal power system (STPS) as a non-conventional energy source reduces the depletion of conventional energy-based power generation. In order to overcome the frequency fluctuation due to uncertain energy sources, such as WTG and STPS [4,5], some energy storage units have been introduced to the hybrid energy system model, such as hydrogen aqua electrolyzers (AEs) and fuel cells (FCs), which are capable of reducing these fluctuations.

The smart grid concept has the ambition to achieve the most economical and reliable operation by considering demand response (DR) [6,7] for smoothing the demanded load curve. The incentive-based and price-based [8,9] programs are the two main programs corresponding to demand response. A price-based program [10,11] or smart pricing provides consumers with dynamic electricity prices. Among all the smart pricing schemes, real-time pricing (RTP) [12] is the most efficient to enhance the supply and demand balance by altering electricity pricing in response to the generation–demand balance.

Residential load represents a larger portion of energy consumption and load modeling in distribution networks [13,14]. Thermostatically controllable appliances like air conditioners (ACs), water heater (WHs) and refrigerators (REZs) hold a major portion of the non-sensitive residential loads [15,16]. The control strategy for thermostatic loads to reduce the demand in peak hours by load by changing the thermostat set point setting [17,18] has been studied by considering the system frequency and real-time pricing (RTP) [19,20].

DR with pricing indicators on residential load control, such as thermostatically controllable loads (TCLs) [21–24], can be modeled with various optimization techniques such as the genetic algorithm (GA)- [25] and salp swarm algorithm (SSA)-based controllers (PI and PID) [26]. In fact, the smartness of the power network lies in the gains and other parameters of the controllers. Hence, in recent times, several example from the literature have leveraged different optimization approaches such as firefly (FF) [27], the particle swarm technique (PSO) [28], the cuckoo search approach (CSA) [29] and the ant lion approach (ALO) [30] under conventional and microgrid power networks. In the line above, the application of SSA is a maiden one which has never been leveraged for frequency regulation of an isolated hybrid microgrid system in the presence of price-based DR (PBDR). Like other techniques, the requirement of a higher number of evaluations with larger computational time [31] is the major drawback of GA, as was considered in the targeted assignment. However, the employment of an adaptive mechanism in the SSA is the main factor to getting faster convergence characteristics with less computational time. The motivation is the minimization of the peak load for better frequency regulation and for better improvement of the stability and reliability of the hybrid-isolated power network. The main objectives of the current research work are listed below:

1. The application of electricity pricing-based demand response (PBDR) for TCLs for the optimal management of energy utilization by the users;
2. Comparison of the dynamic responses of various PI and PID controllers in the hybrid isolated microgrid system with and without PBDR;
3. The optimization of (PI and PID) controller gains by applying the genetic algorithm (GA) and SSA in the developed model.

The rest of this work is organized as follows. Section 2 illustrates the system’s frequency response modeling of the proposed renewable hybrid microgrid. Section 3 describes the application of a real-time pricing scheme on TCLs. Details of the salp swarm algorithm (SSA) are given in Section 4. Section 5 assesses simulation results under various scenarios and compares their frequency stabilization performances. Section 6 draws the conclusions.

2. Dynamic Modeling of Hybrid Energy System

The microgrid system model mentioned in the proposed work consists of organic Rankine cycle (ORC) low-temperature STPSs, wind turbine generators (WTGs), diesel engine generators (DEGs), fuel cells (FCs) and hydrogen aqua electrolyzers (AEs) as energy storage elements. The schematic block
diagram of the proposed microgrid network, as well as its transfer function modeling, are displayed in Figure 1a,b, respectively [2]. The system parameters are tabulated in Table 1.

![Figure 1. Topology of the proposed microgrid (a) the top) and the transfer function diagram of the proposed model (b) the bottom.](image)

**Table 1.** Proposed hybrid energy model parameters [2].

| Generating Units | Gains          | Constant Values (s) |
|------------------|----------------|---------------------|
| ORC-STPS         | $K_S = 1.8$    | $T_S = 0.3$         |
|                  | $K_T = 1$      | $T_T = 300$        |
| DSG              | $K_{DG} = 1/300$ | $T_{DG} = 2$       |
| FC               | $K_{FC} = 1/100$ | $T_{FC} = 4$       |
| AE               | $K_{AE} = -1/500$ | $T_{AE} = 0.5$   |
| WTG              | $K_{WTG} = 1$  | $T_{WTG} = 1.5$    |

2.1. Wind Turbine Generator (WTG)

The captured energy of blowing wind converts mechanical energy to electrical energy with the help of a WTG. As the volatile nature of wind is very much unpredictable, so too does the extractable power of a WTG depend on the velocity of the wind at that moment. It usually includes a gearbox,
and some wind turbines use blade pitch system controllers to control the total amount of transformed power. The electrical generator transforms mechanical energy into electrical energy. The linearized transfer function model [2] of a WTG is illustrated by the following equation:

\[ G_{\text{WTG}} = K_{\text{WTG}} \left( \frac{1}{sT_{\text{WTG}} + 1} \right) \]  

(1)

2.2. ORC Solar Thermal Power System (STPS)

Recently, concentric solar thermal collectors are used by the steam Rankine and Stirling engine technologies. Organic Rankine cycle (ORC)-based STPSs with suitably selected working fluids are typically selected for the use of generation of power in lower temperatures. A trough solar power plant with parabolic trough collectors focuses the sunlight to heat the working fluid in the pipes to some definite temperature (3930 °C). A heat transfer fluid, heated by a solar thermal power system, generates a high temperature (up to 5600 °C). The steam generated by this process is used to drive the steam turbine for the generation of electricity. The transfer function [2] modeling of an ORC solar thermal power system is shown below:

\[ G_{\text{STPS}} = \left( \frac{K_S}{sT_S + 1} \right) \left( \frac{K_T}{sT_T + 1} \right) \]  

(2)

2.3. Diesel Engine Generator (DEG)

A DEG, the combination of a diesel engine and an electrical generator, is used to support backup power generation and has fast dynamic characteristics. The transfer function model of the DEG is given below [2]:

\[ G_{\text{DG}} = K_{\text{DG}} \left( \frac{1}{sT_{\text{DG}} + 1} \right) \]  

(3)

2.4. Fuel Cell (FC)

Considering the electrochemical reaction, an FC produces direct current power and converts that power into alternating current power by enabling an inverter. A fuel cell generator has the non-linearity characteristic, and the linearized transfer function Equation (2) of the FC could be depicted as

\[ G_{\text{FC}} = K_{\text{FC}} \left( \frac{1}{sT_{\text{FC}} + 1} \right) \]  

(4)

2.5. Aqua Electrolyzer (AE)

Due to the randomly variable power output from solar thermal and wind turbine generators, AEs are used to absorb the variable or changeable power. The transfer function modeling of an AE is shown below [2]:

\[ G_{\text{AE}} = K_{\text{AE}} \left( \frac{1}{sT_{\text{AE}} + 1} \right) \]  

(5)

In order to maintain efficiency, stability and reliability, it is also necessary to keep the scheduled frequency under normal operating conditions, which can be achieved by maintaining the supply and demand in a balanced condition. The change in electrical power (\( \Delta P_e \)) is calculated as the distinction between the total power generation (\( P_s \)) and the demanded load (\( P_l \)):

\[ \Delta P_e = P_s - P_l \]  

(6)

where

\[ P_s = P_{\text{WTG}} + P_{\text{STPS}} + P_{\text{DEG}} + P_{\text{FC}} - P_{\text{AE}}P_l = P_{\text{LC}} + P_{\text{UC}} \]
The system frequency varies with the change in total power variation. As such, the frequency deviation can be calculated by

$$\Delta f = \Delta P_e \left( \frac{1}{K_{sys} + D} \right)$$

(7)

Due to the presence of a delay in time between the net power distinction and the frequency deviation, the linearized transfer function modeling for the system frequency variation can be expressed as [2]

$$\Delta G_{sys} = \left( \frac{\Delta f}{\Delta P_e} \right) = \frac{1}{sM + D}$$

(8)

3. Real-Time Pricing for Smart TCLs

Thermostatically controllable loads (TCLs), like air conditioners, water heater and refrigerators, were considered for residential load control. To supervise the energy utilization of the customer, the ON and OFF rotation of the thermostatic appliances could be controlled to maintain the temperature within an acceptable and limited range.

The RTP is the deviation of electricity pricing in real time for the improvement of the supply–demand balance. In fact, the basic principle of RTP [32] is that, when it comes to the overloading condition, the system frequency falls, and the electricity price increases to decrease the load from the consumer side. On the other hand, during the light load periods, the system frequency rises, and the electricity price decreases to increase the load, or the utility gives an opportunity to consume more power to the consumer in these periods. Therefore, it is possible to reschedule power consumption by introducing electricity pricing in demand response determined by RTP.

The key objective of this proposed assignment is to control the frequency of an autonomous hybrid power system using the electricity pricing-based demand response (PBDR) for thermostatically controllable loads. TCLs are rated by their coefficient of performance (COP), and the change in the set point of thermostat results in the deviation in power consumption, calculated by the given equations [33]:

$$COP = \frac{\text{Work done (Q)}}{\text{Electric power input (P_input)}}$$

(9)

The work done (Q) by the thermostatic controllable loads is given by

$$Q = m \times C_p \times (T_{out} - T_{in})$$

(10)

where $m$ is the mass of the coolant, $C_p$ is the specific heat capacity of the coolant, $T_{out}$ is the outside temperature and $T_{in}$ is the inside temperature.

The change in work done ($\Delta Q$) for a change in the thermostat set point ($\Delta T_{st}$), calculated by assuming the thermostat set point is the same as the inside temperature, is

$$\Delta Q = -m \times C_p \times \Delta T_{st}$$

(11)

The change in work done ($\Delta Q$) results in a change in electric power consumption ($\Delta P_{input}$). Thus, from Equation (9), we can express the power consumption as

$$\Delta P_{input} = \frac{\Delta Q}{COP} = \frac{-m \times C_p \times \Delta T_{st}}{COP}$$

(12)

Equation (12) establishes a linear relation between the change in the thermostat set point and the change in power consumed by the TCL unit. The consumers contracted for demand response can adjust the set point temperature of their thermostatic loads so as to ensure optimal use of their power consumption.
With the variation in frequency ($\Delta f$), the change in electricity price ($\Delta \rho$) can be expressed as [33]

$$\Delta \rho = -k \times \Delta f$$  \hspace{1cm} (13)

where $k$ is taken as 0.5 rupees per hertz (Rs./Hz), according to availability based tariff (ABT).

Therefore, the energy price increases when the frequency deviation becomes negative and vice versa. Now, the variation in the thermostat set point with the variation in frequency ($\Delta f$) can be expressed by [14]

$$\Delta T_{st} = k \int 0.5 \times \Delta f \, dt$$  \hspace{1cm} (14)

where $k$ represents the gain factor.

As such, by adjusting the energy consumption of the thermostatic loads, as per the price of the electricity, we can improve the load management by consumers [3]. Controllers are equipped to adjust the thermostatic power, in addition to other generating units. The parameters of these controllers are optimized by using algorithms such as GA and SSA.

In the PID controller design, the integral square error (ISE), given by Equation (15), is selected as the objective function in this optimization problem, while $t$ is the simulation time and $\Delta f$ is the change in frequency:

$$J = \int_0^T (\Delta f)^2 \, dt$$  \hspace{1cm} (15)

This is subject to the following:

$$\begin{cases} k_{p}^{\text{min}} \leq K_p \leq k_{p}^{\text{max}} \\ k_{i}^{\text{min}} \leq K_i \leq k_{i}^{\text{max}} \\ k_{d}^{\text{min}} \leq K_d \leq k_{d}^{\text{max}} \end{cases}$$ \hspace{1cm} (16)

The minimum values of the objective function ($J$) are implemented to regulate the optimum parameters of PI and PID controllers. The block diagram and necessary program were developed in MATLAB/SIMULINK.

4. Salp Swarm Technique (SSA)

SSA is a global optimization technique used for obtaining the best solution, assuming that the salps are searching the food source by creating a salp chain. In this salp chain model, the salps are separated into two sets: leader and followers. The leading salp moves toward the food source and also guides the other followers, and the followers follow the leading salp. In the optimization problem, the best solution is presumed to be the food source, and to reach that search space is the target of the salp swarms [26]. The flow diagram of the SSA is presented in Figure 2, whereas the parameters of considered techniques are illustrated in Table 2.

| Description                      | Value |
|----------------------------------|-------|
| Number of Salp population        | 20    |
| Maximum number of iterations     | 100   |
| Number of search agents          | 20    |
| Probability of crossover         | 0.8   |
| Probability of mutation          | 0.01  |
| Maximum number of iterations     | 100   |
The computational steps of the SSA are given below:

1. Initiation of the salp population with random positions for the solution of the parameters \((K_p, K_i, K_d)\);
2. Calculating the fitness value of each salp, and assigning the salp with the best ability to lead to the food source. Here, the objective function in Equation (15) is considered as a fitness function;
3. Updating the salp positions. For every dimension, the position of the leading and following salps are updated, keeping all the salps in the frontiers of the search space. This updating salp position gives a solution to the problem;
4. Repeating all the above steps except Step 1 until the termination criterion or the best solution is reached.

5. Frequency Response Simulation Results

In Section 4, the dynamic responses of the proposed renewable microgrid systems are observed to evaluate the performance of several PI and PID controllers to contain the system frequency. The response of different case studies under various operating conditions and the optimum gain values of GA- and SSA-tuned controllers (PI and PID) are presented. However, the overview of each case is tabulated in Table 3.

| Case | Subcomponents | Response Time (s) | Operating Conditions |
|------|---------------|-------------------|----------------------|
| 1.   | WTG, ORC low-temperature STPS, DEG, FC, AE and Load | 120 s | PWTG = 0.5 p.u at \(0 < t < 80\) s  
= 0.3 p.u at \(t > 80\) s  
PSTPS = 0.2 p.u at \(0 < t < 40\) s  
= 0.4 p.u at \(t > 40\) s  
\(P_l\) = 0.8 p.u at \(0 < t < 40\) s  
= 1.1 p.u at \(40 < t < 90\) s  
= 0.95 p.u at \(t > 90\) s  |
| 2.   | WTG, ORC low-temperature STPS, DEG, FC, AE and Load | 12 s | Concurrent random changes in WTG, ORC-STPS and Load |
5.1. Case 1: Under Step Vitiation

With the step changes in the power output from wind, solar thermal and uncontrollable loads, as plotted in Figure 3a, the varied power outputs of the DEG, FC and AE are as plotted in Figure 3c,d, where the frequency deviation (Δf) is depicted in Figure 3b. The controller gain parameters (with and without price-based demand response (PBDR)) were obtained through a GA optimization technique, which is given in Table 4. When the load demand was lesser than the total power generation, the aqua electrolyzer (by using the controller) absorbed some power and, for the remaining period, the input power to the AE was considered to be zero, as is shown in Figure 3e.

Table 4. PI and PID controller gains for Case 1.

| Controller Gain | GA Values          |
|-----------------|--------------------|
|                 | Case 1             |
|                 | Without PBDR | With PBDR |
| PI Controllers  |               |
| \( K_{p,DEG} \) | 1.450       | 1.690      |
| \( K_{i,DEG} \) | 1.0333     | 1.31401    |
| \( K_{p,FC} \)  | -1.280     | -1.1634    |
| \( K_{i,FC} \)  | -1.380     | -1.650     |
| \( K_{p,AE} \)  | -1.0084    | -1.482     |
| \( K_{i,AE} \)  | -1.2177    | -1.5316    |
| \( K_{p,LOAD} \)| 0          | 1.980      |
| \( K_{i,LOAD} \)| 0          | 1.490      |
| PID Controllers |               |
| \( K_{p,DEG} \) | 1.450       | 1.690      |
| \( K_{i,DEG} \) | 1.230       | 1.850      |
| \( K_{d,DEG} \) | 0.490       | 0.490      |
| \( K_{p,FC} \)  | -0.970     | -1.150     |
| \( K_{i,FC} \)  | -1.380     | -1.650     |
| \( K_{d,FC} \)  | 0.490     | 0.490      |
| \( K_{p,AE} \)  | -0.99567   | -1.250     |
| \( K_{i,AE} \)  | -1.06374   | -1.375     |
| \( K_{d,AE} \)  | -0.750     | -0.750     |
| \( K_{p,LOAD} \)| 0          | 1.980      |
| \( K_{i,LOAD} \)| 0          | 1.2665     |
| \( K_{d,LOAD} \)| 0          | 0.650      |

The controllable thermostatic loads (e.g., air conditioner, water heater) play an important role in the reduction of system frequency error, as they are considered a major portion of the residential loads of the system. Figure 4a,b shows the thermostatically controllable load power consumption and change in electricity pricing (with and without PBDR) due to a change in frequency. It has been observed that the deviation in frequency could be reduced better, while the thermostat load consumption was minimized using the PBDR strategy with GA-based controller gain. Furthermore, for the PID controllers, thermostatic controllable loads (TCLs) and the frequency deviation were minimized much better than with the PI controllers.
Figure 3. (a) Extractable power of the wind turbine generator (WTG), solar thermal power system (STPS) and thermostatically controllable load. (b) Comparison of the frequency deviation, without and with price-based demand response (PBDR). The power extraction of (c) a diesel engine generator (DEG), (d) a fuel cell (FC) and (e) an aqua electrolyzer (AE) without and with PBDR is also shown.
Figure 4. (a) Controllable thermostatic loads, without and with PBDR. (b) Change in electricity pricing, without and with PBDR.

5.2. Case 2: Under Random Disturbances

In this study, randomly variable power generation from the WTG, STPS and load models, as leveraged in Figure 5a, were considered for the dynamic responses of the hybrid microgrid system to analyze the effects of a concurrent change in power. The net generated power for this scenario could be expressed as

\[ P_s = P_{DEG} + P_{WTG} + P_{STPS} + P_{FC} - P_{AE} \]
In order to minimize the deviation in the total generated power and demanded load, the output powers of the DEG, FC and AE were automatically adjusted to various values through various controllers, shown in Figure 5b,c–e, which plots the comparison between the frequency deviations for pricing-based demand response (PBDR) using the GA and SSA optimization techniques. Figure 6a,b frames the thermostatically controllable load power consumption and the change in electricity pricing due to the change in frequency. In the case of pricing-based demand response, thermostatic load consumption was minimized by using the GA- and SSA-based controller gain. For the PID controller, thermostatically controllable loads (TCL) reduced the frequency deviation much better than the PI controller. Table 5 depicts the optimized gain values of the PI and PID controllers obtained from the

Figure 5. (a) Output power of the WTG, STPS and TCL. (b) GA- vs. SSA-optimized comparative frequency deviation with PBDR. (c–e) Comparative output power of the DEG, FC and AE with PBDR.
GA and SSA. The rigorous observation tells us that the performances of all SSA-based controller gain values were better than the GA-optimized values. Overall, the SSA-based PID controller gave the better performance compared with the GA-tuned PI, PID and SSA-tuned PI controller.

Figure 6. (a) Controllable thermostatic loads with PBDR. (b) Change in electricity pricing with the change in frequency, GA- vs. SSA-optimized with PBDR.
Table 5. GA- and SSA-optimized controller gain values for Case 2.

| Controller Gain | Case 2 | With PBDR | GA-Optimized | SSA-Optimized |
|-----------------|--------|-----------|--------------|---------------|
|                 |        | PI Controllers |               |               |
| $K_{p \text{DEG}}$ | 1.980  | 1.9588    |               |               |
| $K_{i \text{DEG}}$ | 1.7690 | 1.5255    |               |               |
| $K_{p \text{FC}}$  | −1.270 | −1.4183   |               |               |
| $K_{i \text{FC}}$  | −1.950 | −1.9325   |               |               |
| $K_{p \text{AE}}$  | −1.3801 | −1.6188 |               |               |
| $K_{i \text{AE}}$  | −1.325 | −1.4049   |               |               |
| $K_{p \text{LOAD}}$ | 2.100  | 1.7953    |               |               |
| $K_{i \text{LOAD}}$ | 1.56948 | 1.6175   |               |               |

| PID Controllers  |        |               |               |               |
| $K_{p \text{DEG}}$ | 1.980  | 1.7348    |               |               |
| $K_{i \text{DEG}}$ | 1.850  | 1.6828    |               |               |
| $K_{d \text{DEG}}$ | 0.490  | 0.5263    |               |               |
| $K_{p \text{FC}}$  | −1.270 | −1.4189   |               |               |
| $K_{i \text{FC}}$  | −1.950 | −1.906    |               |               |
| $K_{d \text{FC}}$  | −0.725 | −0.6976   |               |               |
| $K_{p \text{AE}}$  | −1.350 | −1.6316   |               |               |
| $K_{i \text{AE}}$  | −1.478 | −1.5043   |               |               |
| $K_{d \text{AE}}$  | −0.750 | −0.6865   |               |               |
| $K_{p \text{LOAD}}$ | 2.031  | 1.9147    |               |               |
| $K_{i \text{LOAD}}$ | 1.860  | 1.5507    |               |               |
| $K_{d \text{LOAD}}$ | 0.8473 | 0.8175    |               |               |

6. Conclusions

In this paper, a real-time price (RTP)-based demand response (DR) program in an autonomous hybrid energy system is proposed. Such a program reduces the total energy consumption and shifts the loads from high price periods to low price periods. The DR program introduces RTP to control the thermostat set point of thermostat loads (e.g., air conditioner). When the energy rescheduling technique with PBDR is applied, the thermostat set point changes linearly with the price. The modeling of the wind turbine generator, solar thermal power system and load are selected properly for various case studies to illustrate the dynamic performance of the proposed hybrid system model.

To minimize the fluctuations in frequency, the output power from the sources and power consumption by the TCL loads (using electricity pricing-based DR) are controlled by PI and PID controllers. By using GA and SSA optimization techniques, the gains of these controllers are optimized. Extensive performance simulations are performed to compare and contrast the operation with different controller and optimization combinations. It was observed from the dynamic response results that the PID controller gave a better performance than the PI controller, in terms of the peak overshoot and settling time. It was also observed that the dynamic performance of all SSA-optimized controllers was better than using GA-optimized controllers to enable automatic generation control in the proposed hybrid energy system.

These results are valuable in understanding frequency fluctuations in isolated hybrid microgrids and designing optimal controllers and DR schemes for economic operation.

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Nomenclature

\( \Delta f \) \hspace{1cm} \text{System frequency fluctuation}
\( K_{sys} \) \hspace{1cm} \text{Overall constant frequency characteristic}
\( G_{sys}(s) \) \hspace{1cm} \text{Overall transfer function of proposed system}
\( P_{DEG} \) \hspace{1cm} \text{Extractable power of diesel generator}
\( G_{DEG}(s) \) \hspace{1cm} \text{Transfer function of DEG}
\( K_{DEG} \) \hspace{1cm} \text{DEG’s gain}
\( T_{DEG} \) \hspace{1cm} \text{Constant time of DEG}
\( P_{FC} \) \hspace{1cm} \text{Extractable power of FC}
\( K_{FC} \) \hspace{1cm} \text{FC’s gain}
\( T_{FC} \) \hspace{1cm} \text{FC’s constant time value}
\( G_{FC}(s) \) \hspace{1cm} \text{Transfer function of FC}
\( P_{STPS} \) \hspace{1cm} \text{Dispatchable power of organic Rankine cycle-based STPS}
\( G_{STPS}(s) \) \hspace{1cm} \text{Overall transfer function of organic Rankine cycle STPS}
\( T_{s} \) \hspace{1cm} \text{Solar receiver’s constant time value}
\( T_{T} \) \hspace{1cm} \text{Constant charge time of the turbine}
\( K_{S} \) \hspace{1cm} \text{Solar receiver’s gain}
\( K_{T} \) \hspace{1cm} \text{Turbine’s gain}
\( G_{AE}(s) \) \hspace{1cm} \text{Overall transfer function of AE}
\( P_{AE} \) \hspace{1cm} \text{Extractable power hydrogen aqua electrolyzer}
\( K_{AE} \) \hspace{1cm} \text{Hydrogen aqua electrolyzer’s gain}
\( T_{AE} \) \hspace{1cm} \text{Hydrogen aqua electrolyzer’s fixed time}
\( P_{S} \) \hspace{1cm} \text{Total generated output power}
\( P_{l} \) \hspace{1cm} \text{Demanded load power}
\( \Delta P_{e} \) \hspace{1cm} \text{Mismatch between generated power and demand}
\( M \) \hspace{1cm} \text{Overall proposed system inertia}
\( D \) \hspace{1cm} \text{Overall proposed system damping coefficient}
\( P_{WTG} \) \hspace{1cm} \text{Dispatchable power WTG}
\( G_{WTG}(s) \) \hspace{1cm} \text{Overall transfer function of WTG}
\( K_{WTG} \) \hspace{1cm} \text{WTG’s gain}
\( T_{WTG} \) \hspace{1cm} \text{WTG’s time constant}
\( \Delta Q \) \hspace{1cm} \text{Change in work done by thermostatic loads}
\( \Delta \rho \) \hspace{1cm} \text{Change in electricity pricing}
\( \Delta T_{ST} \) \hspace{1cm} \text{Change in thermostat set point}
\( \kappa \) \hspace{1cm} \text{Gain factor of smart thermostat}
\( P_{LC} \) \hspace{1cm} \text{Power consumption by controllable loads}
\( P_{UC} \) \hspace{1cm} \text{Power consumption by uncontrollable loads}

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