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Energy Management Strategies of Grid-Connected Microgrids under Different Reliability Conditions

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Abstract: The demand for a reliable, cheap and environmentally friendly source of energy makes the integration of renewable energy into power networks a global challenge. Furthermore, reliability, as one of the core elements of efficient and cost-effective energy management options, is still among the dominant factors/techniques that receive more attention for realistic penetrations of renewable energy into the electricity grid. This paper proposes an efficient way of energy management for a grid-connected microgrid. The grid-connected microgrid used in the analysis consists of solar photovoltaic (P.V.) and battery. In this microgrid configuration, oftentimes, the output power might not be equal to the system demand; in this regard, it is expected that the mismatch between these output powers is not zero. However, to reduce the mismatch between demand and supply to be close to zero, this paper proposes strategies of increasing the rated power of solar, battery and grid separately and combining them with a view of finding the cheapest option among these strategies. The results have shown that the cost increment for different options is USD 280.792, 84.48 and 48.204 for storage, P.V. and grid, respectively. These have shown that the storage option is the most expansive option for improving P.V. grid-connected microgrids. This is followed immediately by the P.V. option, which is weather dependent. On the other hand, the grid option is the cheapest option for system reliability improvement. This paper is expected to be useful to both new researchers and experts who are working in energy management with an emphasis on the reliability aspect.

Keywords: microgrid; algorithms; solar; battery storage; energy management; reliability

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1. Introduction

A microgrid can be defined as a small-scale power network with distributed sources and battery storage connected to the load points that are typically close to one another. In most cases, this type of power network increases the reliability and resiliency of the grid during unforeseen weather events. Therefore, microgrids offer many advantages, such as better efficiency, reliability, and reduced transmission losses. Additionally, emission reductions are achieved, and accessibility by remote communities/load is increased significantly. The others are grid support services, integration of renewable energy sources into the national grids, voltage regulations, and environmental developmental activities [1–5]. In terms of connection, microgrids can be connected to the grid or in standalone modes. Another possibility is the classification of microgrids as AC, DC or hybrid AC-DC microgrids. Normally, when it is connected in grid mode, the microgrid supports the main grid in many areas, such as voltage regulations, flexibility, and reliability. It is important to note that in this type of connection, renewable energy resources operate and deliver power at maximum power point tracking (MPPT). On the other hand, the island mode is a situation where the microgrid is disconnected from the main grid and, hence, power is supplied from renewable resources [2–9] and other distributed generators (D.G.s). Therefore, it can be seen that a balance between supply and system demand is always critical in both modes of microgrid systems operations. This issue is defined as one of the energy management problems of microgrids. Therefore, the development of energy management is critical to the success of renewable energy integrations.

In this paper, the proposed energy management strategies are presented in the flow chart shown in Figure 1. The rest of this paper is structured as per the process diagram. A review of the literature is presented in Section 2. Section 3 defines the system operation and configuration. Mathematical modeling of the microgrid is presented in Section 4. Model simulation and fuzzy logic model development are presented in Section 5. Section 6 examines the proposed reliability improvement. Options for the microgrid system reliability implementation options are in Section 7, while Section 8 is on the economic analyses of the proposed method of managing energy for a grid-connected microgrid. The system diagram, results discussion, and conclusion are presented in Sections 9–11, respectively.

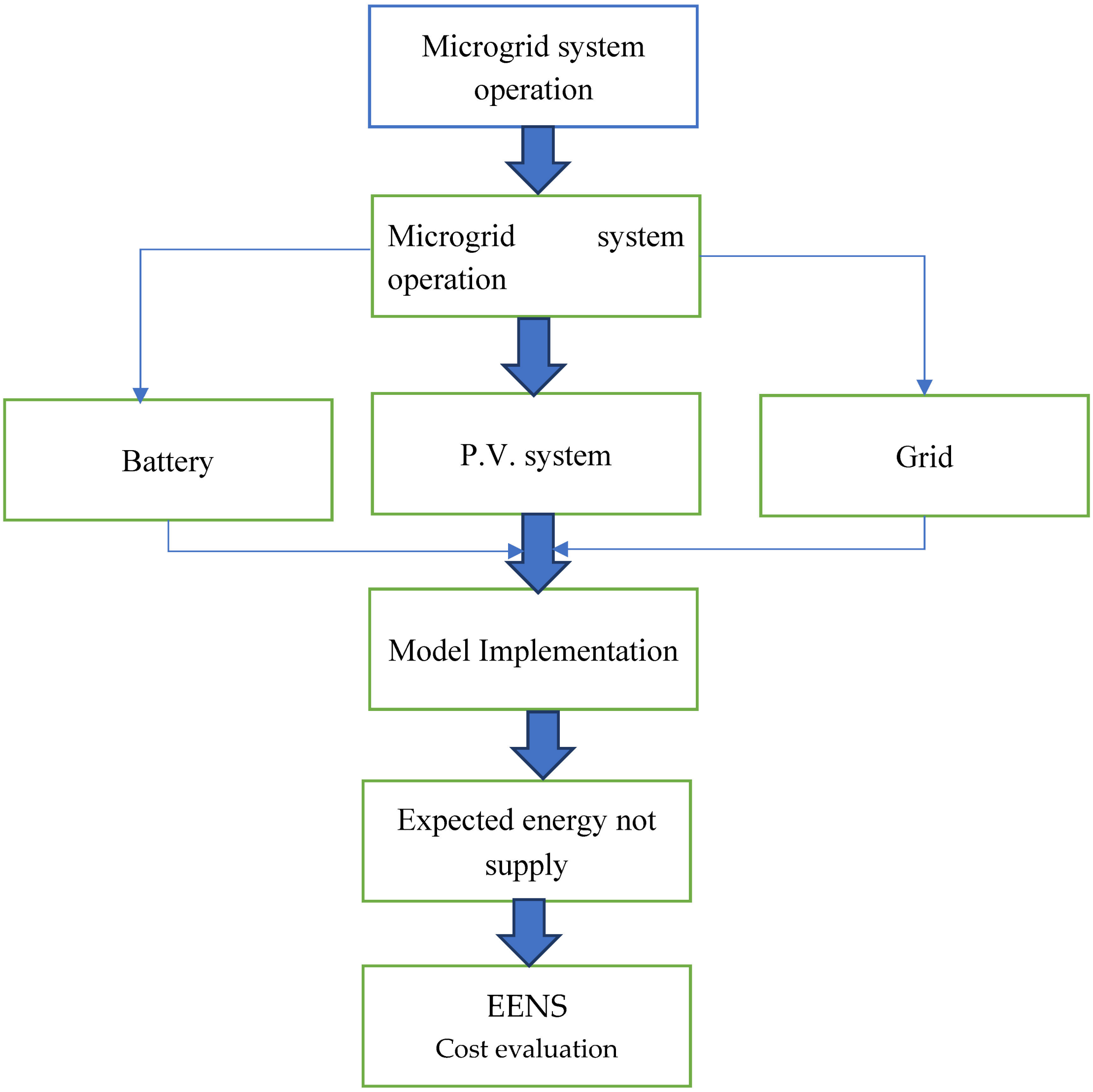


Figure 1. Energy management implementation using different reliability improvement options.

2. Literature on Energy Management of Microgrids

The management of energy among the grid, distributed generations (D.G.s), renewable energy systems (RESs), and loads is important in a microgrid. There are several papers on the use of microgrids in the exchange of energy to and from the grid. Authors in [2] have developed a spinning reserve for isolated microgrids with the aim of reducing cost and computational time using different optimization algorithms. The developed model was eventually converted into a mixed integer linear programming model and solved in the general algebraic modeling system (GAMS). In Pakistan, techno-economic analyses were carried out in Hybrid Optimization of Multiple Energy Resources (HOMER) software for optimal sizing of microgrids with a view of reducing net cost, energy generation and emission, simultaneously [10]. The authors were able to simultaneously minimize annual waste from the thermal unit and grid sales. Moreover, they considered both island and grid-connected microgrids. Evidently, the output of the analyses was site dependent in all respects. In [11], the authors were able to develop a microgrid model for load customers in residential areas irrespective of the load in HOMER software. The levelized and present costs of energy were the optimization parameters. The analyses have shown how grid outages and output power of the solar energy conversion system are related.

In some cases, battery storage has been judged as one of the most difficult parts to address while analyzing renewable energy systems. In this regard, some authors have tried to study the effects of some battery storage parameters on the performances of renewable energy systems. One such study is the optimal scheduling of microgrids, considering battery degradation and running costs [12]. The developed model has reduced the cost of energy, peak demand, and battery degradation cost, and by applying a flexible assignment method for state of charge, the cost of the system was further reduced.

In another development, linear programming has been applied in [13] to develop a model for residential applications, taking grid availability into consideration. The work used a small hardware device for the analyses considering different scenarios in load shading analysis. Other factors that affect microgrids analyzed in literature include energy reserve, frequency regulation, and investment deferral [14]. The possibility of integrating advancing metering in microgrid has been demonstrated in [15]. Other efforts include those of authors in [16], in which the optimal scheduling of energy management for microgrids has been proposed. In this work, battery storage has been proposed as one of the candidates for the profit enhancement of a microgrid.

It is seen that the cost reduction depends on load shading. By extension, the same programming language was used in [17] for the analyses of the hypothetical factory model, and the aim was to determine the optimal energy mix considering operational and investment costs. In this case, linear programming was used for the solution, while Pareto fronts were used to determine the optimal values of the conflicting cost parameters. Using market clearing price in the model, the proposed method reduced the operational and investment costs accordingly. More efforts can be seen in [18], where a virtual power plant was developed with a microgrid. Using a backtracking search algorithm and integration of the controller, the developed model reduced the operational cost and losses of the system. Neural network application has been demonstrated in [19] to determine an optimal solution taking day-ahead load and variability in prices. Furthermore, battery storage life has been increased by reducing the battery life cycle, and, finally, the overall system cost has been reduced by more than 50%.

Literature has shown that most of the works around microgrid energy management have concentrated on financial analyses of such systems. Some of them were solely on the standalone modes, and, in some cases, others calculated savings due to integrations of renewable energy resources onto the national grid with a view of cost savings determinations. However, energy management with an emphasis on reliability is very rare in the literature. This research simultaneously considers energy management and reliability with a view of the construction of the system cycle in a single work. A comprehensive model for the procedure has been presented, such that all factors were considered in the analyses.

More literature on the cost reduction related to microgrids can be seen in [20,21]. Authors in [20] developed a two-stage model that simultaneously considered supply and demand entities using frequency security. The developed scheme reduced the cost of the system significantly by the application of incentive initiatives. Smart home appliances' contributions to system cost reduction have been analyzed in [21]. The results of the analyses have shown the possibility from the theoretical point of view. In a similar paper, two algorithms were hybridized in order to reduce the cost of microgrids and maximize the profit of the entire system. In this case, different probability distribution functions were used to model the uncertainties of renewable energy sources. Furthermore, uncertainties were considered in the sizing of microgrid, and the proposed method has increased system reliability in [22]. Some authors found that using the direct algorithm (DA), it is possible to achieve a cost reduction and decrease computational times for the optimum design of a microgrid [23]. Kelly criterion was applied in [24] in order to analyze the energy management of microgrids, such that uncertainties in such systems could be reduced. The uncertainties considered were load and renewable resources to eliminate the metrological effects on the microgrid systems. Authors in [25] developed energy management for a prosumer microgrid considering market situations. In this case, the energy management developed was for the prosumer system. The proposed method allowed the authors to analyze different protocols for both energy and market situations. Authors in [26] considered a forecast error in the prosumer scheduling of microgrids. The developed model was solved using different types of situations (controllable and uncontrollable situations). Many papers are available on energy management, usually with applications on cost reduction [27–30], battery storage application in areas of regulation [31], voltage regulation [32,33], demand-side issues [34], distribution system deferral [35,36], price-based scheduling [37] and power reliability [38]. It is seen from the review of existing literature that some issues on energy management have not been given the expected attention. Furthermore, the effect of increasing the rated power of microgrid components on the cost and reliability of microgrids has not been given the expected attention. The aim of this paper is to develop an energy management strategy for renewable energy microgrids based on reliability improvement. Furthermore, the paper is expected to help microgrid planners have a clear view of grid-connected microgrid system behavior considering different system reliability improvement techniques. This study is based on weather conditions and the rated power of sub-systems. This can assist in the determination of the cost-effective way of improving the reliability of the system for proper planning, control and maintenance of future electricity networks. Furthermore, the strategies proposed to achieve these include variations in the rated power and solar radiation of microgrids. In view of these, this paper has identified the following contributions:

- An intelligent EMS is developed for optimal use of grid-connected microgrids consisting of grid, P.V. and battery storage systems that could ensure reliable operation of the system at low cost using fuzzy logic.
- A procedure has been proposed for the evaluation of expected energy, not supply, evaluation of a microgrid that could guarantee reliable and continuous system operations.
- A systematic procedure has been proposed for the construction of the system cycle.

3. System Configuration and Operations

The schematic diagram of the microgrid is shown in Figure 2. The circuit consists of six building blocks. In this paper, microgrid and power management strategies are proposed considering the grid-P.V.-battery, King Saud University microgrid. The university load is connected to the grid with the aim of achieving 100% reliability with the least emissions and with the priority of achieving minimum cost of energy. It is expected that with help of the energy management strategies, the overall reliability of the system will increase.

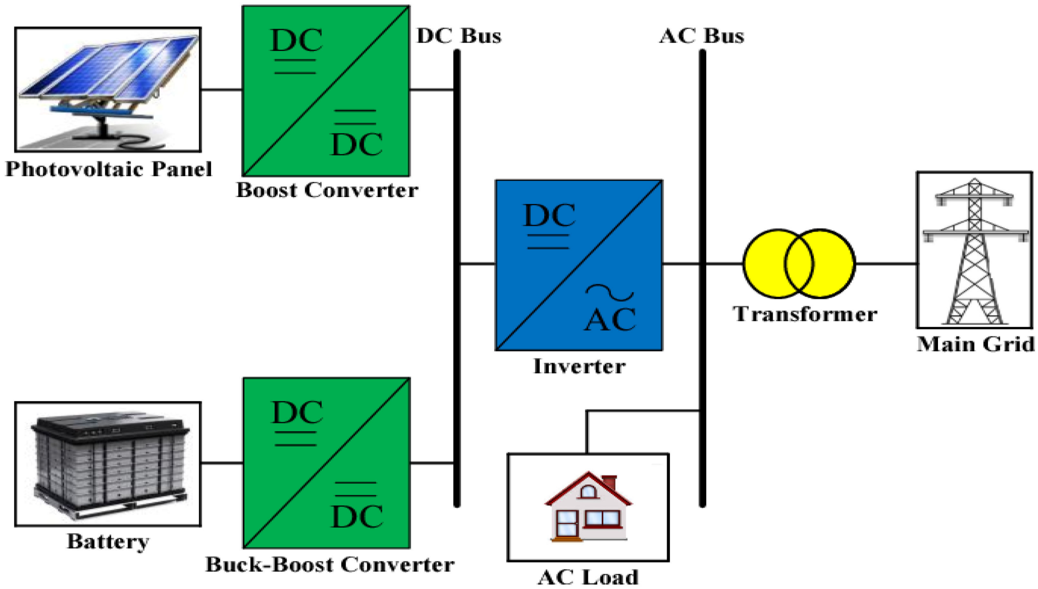


Figure 2. Proposed hybrid Microgrid.

4. Mathematical Models of the Microgrid System Configuration

4.1. P.V. System Model

The output power of solar energy conversion systems can be determined using many mathematical models. In this paper, the output power of solar P.V. is obtained using the Equation (1)

$$PSEC\ (t) = I(t) \times V(t) \times N_{PV} \tag{1}$$

This presentation has allowed us to use the number of panels as a design variable, which also depends on the application; the panels can be connected in series or parallel in order to obtain higher current or voltage.

4.2. Energy Storage System Modelling

In this work, a lead-acid battery is chosen for this research. Therefore, the battery storage system is subjected to the following constraints:

$$\xi_{min} \leq \xi(t)\ \leq \xi_{max} \tag{2}$$

$$\xi_{min} = (1 - DOD) * \xi_{max} \tag{3}$$

In this manner, the charging and discharging behavior are expressed using the following:

$$\text{Charging b},\ (\text{t}) = \sum_i^{N_b} P_{b,c}(t)\ \Delta t \tag{4}$$

$$\text{Charging b},\ (\text{t}) = \sum_i^{N_b} P_{b,d}(t)\ \Delta t \tag{5}$$

Battery state of charging according to battery behavior is defined as:

$$\xi(t+1) = (\mathbf{1} - \zeta)\xi(t) + \begin{cases} (\mathbf{1} - \zeta)\xi(t)\Delta t + P_{b,c}(t)\eta_c \\ (\mathbf{1} - \zeta)\xi(t)\Delta t + \frac{P_{b,c}(t)}{\eta_d} \end{cases} \tag{6}$$

In this setting, the battery cost is defined as C_b

$$C_b = \left[C_{ub}N_b + C_{(om,\ b}N_b + C_{rb}\right] \tag{7}$$

4.3. Grid Cost Model

The variable, in this case, is the revenue from buying electricity from the grid and the cost of selling electricity to the utility grid as defined in Equation (8).

$$C_{grid} = \begin{cases} C_{ugb}P_g \ + C_{ugb}P_{g,\ max} \\ C_{ugs}P_g + C_{ugb}P_{g,\ max} \end{cases} \tag{8}$$

In this case, the following are the energy management scenarios developed in this work.

Scenario I: The first priority in this design is that any excess power from renewable energy is used to charge the battery storage system if the following condition are met for battery charging.

For this condition: $P_L(t) \ \le P_{RE}(t)$ & $\xi(t) \le \ \xi_{max}$

$$\xi(t+1) = (\mathbf{1} - \boldsymbol{\zeta})\xi(t) + (P_L(t) - P_{RE}(t))\eta_c \tag{9}$$

Power to be sold to the grid is determined using:

$$P_{grid,\ s}(t) = P_{RE}(t) - P_L(t) - P_{b,c}(t) \tag{10}$$

Scenario II: If the energy from the RE source is less than the system demand requirement, the battery storage will be in the state of discharges shown in the equation:

$$P_{b,d}(t) = \{(P_L(t) - P_{RE}(t))\ (\xi(t) - (1 - < DOD_{max}\ )\xi_{max})\} \tag{11}$$

Scenario III: When the power from the battery and RE sources is less than the system demand, the external grid can sell electricity to the university to satisfy the system demand.

For $P_L(t) > P_{RE}(t) + (\ \xi(t) - \xi_{min})$, we have:

$$P_{,\ b}(t) = (\xi(t) - (1 - < DOD_{max}\ )\xi_{max}) \tag{12}$$

$$P_{grid,\ b}(t) = P_L(t) - P_{RE}(t) - P_{b,d}(t) \tag{13}$$

Scenario IV: In an extreme situation, when the external grid cannot supply the deficit, this results in power loss, defined as loss of power supply (LPS), as presented in Equation (14).

$$LPS(t) = P_L(t) - P_{RE}(t) - P_{b,d}(t) \tag{14}$$

The final step is the implementation of the developed model in MATALB. The developed model has been implemented in a real microgrid with power consumption shown in Figure 3. The modelling parameters used in the analyses are also presented in Table 1.

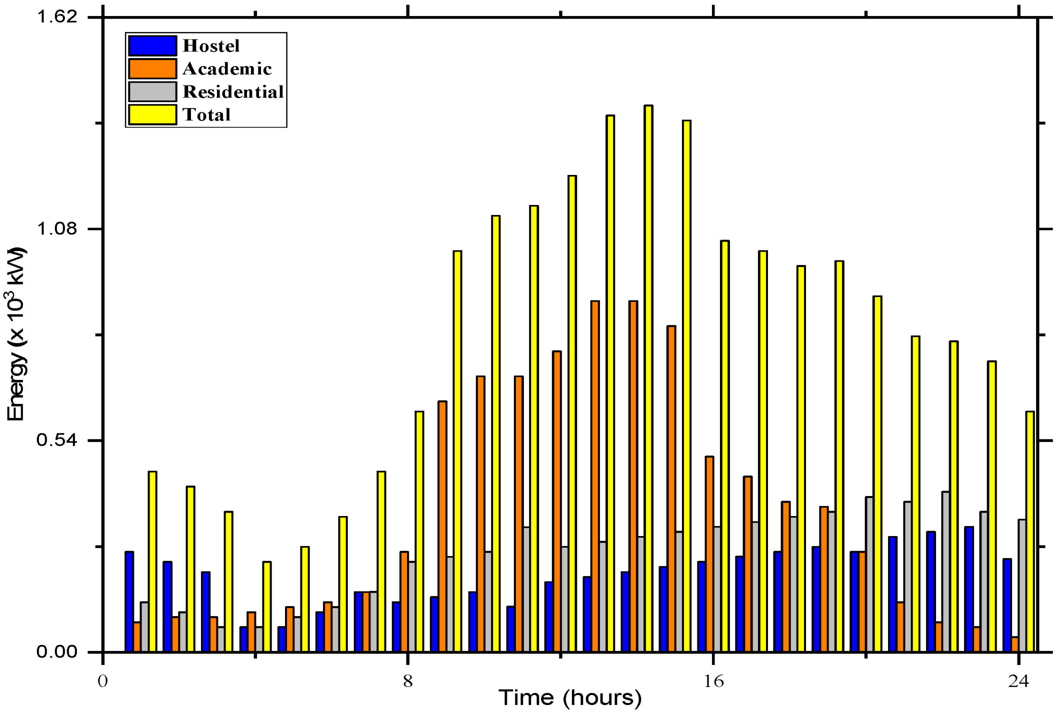


Figure 3. Load demand of the microgrid.

Table 1. Parameters used for microgrid model.

Battery Parameter	P.V. Parameter
Nominal voltage = 24 v Rated capacity = 50 Ah Initial state of charge = 45% Battery response time = 1 s Cut off voltage = 18 v Fully charged voltage = 27.9 v Nominal discharge current = 21.7 A Internal resistance = 0.0048 ohms	Shunt resistance = 415.5 ohms Series resistance = 0.221 ohms Total number of cells in series = 54 Total number of cells in parallel = 1 Short circuit current = 8.21 A Open circuit voltage = 32.9 v Current at maximum power = 7.58 A Voltage at maximum power = 26.4 v Rated power = 200 w Nominal tempt = 298 k Electron charge = 1.6×10^{-19} C Boltzmann's constant = 1.38×10^{-23} Band gap energy of the semiconductor = 1.1 eV The ideality factor of the diode = 1.3

5. Simulations and Fuzzy Logic Design

5.1. Fuzzy Logic Controller Design

Fuzzy logic is an artificial intelligence proposed as the energy management controller. It is used in this study to critically make the decision between the different energy sources by intelligently controlling the sources based on the time of day and the energy cost [39]. However, this proposed controller makes use of language variables rather than the numeric data for its implementations in energy management and dispatch. This has shown strong results by reducing energy costs and improving system performance [40,41]. Figure 4 shows the implementation of fuzzy logic. It is clear that the model consists of major building blocks, including fuzzification, defuzzification, inference and rule base, as shown in the block diagram representation of the entire process.

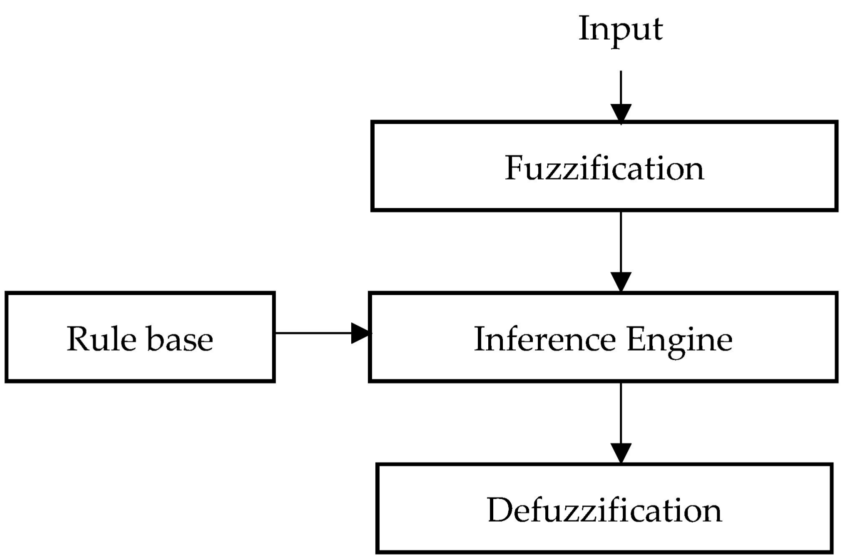


Figure 4. Fuzzy logic model diagram.

The proposed smart system consists of four (4) input and one (1) output, which is constructed using a Mamdani fuzzy interface system, as shown in Figure 5.

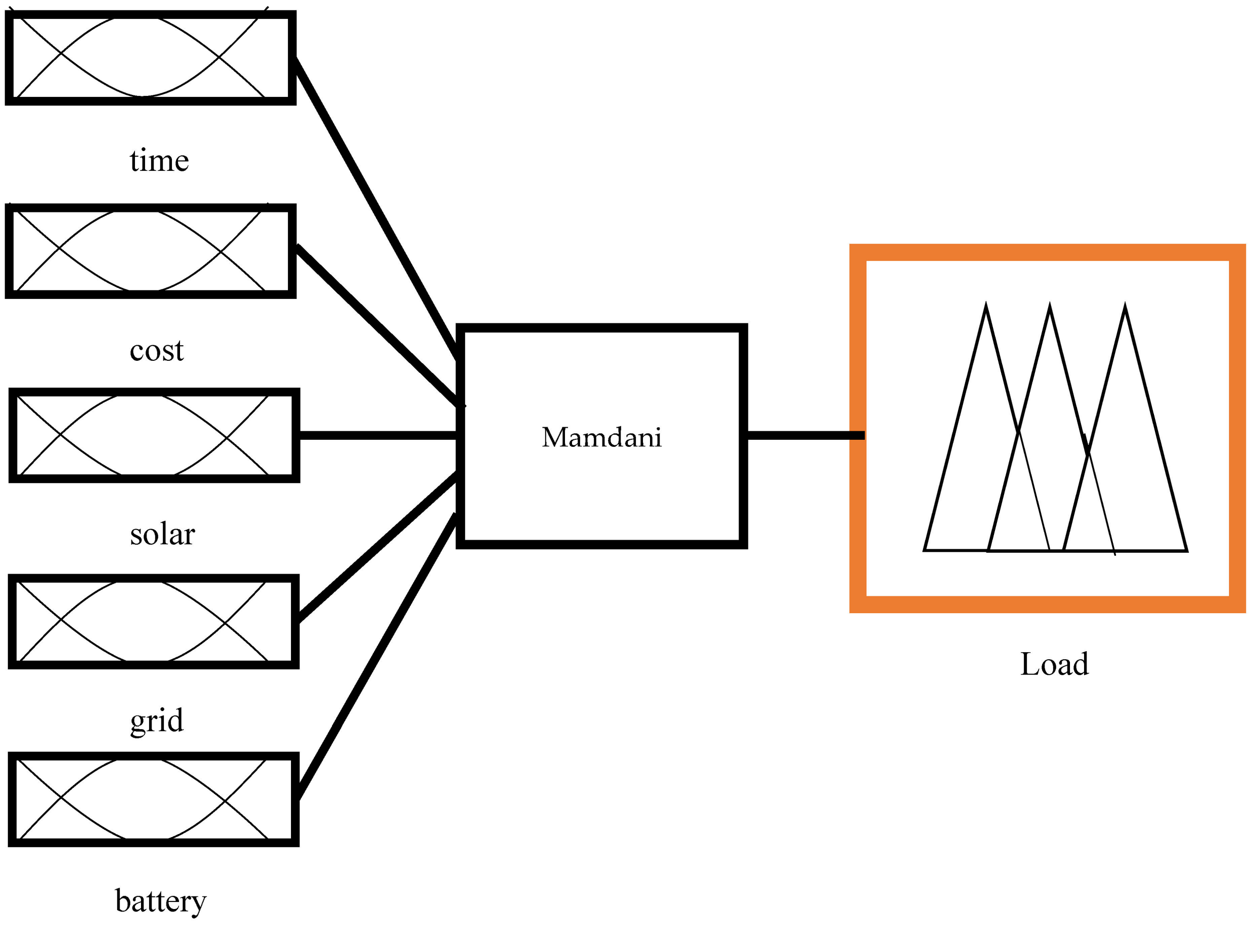


Figure 5. The block diagram of the proposed fuzzy logic controller.

The inputs are made of the time of day, the dynamic energy cost, the grid, the solar P.V. and battery. The fuzzy logic controller manages the various input based on the energy cost at a particular time; this is used to control the load that is operated by various energy sources. The output of the controller is either to connect the grid or solar P.V./battery to the load when the cost is high or low for that particular time of day. The fuzzy logic controller interacts between the inputs and output using the IF-THEN statement known as rules. The IF part of the rules describes the input parts. Also, Tables 2–5 presented the time fuzzy set, cost fuzzy set, grid fuzzy set respectively. Furthermore, this work set a total of 32 rules to construct this energy management system considering different operational conditions as shown in Table 6.

The inputs and output have two and one membership function (M.F.), respectively, which is represented as follows: time (day and night), cost (off-peak and peak), grid (low, high), solar P.V. (low, high), battery and output load, respectively. In this research, triangular M.F. is used due to its high level of precision and high computation accuracy. The input from sample data used in this work have 2 M.F. which are classified as illustrated below:

Table 2. Time fuzzy sets.

S/N	Time	Range
1	Day	1–12
2	Night	12–24

Table 3. Cost fuzzy set.

	Cost	Range
1	Off-peak	0–43.3
2	Peak	43–58.5

Table 4. Solar P.V. fuzzy set.

S/N	Solar PV	Range
1	Low	0–9
2	High	10–20

Table 5. Grid fuzzy set.

S/N	Grid	Range
1	No	0–0.1
2	Yes	1–6

The energy management controller aims to achieve the following listed below:

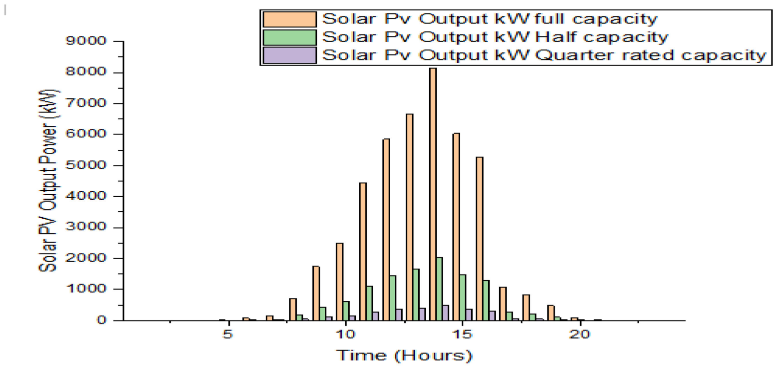
I. Load demand must be fulfilled at any particular time of the day.
II. Energy sources must be managed based on cost.
III. State of charge should not go below a given threshold to avoid overcharge and discharging.
IV. Grid energy as the primary source of energy.
V. Manage the fluctuation of solar PV.

Table 6. Rule base for energy management system.

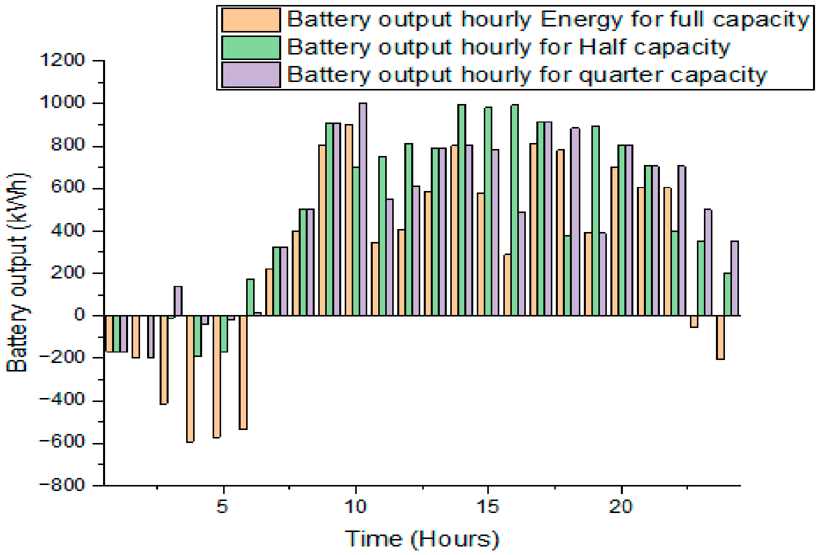
Time	Cost	Battery	Grid	P.V.	Fuzzy Output
Day	off-peak	Basic	YES	Low	Connect to grid
				High	Connect to grid
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery
		Heavy	YES	Low	Connect to grid
				High	Connect to grid
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery
	peak	Basic	YES	Low	Connect to grid
				High	Connect to P.V./Battery
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery
		Heavy	YES	Low	Connect to grid
				High	Connect to P.V./Battery
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery
Night	off-peak	Basic	YES	Low	Connect to grid
				High	Connect to grid
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery
		Heavy	YES	Low	Connect to grid
				High	Connect to P.V./Battery
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery
	Peak	Basic	YES	Low	Connect to grid
				High	Connect to grid
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery
		Heavy	YES	Low	Connect to grid
				High	Connect to P.V./Battery
			No	Low	Connect to P.V./Battery
				High	Connect to P.V./Battery

5.2. Case I

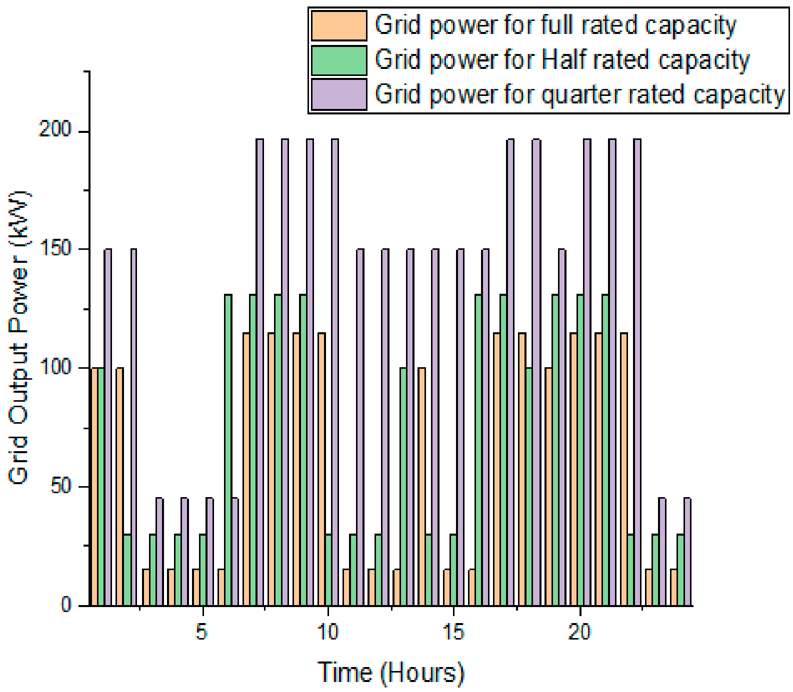
In this case, the microgrid is in its normal form, with all the power sources operating at full capacity. The output power obtained is shown in Figure 6a–c. In each case, the system-rated powers have been varied in order to study the effect of the rated power on the overall system response. The results presented are the output powers of the solar energy conversion system, the response of the battery storage system connected to the grid, and the external grid power supply to the microgrid (Figure 6b). The results were obtained when the rated power for each unit is adjusted by half and quarter of the actual value. Figure 6a shows that the output power of the P.V. system does not change with the same value. In a similar manner, the contribution of the external grid in each scenario depends on the rated power of each unit, as presented in Figure 6c. When the rated power of the entire microgrid was reduced by half and quarter of rated power, the contribution of the external grid increased.



(**a**)



(**b**)



(**c**)

Figure 6. (**a**) Output power of P.V. for full rated power variations. (**b**) Output variations of battery storage for full rated power. (**c**) Output power of Grid for full rated power variations.

5.3. Case II

The second part of the simulation was on the variations of the individual- rated power of each unit. The variation is from decreasing the rated power by half of the actual value, and this is followed by further reduction by another quarter of the actual value. The results of these simulations are presented.

6. Output Power Management

In this paper, the FASTCLUS method is selected for data clustering because it is suitable for the data sets. The advantage of the proposed method is its suitability for taking the fluctuations in the output power on an hourly basis. In addition, parameters of the algorithm can be obtained; these include the cluster centroid, frequency and in-cluster. These were used on the output powers and described by a vector (d^n) as follows:

$$d^n = [L^n,\ d_1{}^n,\ d_2{}^n, \ldots, d_m{}^n] \tag{15}$$

where L^n = load in terms of the fraction of the peak load for state n, $d_1{}^n$ = ratio of the output powers of conversion system to their rated powers in state n. Therefore, a value in the range ($0 < \frac{E_{RE}{}^i}{E_{RE}{}^m} < 1$) is obtained. The results were converted into nine clusters shown in Figure 7.

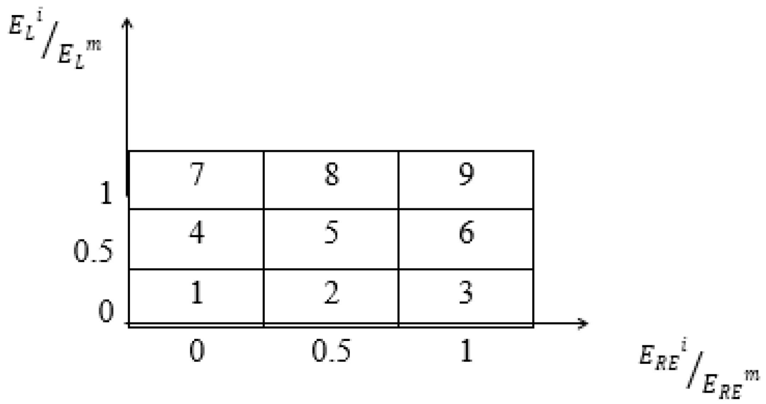


Figure 7. Cluster centroid.

In order to explore different options of improving the reliability of the proposed system, the following alternatives are proposed:

1. System reliability improvement by capacity of renewable energy system;
2. System reliability improvement by the use of storage units;
3. System reliability improvement by increasing output power of the grid.

7. Proposed Reliability Improvement Options for the Microgrid

In this section, the developed algorithm is for system reliability improvement by increasing the capacity of P.V. of the microgrid. Thus, an algorithm for this alternative is described as follows:

7.1. System Reliability Improvement by Capacity of P.V. System Energy System

Steps (1–6) below explained the process involved in the determination of the energy not supplied by this alternative as follows:

1.
$$P_{rn} = A \times P_r \tag{16}$$

where P_r = rated power of P.V. system, and the factor that this alternative capacity increment is defined as A.

2. New energy output can be is obtained using:

$$E_{rn}{}^{i} = A \times E_{r}{}^{i} \text{for } i = 1,\ 2\ldots \quad (17)$$

$n =$ number of states

3. Annual grid energy annual energy is defined:

$$DE = \sum_{i=1}^{n} E_{D}{}^{i} F^{i} \quad (18)$$

4. Fuel saving is defined as:

$$FS = (TADE - DE) \times cf \quad (19)$$

5. New annual system cost can be defined as follows:

$$TSC = F + (P_{rn} - P_{r}) \times ACC_{RE} - FS \quad (20)$$

where ACC_{RE} = capital cost of P.V. system.

6. In each case, the EEENS is obtained with a view of making it equal to zero (EENS = 0).

7.2. Battery Storage Option

In this option, knowledge of other cost options is very important. In view of this, Markov transition matrix is proposed. In order to develop this, the element of the matrix is the state of transition. This will allow for the development of a system diagram, which eventually is used to obtain the cost associated with this option of improving system reliability. Therefore, the average number of days is obtained using:

$$N = [I - Q]^{-1} \quad (21)$$

where Q is the matrix obtained from the transition matrix T.

❖ Duration in each state:

The mean number of days to reach a state j, given that the system starts at cluster i, is obtained by defining j as an absorbing state. Finally, the average number of steps is determined by defining a matrix N as follows:

$$M_{i,j} = \sum_{k=1}^{N-1} N_{k,j} \quad (22)$$

N is the number of states.

$M_{i,j}$: is the average time required to enter j, given that system in state i.

Hence, for this development, some states are grouped using this relation.

$$E_{RE}{}^{i}/E_{RE}{}^{m} = E_{L}{}^{i}/E_{L}{}^{m},\ i = 1,\ 5 \text{ and } 9 \quad (23)$$

$$E_{RE}{}^{i}/E_{RE}{}^{m} - E_{L}{}^{i}/E_{L}{}^{m} \approx 0.5 \text{ for } i = 2 \text{ and } 6 \quad (24)$$

$$E_{L}{}^{i}/E_{L}{}^{m} - E_{RE}{}^{i}/E_{RE}{}^{m} \approx 0.5 \text{ for } i = 4 \text{ and } 8 \quad (25)$$

7.3. System Reliability Improvement by Increasing the Output Power from the Grid

Reliability improvement using this option is obtained using the equations described below; the energy of the grid is distributed as follows:

1. When the P.V. power is equal or greater than the system demand:

$$E_{RE} \geq E_L,\ E_G = 0.0 \quad (26)$$

2. When the P.V. output power is less than the demand:

$$E_{RE} < E_L,\ E_G = E_L - E_{RE} \quad (27)$$

Hence, the grid capacity requirements are evaluated and obtained as below, bearing in mind that it operates within its limit:

$$C_a = C_{G1} \times (PG_{rn} - PG_{rn}) + cf \times \sum_{i=1}^{n} E_{GA}{}^{i} \times F^{i} \quad (28)$$

Finally, the cost associated with this option can be defined as:

$$TCS = F + C_a \quad (29)$$

The proposed energy management is developed considering the literature and, therefore, microgrid energy management can be in any form as presented in Figure 8. Furthermore, in order to justify the developed energy management system, it has been well established that the cost-minimization problems in the EMS are solved using many approaches shown in Figure 9.

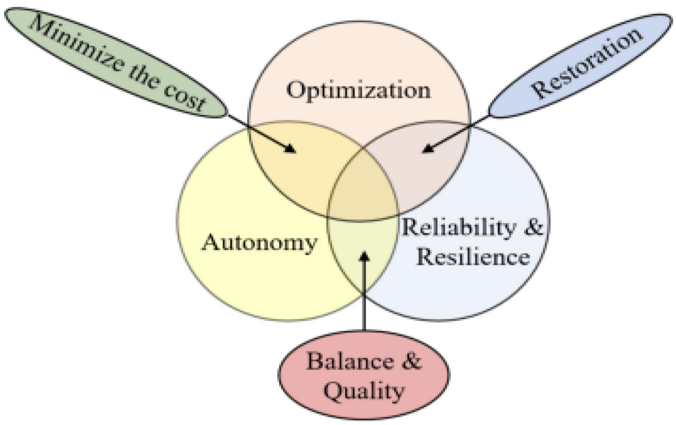


Figure 8. Showing problem that can be solve by energy management systems.

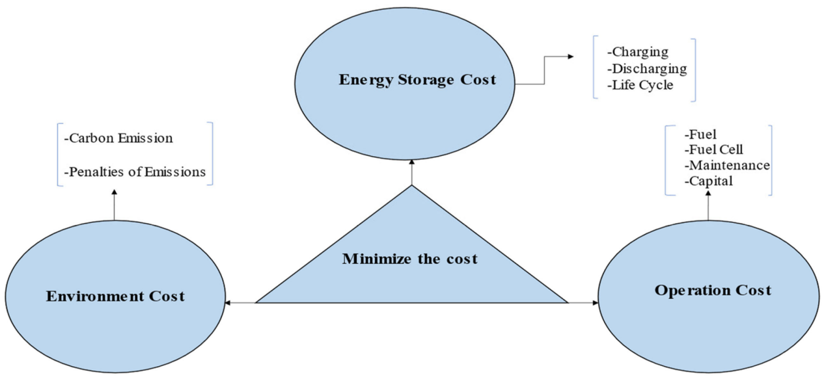


Figure 9. Approaches for solving energy management problems.

In this research, variability in weather of the King Saud University is considered. In addition, the variations in load, rated power and different weather conditions were taken into consideration. In view of this, the following system conditions are analyzed:

- When the power is provided by the solar energy sources only.
- When the load is fully supply by the external grid.
- The battery storage is added into the microgrid.

The real energy microgrid is located in King Saud University, situated in Riyadh, Saudi Arabia. Furthermore, the load has been presented carefully for two seasons in a year. It is assumed that the load patterns are the same throughout the year. Since the measurements were for the peak load days, the result is expected to cover the worst case. In addition, selecting the worst case will allow us to give careful judgment, economically. Therefore, when the load demand is less than the output from the renewable energy sources, the excess power will be sold to the grid.

The data of the microgrid is obtained from actual measurements using an energy meter installed locally within the electricity network. This allows us to analyze the cost of energy. The results of the measurements are presented in the figures below. The load patterns for the two scenarios are different as having two different peaks. The academic and administrative blocks are peak in the afternoon, while the student and residential areas peak after closing the university, as presented in the load profiles.

These presentations will allow us to study the effects of other parameters on the cost of energy and reliability. Some of the parameters to consider for these analyses include weather variation and load variation. The results obtained from the proposed steps above are presented in the following sections.

7.4. PV System Variation

Figure 10a–c shows the variation of system responses when the rated power of the P.V. system is varied. The output of this simulation has shown that the power output of the solar P.V. does not correspond with the same percentage decrease in the rated power of the solar P.V. system connected to the grid. In view of this, the external grid was forced to inject more power into the system, which amounts to higher energy cost to the system. It can be seen clearly that the power injected is not the same percentage as the corresponding adjustment of the rated power of the solar P.V. system. This is presented in Figure 10a. It can be seen that half of the rated capacity decreased and is always given higher output power compared to half of the rated power variation. However, opposite variation is observed in the case of grid output power; in this case, the output power increased with decrease in the term.

7.5. Battery Storage Characteristics

When the rated power of the battery storage system is changed, the output power of the P.V. system, battery storage and output power from the grid changed in order to accommodate new system dynamics, as presented in Figure 11a–c. A critical look at the results shows that external grid output power for a quarter of the rated power is higher than the half-rated power in order to accommodate the change which is due to the need for more power to the entire microgrid. A similar trend is observed in Figure 11c, where the battery storage available energy is always in agreement with grid output power. On the other hand, the output power of the P.V. system is opposite that of both grid and the storage energy. These, in turn, will increase the cost of running the entire system as presented in Section 8.

7.6. Grid Variations

Looking at the results obtained from these simulations has shown that the output power of the P.V. system is constant for this case, as shown in Figure 12a. The contribution to the grid decreased from 75 kW to 37.5 kW, as shown in Figure 12b. This grid responded to the system turbulence with the same factor was handled by the battery storage shown in Figure 12c.

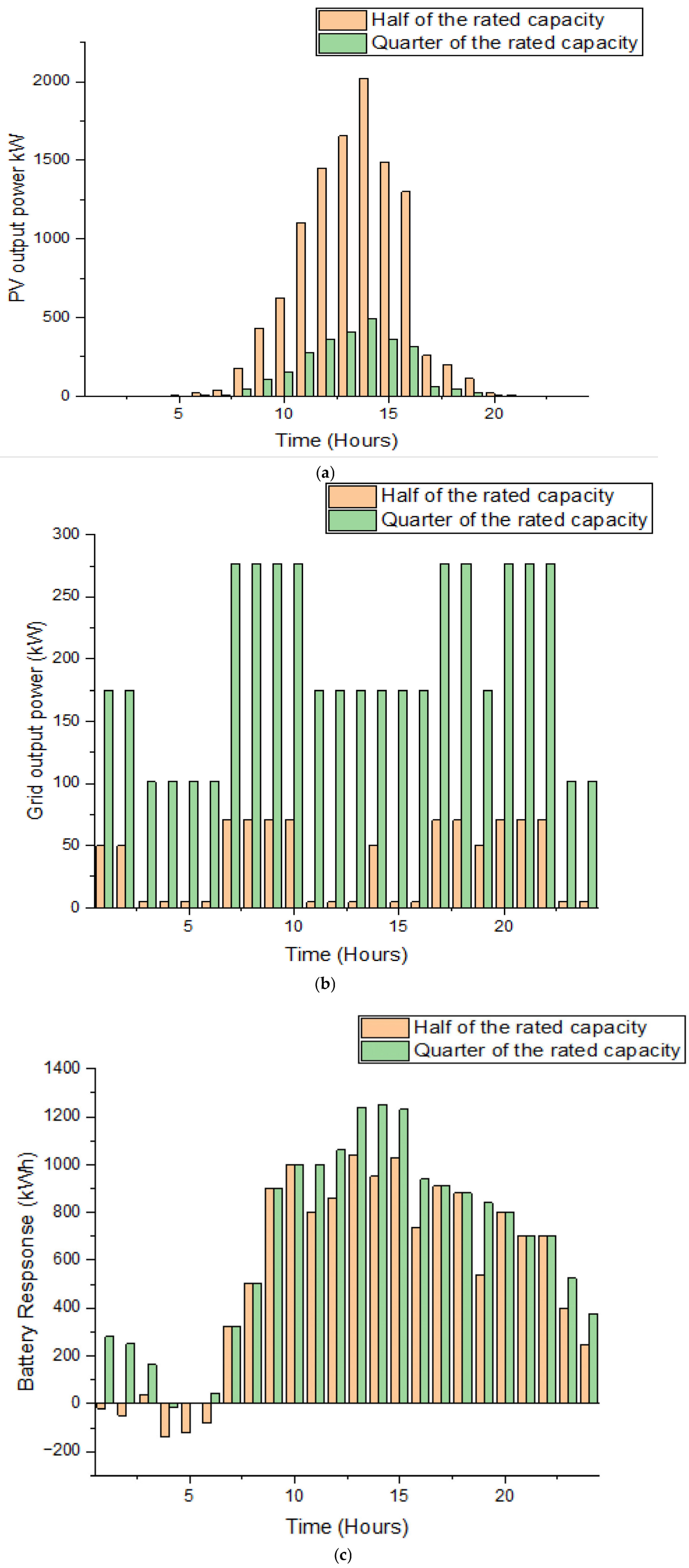
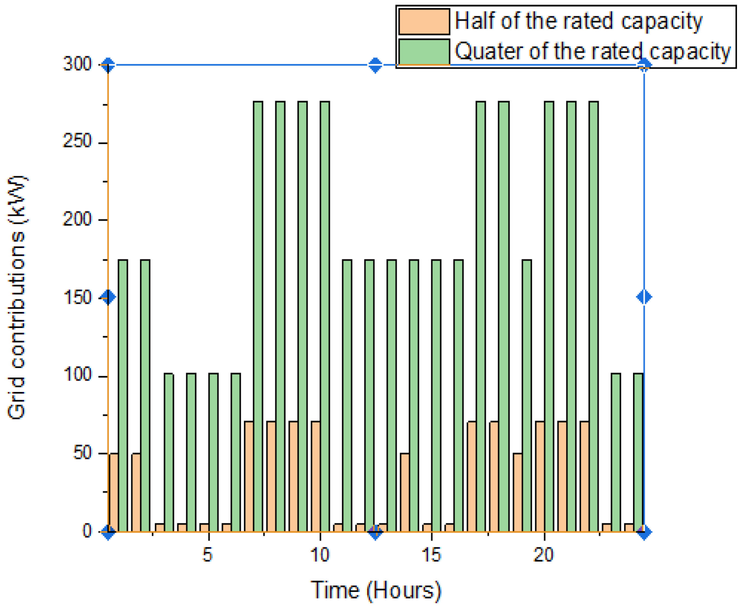
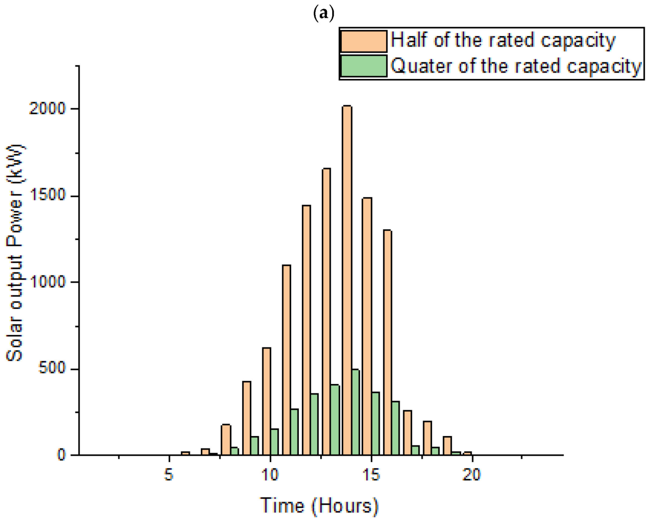


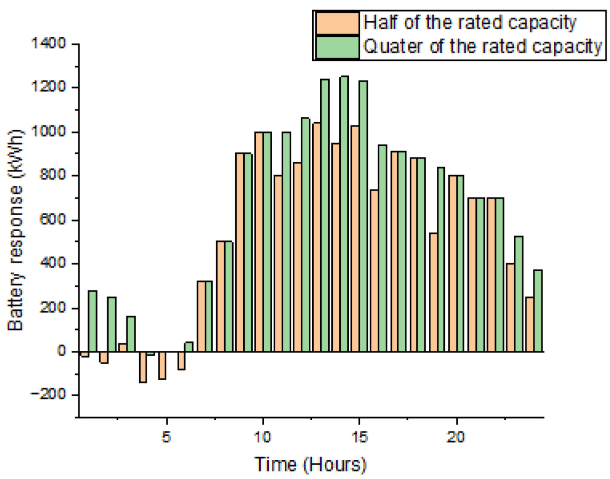
Figure 10. (**a**) P.V. system output power response for P.V. system variation of rated power. (**b**) Grid output power for P.V. system variation of rated power. (**c**) Battery storage response for P.V. system variation of rated power.



(**a**)

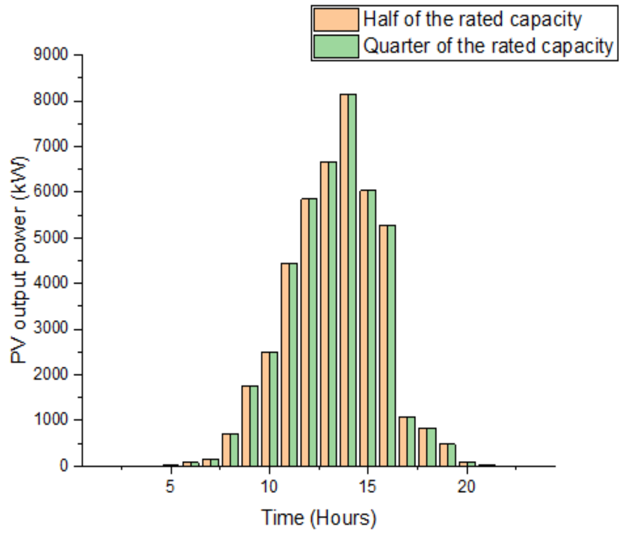


(**b**)

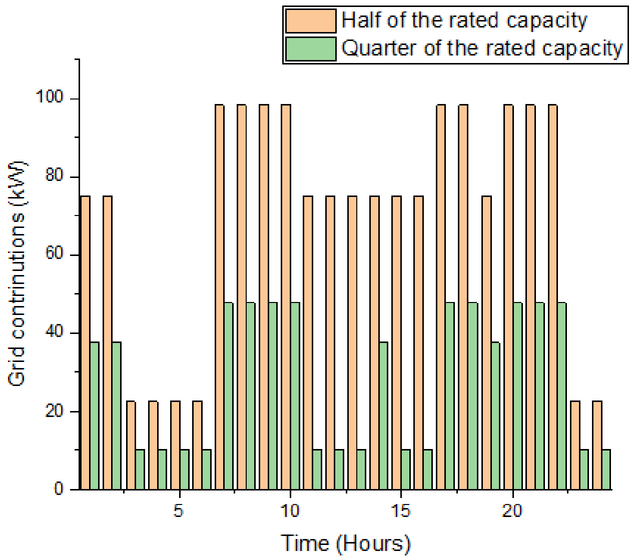


(**c**)

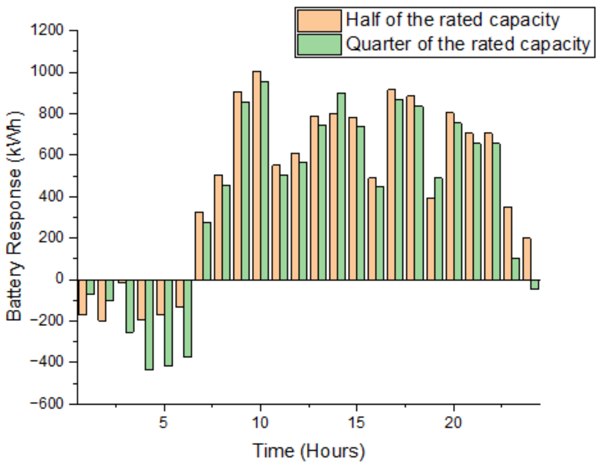
Figure 11. (**a**) Grid output power for battery storage variation of the rated power. (**b**) P.V. system output power for battery storage variation of the rated power. (**c**): Battery storage response for battery storage variation of the rated power.



(**a**)



(**b**)



(**c**)

Figure 12. (**a**) P.V. system output power for grid rated power variation. (**b**) Grid output power for grid rated power variation. (**c**) Battery storage response for grid rated power variation.

8. Economic Analyses of the Model

The expected energy, not supply, has a value in terms of cost to the entire grid operation. In this case, the system is expected to sometimes operate with the help of the external grid. In this regard, the cost associated with this operation is evaluated. This is linked to the proposed system operation by changing the rated power of each generator. Options proposed vary the rated power of each unit. The resultant effects are shown in Figure 13. Mathematically, the expression used for the cost evaluation is presented in the equation below that. This expression is used for planning power systems. It can be observed that the cost of improving the availability of the system is higher when a storage system is used. This is followed by the improving of the solar energy conversion system while the adjustment in external grid supply is the least among all the available options. From a critical look at the results presented in Figure 12, it can be seen that changing the rated power of P.V. increases the cost of system operation by 84.48 USD. A battery storage system cost will increase system operational cost by 280.792 USD. In a similar manner, the cost associated with grid variations decreased the system cost by 48.204 USD. Thus, it is clear that a battery storage option is the most expensive way of improving the reliability of the microgrid. The cost of energy used in this research, according to Saudi Arabia is 0.048 USD/kWh. Furthermore, Equation (30) is used in the determination of the cost of energy in all the cases.

$$OC = EENS * (cost/kWh) \tag{30}$$

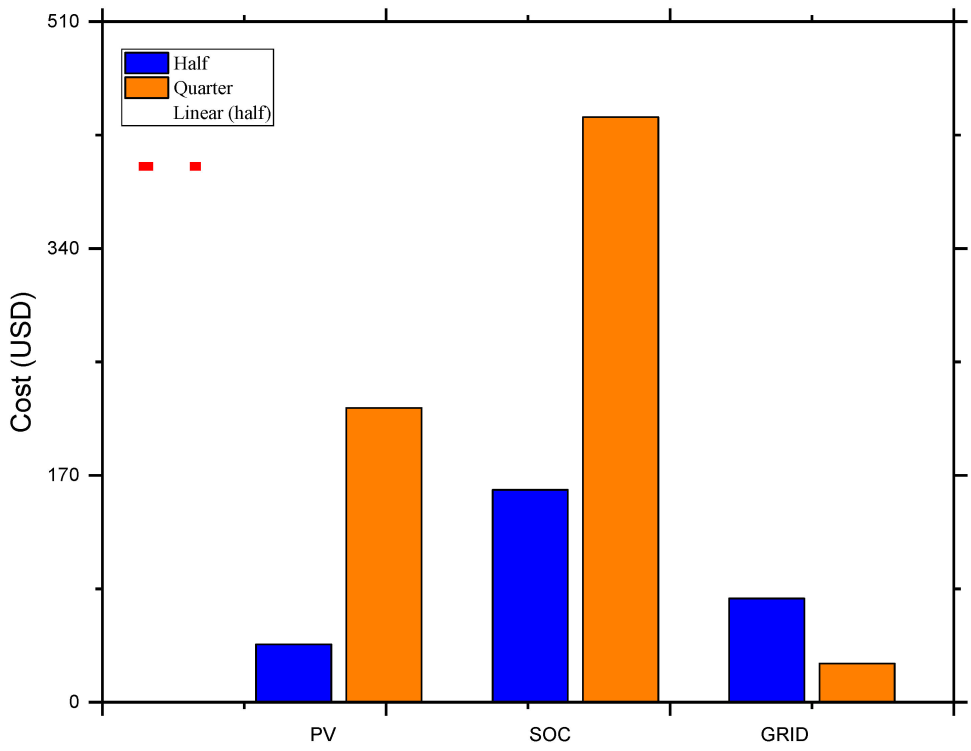


Figure 13. Cost associated with each variation.

9. Development of System Cycle

Model analysis and presentations enable us to develop the system cycle considering expected energy, not supply, as the reliability parameter for winter and summer, as shown in Figure 14. It can be seen from Figure 14 that the expected energy, not supply, is dependent on the seasonal variations. The variation can be observed, such that the winter season has the least expected energy variation. The variation also depends on the hour of the system operation. Eventually, this is a daily pattern of the microgrid cycle.

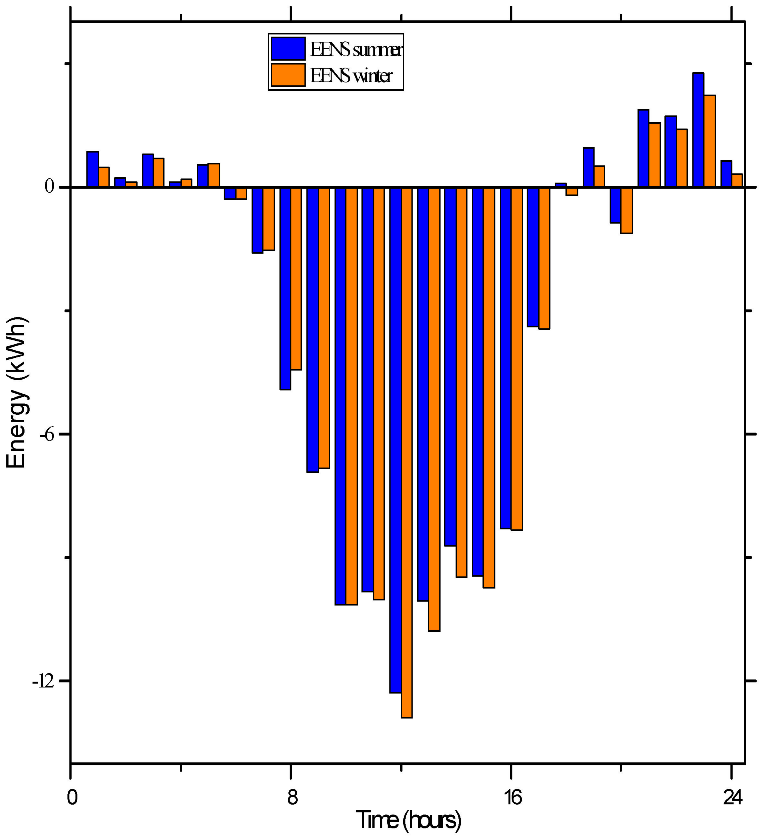


Figure 14. Microgrid responses for different scenarios.

10. Results Discussion

In the first case, it can be observed that the entire microgrid expected energy, not supply, is a function of weather. In each cycle, the EENS for summer and winter are not the same and are time dependent. Furthermore, even the distribution per day is a function of the hour of operation. In addition, when the output power from the sources was increased, the EENS decreased. Unfortunately, the decrease is not the same percentage, with more penetration of power sources connected to the network. This simply means the system is already operating at its optimum configuration. Therefore, more injection does not guarantee the same complement in the system response and output.

11. Conclusions

A systematic, cost-effective way of managing output power of microgrids consisting of renewable energy and external grids has been proposed in this paper. The paper proposed options including increasing the capacity of solar energy conversion systems, battery storage and grids. In each case, a systematic procedure has been developed that can be used to determine the cost of increasing the reliability of the microgrid systems. These procedures enable the determination of expected energy, not supply, as an energy management issue. The response of the microgrid during both summer and winter were observed. The results have shown that the expected energy, not supply, of the microgrid depends on the weather period. When the system is operating at optimum, increase in the output power might not translate to the same decrease in the expected energy, not supply, of the entire microgrid. The storage system is the most expensive way of increasing the reliability of the microgrid. This confirmed the need to develop schemes for more reliable and economic operations of a microgrid, and this is a functioning network configuration. All of these are energy management issues.

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