AIMS *Energy*

Research Article

Optimal sizing of a residential microgrid in Egypt under deterministic and stochastic conditions with PV/WG/Biomass Energy integration

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Abstract: Rural electrification represents a great worry for developing nations. Isolated microgrids establishment is the brightest solution for this problem. Optimization strategies for mathematical simulation and modelling are accomplished in this research to size an isolated residential microgrid in Egypt consists of wind generators (WG), photovoltaic (PV), battery energy storage system (BESS) and Biomass generator. This paper's novelty relies on the techno-economic performance comparison of three sizing strategies of isolated microgrid based on renewable sources, considering the sources' uncertainty. Also, the environmental and economic effects of using rice straw in biomass gasification are introduced to handle the problem of dark clouds from its open-air burning. Three categories with nine combinations of renewable energy sources (RES) are introduced in this paper to select the ideal option. Multi-objective genetic algorithm (MOGA) optimized the systems under both deterministic and stochastic conditions, taking into consideration the uncertainties of solar radiation and wind speed using Monte-Carlo techniques. The obtained results are compared with the results of epsilon multi-objective genetic algorithm (ε-MOGA). Simulation outcomes show that PV with BESS is the most economical option for microgrid sizing with a total system cost of \$ 4.04 million. Besides, Scenario 6's hybrid system provides an appropriate ecological-reliable configuration, especially when considering sources' uncertainties.

Keywords: optimal sizing; microgrid; renewable energy; Biomass; uncertainties

1. Introduction

In Egypt, many new projects are being performed in various areas, such as those in the new valley of the western desert and those in Egypt's northern coastal borders. These projects will help in the horizontal transferring of people from the cramped Nile valley to other uninhabited different locations to reduce the metropolis's crowdedness as approximately 95% of the country's population live along the sides of the Nile river and inside the Nile Delta [1]. Egypt's electricity consumption grew rapidly in the last few years as a result of economic growth. Still, it remains a challenge for Egypt to provide stable electricity access to rural areas. The population augmentation and the new towns' establishment are presenting an extreme burden on the electrical network. The Egyptian government is trying these days to turn to renewable energy sources to tackle fossil fuel shortage. Egyptian economy balance would be threatened without depending on renewable sources as it will be a great importer of fossil fuels. Integrating renewable energy sources to power systems and microgrids establishment are the best options for handling the electricity crises and decreasing the burden on the grid [2].

Microgrid systems transfer the conventional power system with a single power supply and radial network into a new distribution system with multi-power sources. It can be categorized as isolated or grid-connected, relying on the connection with the public grid [3]. In isolated microgrids, it is essential for each microgrid to self satisfy its load requirements as it is considered a small power system with its own generation, transmission, control and distribution [4]. Renewable energy system is a suitable cheap technological approach for rural electrification. It stimulates the economy and communities to enhance their standards. Small-scale distributed renewable generation systems are considered these days as a vital solution for energy problems [5].

Globally, the total renewable power capacity reached 2195 GW. Renewable energy sector employed around 10.3 million people (directly and indirectly), and approximately $ 280 billion were spent on new investments [6]. Almost 145 countries have implemented policies to promote clean energy technologies over the last few decades. According to the reports of BP Energy (2020), renewable energy (including biofuels) recorded a large increment in energy consumption of (3.2 EJ) in 2019. Egypt has committed to increasing its dependency on sustainable energy technologies. According to the international renewable energy agency's (IRENA) reports, the total combined renewable capacity to the grid was represented by 3.7 gigawatts (GW) in 2018. This amount is composed of 2.8 GW from hydropower and about 0.9 GW from solar and wind power. The Egyptian government aims to have 20% of its electricity from renewable energies by 2022 and 42% in 2035 [7]. Egypt has abundant chances to achieve these goals, as it enjoys plenty of renewable energy resources, including hydropower, wind, solar and biomass. Egypt has a significant potential for investments in solar energy sector because it is one of the Sunbelt countries. Besides, its sunlight period is between 3500 and 4500 $hr/year$ with around 12–30 $MJ/m^2/day$ [8]. Egypt is also encouraging wind farms establishment. Its average wind speed is about 10.5 m/s for average 100-meter hub heights.

Hybrid renewable generation offers more flexibility and lower cost alternatives compared to relying upon one source. Countries with a wealth of sunlight radiation, strong potential of bio-degradable waste and a decent wind energy supply can handle the electricity access for far areas. By considering the sustainable energy sources uncertainties (solar, wind, etc.), battery energy storage systems (BESS) and other reservoirs like biogas energy sources are nominated to be integrated with renewable sources to ensure uninterrupted electricity and power security [9].

Biomass is a renewable energy source that can be easily transformed into electricity through the gasification process. Compared with fossil fuel technologies, biomass technology has many environmental and economic advantages. High-capacity biomass gasification units are the best choice because of their investment efficiency and effectiveness. Small-scale biomass gasification is vital in providing electricity for localized usage where the low electrification level and the unstable transmission network [10]. Rice straw is an attractive biomass solid waste due to its availability in rural areas and its high calorific value. Rice is one of the most common crops in Egypt. Open-field burning is the main environmental issue of rice farming in most countries. Farmers have a limited time to clear their fields after the harvest ends. They burn the rice straw to start planting seeds for the next season. This behaviour has many impacts on carbon dioxide (CO_2) emissions, which is the main combustion product that creates dark clouds, and plays a major role in children's exacerbating asthma. Managing the straw after rice harvest is a critical problem these days, and one of the appropriate solutions is using it as a fuel in gasification-electricity procedures [11, 12].

1.1. Background Review

Many authors have studied the optimum operation of hybrid microgrids, including renewable energy sources. Reference [13] studied the microgrid's short-term economic and environmental dispatch problem using enhanced quantum particle swarm optimization (QPSO) to improve the units' performance that helps to minimize polluting gas emissions. In reference [14], a detailed comparison of three different DC microgrids has been held (one grid-powered based on conventional fuel generation, and the other two off-grid based on solar energy generation). The comparison aimed to highlight the most notable positive and negative aspects regarding technical efficiency, economic and environmental impacts. In reference [15], a detailed literature review of the current microgrid's sizing methods was presented. The surveyed methods were split into two major groups of cost-based and non-cost-based sizing methods. Reference [16] provides a comprehensive overview of the most widely used tools for designing HRESs. It also explains how social factors such as job development and social acceptance improve such software packages' capabilities. Renewable energy integration to replace diesel power generation is projected to be cost-effective for off-grids and substantially reduces greenhouse gas emissions. Hybrid systems are highly recommended for isolated microgrids to guarantee reliability overcome battery problems [17]. In reference [18], the authors explored the possibility and the benefits of merging renewable energy technologies such as solar and wind with traditional power generation systems like diesel and natural gas sources. In [19], the optimum generation capacity and storage for a hybrid (PV/wind/BESS) system based on instantaneous wind speed variations are introduced to maintain system reliability and reduce the investment cost. In reference [20], optimal sizing of PV/diesel/battery system is researched, including V2G. In reference [21], PV/WG isolated microgrid is sized using the critical month by algorithmic optimization techniques and Homer Pro. In reference [22], Grasshopper Optimization Algorithm (GOA) is used in optimal microgrid sizing to supply energy demand reliably based on the deficiency of power supply probability (DPSP) and the cost of energy (COE). Energy storage systems act as a tool for handling peak load demand as well as boosting the gains from the thermal power plant while enhancing the system stability and reliability [23]. Authors in ref [24] studied the integration of BESS in efficient rural electrification. BESS' optimum sizing guarantees the system reliability and extends battery life which affects the replacement cost. In reference [25] general parallel genetic algorithm is

used to maximize the technical benefits for the distribution system by optimally integrating PV and energy storage systems.

Biomass is a valuable resource that supplements other renewable sources if it is used in electricity generation. It has zero emissions if combined with technologies for carbon capture and storage [26]. Biomass gasification is a low-cost tool for providing electricity to off-grid rural communities [27]. For the Sharjah town's optimal electrification, micropower optimization methods are used to design a solar/biomass hybrid renewable energy-based microgrid [28]. Reference [29] used rice husk as the basis of energy for paddy parboiling and drying, also studied the worked gasifier's energy, exergy analysis and the gas-fired boiler equipment. Large-scale biomass to hydrogen technology is one of the brightest future technology in the sustainable energy sector [30]. Gasification technology is viewed as an effective thermochemical process either to substitute fossil fuel in existing diesel engines or to produce electricity using gas engines [31]. This technique enables the implementation of electrification programs in rural areas and improves grid quality. Reference [32] has studied the combustion of rice straw to obtain energy and its related problems in China. Roughly 3.1 million tons/year of rice straw in Egypt are projected to be disposed of by burning directly in the open air, so the recycling is an urgent necessity. Reference [33] investigated rice straw's ability for energy production in Egypt. The simulation also illustrated the rice straw power plant's efficiency to determine the required amount of energy, minimize fossil fuels reliance and greenhouse gas emissions reduction.

On the other hand, RESs have been shown to have short-term fluctuations, and their energy profiles are not entirely predictable. Using information from nearby substations improves prediction accuracy and reduced data imputation errors [34]. Uncertainty modelling outlines renewable sources' fluctuations. Reference [35] showed the impacts of load and wind uncertainties in increasing the cost by 22%. In reference [36], the stochastic energy operation management is studied for grid-connected MG, including WT/PV/Micro-Turbine/Fuel Cell and BESS. Scenario-based strategies convert the stochastic problem to several deterministic problems. Monte-Carlo method is a suitable method for scenarios generation [37]. Genetic algorithm and Monte-Carlo method are used in optimal BESS sizing, taking into consideration the wind power uncertainty due to wind speed fluctuation in reference [38]. Optimal design and operation for isolated microgrids are discussed in reference [39], considering solar energy generation's stochastic behaviour. In reference [40], The point estimate method (PEM) is used to view the uncertainty linked to wind and solar powers. Reference [41] studied the consequences of renewable sources, market price and load uncertainties in optimal scheduling of a grid-connected microgrid over a 24-hour horizon, using the modified bat algorithm (MBA). The probability density functions are used in modelling renewable energy sources uncertainty. In reference [42], a multi-scenario optimization model based on the minimum life cycle cost is applied using the general algebraic modelling system (GAMS) to choose the best siting, sizing, and type of renewable sources in the distribution system.

1.2. Paper contribution

The power sector is essential to Egypt's socioeconomic growth and lowering poverty goals [43]. Depending on the previous literature, this paper presents a renewable energy study for rural communities electrification without grid connections. A comparison between different combinations of sources is also presented, using PV modules, wind, and biogas generators. The main contribution of the proposed scheme in this manuscript depending on all the above, are as follows:

1. An optimal sizing approach of a real new residential area in Egypt using renewable energy sources is proposed.
2. Uncertainty of renewable energy methodology is considered with a complete study for its effects on the optimal sizing and cost schemes.
3. The bio-gasification generation is implemented to deepen its effects on the environment and power system generation.
4. Environmental effects of rice straw recycling through biomass gasification are introduced.
5. Three different operation mechanisms are introduced according to the availability of power conversion sources.
6. Nine case studies with detailed analysis are presented to confirm their used renewable generation robustness and effectiveness.
7. A comparison of two optimization algorithms is held to ensure the system's feasibility.

1.3. Paper structure

The frame of the remaining sections is written as follows; in section 2, the system is described while the objective functions are discussed in section 3. In section 4, the system constraints are introduced. Different optimization techniques are discussed in section 5. The system uncertainties are illustrated in section 6. Also, the simulation and comparison between nine optimized scenarios are shown in section 7. The results are discussed in section 8, while the conclusion and future work are then held in section 9.

2. System modelling

The proposed system configuration with the available power generation units is presented in Figure 1. The system's operation is categorized into three different operation mechanisms depending on the used units and the storage system availability. The first category uses renewable energies without using batteries. The load generation mismatch is faced through biomass generation. The second category uses a combination of renewable energy sources, BESS, and biomass generation to ensure full system reliability. In the third category, the system consists of renewable energy sources with batteries and without biomass generation availability. Different scenarios of each category are studied in this paper, taking into consideration the system constraints to reach the optimal cost and reliable configuration of each scenario. Also, a comparison between scenarios is held to show the economic feasibility and the environmental response of each system. Figure 2 shows the mechanisms of each category. The system components are discussed in the following paragraphs.

2.1. PV modelling

Photovoltaic (PV) is the simplest energy technology to convert solar energy into electricity. It features easy installation, high reliability and low maintenance cost. PV solar modules' power depends mainly on environmental and meteorological data like solar radiation and the daily sun existence duration. The instantaneous generated output power of a PV system ($P_{pv}(t)$) with respect to the incident solar irradiance $I_d(t)$ in (Wh/m^2) can be calculated by using [44]:

$$P_{pv}(t) = \eta_{pv} * S_{pv} * \frac{I_d(t)}{I_{d,Stc}} \tag{2.1}$$

Where η_{pv} is PV's efficiency, S_{pv} and $I_{d,Stc}$ are the rated capacity of the PV in kW and solar radiation at the standard test condition, respectively.
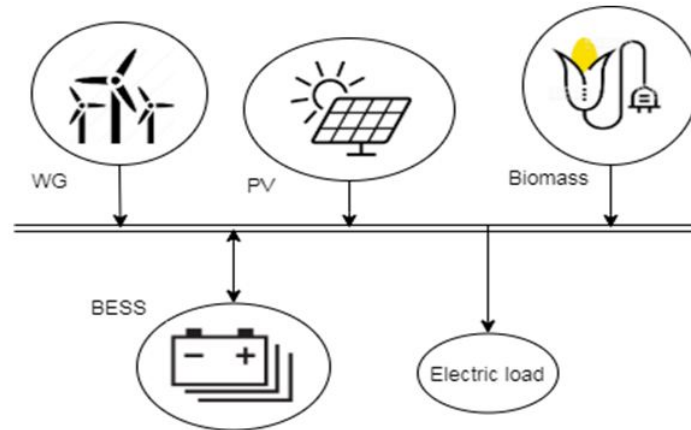

Figure 1. Proposed system.

2.2. WG modelling

The instantaneous wind generator's (WG) output power depends on the wind speed at a specified hub height. The output power of a WG can be described by using the function described in Eq (2.2):

$$\left\{ \begin{array}{ll} S_{wt} * \frac{w^3 - w_{cin}^3}{w_r^3 - w_{cot}^3} & (w_{cin} \leq w \leq w_r) \\ S_{wt} & (w_r \leq w \leq w_{cot}) \\ 0 & (w < w_{cin} \: or \: w > w_r) \end{array} \right\} \tag{2.2}$$

Where S_{wt} is the rated power capacity of the WG. w_{cin}, w_r and w_{cot} are the cut-in, rated and cut-out wind speed, respectively [45].

2.3. Biomass generation modelling

Biomass gasification is the method of transforming solid bio-waste into an ignitable gas mixture composed mainly of carbon monoxide, oxygen, methane, hydrogen, etc. It can be used for thermal purposes or as a fuel for mechanical or electric power generation in internal combustion engines.

The power of biomass depends mainly on the calorific value and the available biomass amount [46]:

$$P_{bg} = \frac{Total\ biomass\ available\ (Ton/yr) * 1000 * CV_{bm} * \eta_{bm}}{365 * 860 * Operating\ hours\ /day} \tag{2.3}$$

The biogas operating and maintenance cost includes two parts (fixed and variable cost), depending on the proposed power and the used fuel amount:

$$OM_{bg,npv} = \theta1_{bg} * P_{bg} * \sum_{j=1}^{N} \left(\frac{1 + \mu_{bg}}{1 + i_r}\right)^j + \theta2_{bg} * PW_{bg}^{yr} * \sum_{j=1}^{N} \left(\frac{1 + \mu_{bg}}{1 + i_r}\right)^j \tag{2.4}$$

The amount of biogas fuel cost is described in Eq (2.5):

$$F_{bg,npv} = \theta3_{bg} * BF_r^{yr} * \sum_{j=1}^{N} \left(\frac{1 + \mu_{bg}}{1 + i_r}\right)^j \tag{2.5}$$

The capital and salvage values of biomass unit are described in Eqs (2.6) and (2.7):

$$C_{bg} = \gamma_{bg} * P_{bg} \tag{2.6}$$

$$SV_{bg,npv} = \lambda_{bg} * P_{bg} * \left(\frac{1 + \delta}{1 + i_r}\right)^N \tag{2.7}$$

Where CV_{bm} is the biomass calorific valve, η_{bm} is the overall conversion efficiency, $\theta1_{bg}$ is the annual fixed operation and maintenance cost ($\$/kW/year$), P_{bg} is the power produce by biogas generator, i_r is the interest rate, μ_{bg} is the escalation rate, $\theta2_{bg}$ is the variable operation and maintenance cost ($\$/kWh$), PW_{bg}^{yr} is the annual working power of biogas generator ($kWh/year$), $\theta3_{bg}$ is the biomass fuel cost ($\$/ton$), BF_r^{yr} is the annual required biomass fuel ($ton/year$), γ_{bg} is the initial cost of biogas system ($\$/kW$), λ_{bg} is the resale price of the system ($\$/kW$), and δ is the inflation rate [47].

2.4. Storage system modelling

Battery energy storage systems are used to match the generated energy with the consumed energy and enhance the system's energy balance by storing the energy from different sources such as solar and/or wind generators. For example, excess energy due to high levels of wind speeds or solar radiation will be stored in batteries. This stored energy will be released for smoothing the injected power into the system, especially in low renewable energy capabilities [48].

The charging equation:

$$SOC(t) = SOC(t - 1) * (1 - \sigma) + \left(P_g(t) - \frac{P_l(t)}{\eta_{inv}}\right) * \eta_{bc} \tag{2.8}$$

The discharging equation:

$$SOC(t) = SOC(t - 1) * (1 - \sigma) + \left(\frac{P_l(t)}{\eta_{inv}} - P_g(t)\right) / \eta_{bd} \tag{2.9}$$

Eqs (2.10) and (2.11) describe the capital and replacement cost values of BESS:

$$C_{Bat} = N_{Bat} * \alpha_{Bat} \tag{2.10}$$

$$R_{npv,bat} = N_{Bat} * \alpha_{bat} * \sum_{j=5,10,15} \left(\frac{1 + \mu_{bat}}{1 + i_r}\right)^j \tag{2.11}$$

Where SOC is the state of charge, σ is the hourly rate of self-discharge, $Pl(t)$ is the load demand, $P_g(t)$ is the generated power, N_{Bat} is the number of battery units, η_{bc} is the charging efficiency, η_{bd} is the discharging efficiency, μ_{bat} is the escalation rate, α_{bat} is the cost of battery set in $\$$ and η_{inv} is the inverter efficiency [49].
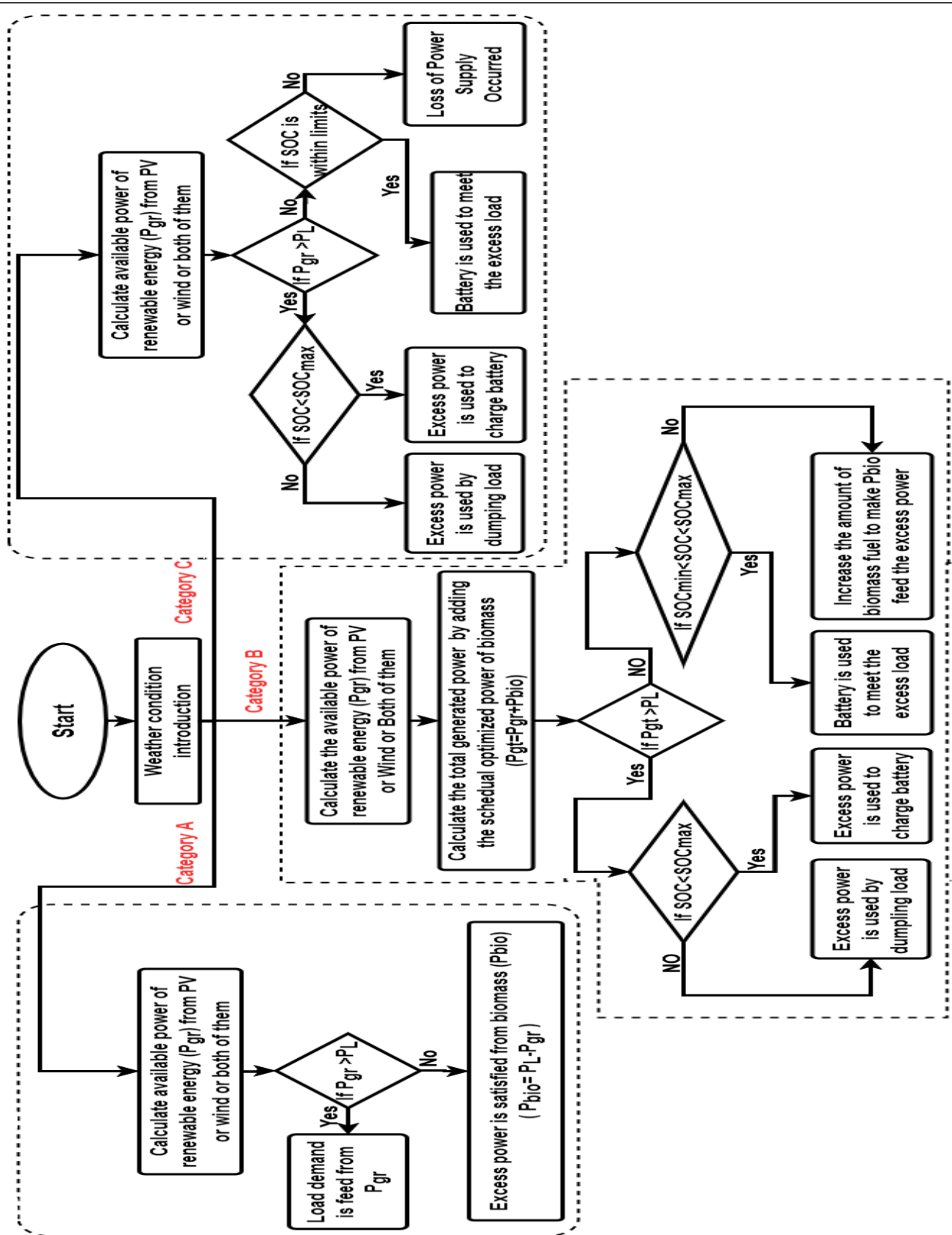
Figure 2. Categories flow charts.

3. Objective function

The optimum system sizing's objective functions are the minimization of load-generation mismatch (loss of power supply LPS) and the total system cost minimization. The first objective function is described in the following equation:

$$F1 = min : (LPS(t)) = min : (|Pl(t) - \left(P_g(t)\right)|) \qquad (3.1)$$

If the system uses BESS, the first objective function will be expressed as :

$$F1 = min : (LPS(t)) = min : (|Pl(t) - \left(P_g(t) + SOC(t-1) - SOC(t)\right)|) \qquad (3.2)$$

Where $P_g(t)$ and $Pl(t)$ are the summation of the generated power and load power, respectively.

The total cost minimization is the second objective function:

$$F2 = min : (cost) = min : \sum C_k + OM_k + R_k - SV_k$$
$$\forall k \in PV, W, Bat, Bio \qquad (3.3)$$

Where C_k is the capital cost of component k, OM_k is the operating and maintenance cost of component k, R_k is the replacement cost, and SV_k is the salvage cost of each component.

4. System constraint

For optimal sizing and achieving all objective functions, the system is subjected to some restrictions.

4.1. Limits constraint

The limits constraints of maximum and minimum power values of each component are represented in Eqs (4.1)–(4.4):

$$0 \le P_{PV} \le P_{Pv,max} \qquad (4.1)$$

$$0 \le P_W \le P_{W,max} \qquad (4.2)$$

$$0 \le P_{bio} \le P_{bio,max} \qquad (4.3)$$

$$0 \le N_{Bat} \le N_{Bat,max} \qquad (4.4)$$

4.2. SOC constraint

Battery's SOC defines the remaining power and reflects battery effectiveness. At any time, the value of SOC has to be within the specified limits (20% and 80% for most control strategies) to prevent batteries' damage, secure battery, avoid over-discharging, and increase battery life-time [50, 51]. The state of charge is controlled within limits for also dealing with the sudden fluctuations and changes in renewable energies, especially for deterministic scenarios [52].

$$SOC_{min} \le SOC(t) \le SOC_{max} \qquad (4.5)$$

where

$$SOC_{min} = 0.2 * N_{Bat} * C_b \qquad (4.6)$$

$$SOC_{max} = 0.8 * N_{Bat} * C_b \qquad (4.7)$$

4.3. Power balance constraints

The total generated power by the available generating units of each scenario, such as WG, PV, biogas generator and ESS should always meet the load demand requirements in all considered scenarios. Eq (4.8) shows the sum of available PV and WG powers at each time, depending on their availability in each scenario configuration. Eqs (4.9)–(4.11) show the power balance constraint of each category.

$$P_{gr}(t) = P_w(t) + P_{PV}(t) \tag{4.8}$$

For category (A):

$$P_{gr}(t) + P_{bio}(t) = P_L(t) \tag{4.9}$$

For category (B):

$$P_{gr}(t) + P_{bio}(t) + P_{BESS}^{dis}(t) - P_{BESS}^{ch}(t) = P_L(t) \tag{4.10}$$

For category (C):

$$P_{gr}(t) + P_{BESS}^{dis}(t) - P_{BESS}^{ch}(t) = P_L(t) \tag{4.11}$$

5. Optimization techniques

Multi-objective optimization methods are used in this paper to consider all potential trade-offs between different objective functions, which are normally conflicting. Two optimization algorithms are discussed in this paper to find the optimum solution. Each algorithm uses the available input data (load demand profile, generating components, available resources and weather data) to achieve all the system's objectives. Optimal system configuration determines optimal system size, net present cost, total capital cost and the corresponding CO_2 reduction. The architecture of the optimization tool is illustrated in Figure 3.

Figure 3. Architecture of the optimization tool.

5.1. Multi objective genetic algorithm (MOGA)

Multi-objective genetic algorithm is a meta-heuristic mechanism motivated by the natural selection technique, which is a part of larger classes of evolutionary algorithms. Genetic algorithms are widely used and biologically inspired by developers to produce high-quality optimization and search prospects, like mutation, crossover and selection.

MOGA utilizes a weighted sum of various objective functions in the selection stage and merges them into a scalar fitness function. The design characteristic of the various objective functions weights are not specified and randomly changed through each selection. Thus the search orientation in this algorithm is not fixed.

At each generation over the process of MOGA, an empirical series of pareto optimal solutions are stored and updated. Also, a certain number of solutions are picked at random from the series. Those solutions are considered elite individuals. The elite mechanism has the benefit of preserving the diversity of each population [53].

The block diagram of the proposed MOGA algorithm is shown in Figure 4, and it is described below:

- Stage 1 (Initialization): generate an initial population.
- Stage 2 (Evaluation): calculate the values of the objective functions for the created population.
- Stage 3 (Selection): use random weights to determine each population's fitness value, then pick a pair of strings from the existing population.
- Stage 4 (Crossover and Mutation): a crossover strategy is implemented for each chosen pair to produce a new population via the crossover process. After that, the mutation process is carried out.
- Stage 5 (Elitist): delete some strings of created strings haphazardly and substitute them with elite strings picked at random from temporary optimal pareto solutions.
- Stage 6 (Termination): if the stopping requirement is not satisfied, go to Stage 2.
- Stage 7 (Optimal Solution): the MOGA suggests the preferable options.

5.2. $\varepsilon-$ MOGA algorithm

The $\varepsilon-$multi-objective genetic algorithm depends on the vision of $\varepsilon-$dominance to test the optimisation's stored results in the A(t) archive. $\varepsilon-$pareto set (x*) is produced, and it seeks to reach the optimal pareto front F(x*) with bounded memory sources. Furthermore, It continuously changes the pareto front boundaries and avoids any loss of the solutions belonging to the front ends. The objective space is sectioned to a particular number of boxes N_{box} which can be calculated from:

$$N_{box} = \frac{F_i^{max} - F_i^{min}}{\varepsilon}, F_i^{max} = maxF(x)_i, F_i^{min} = minF(x)_i, \forall x \in X^* \tag{5.1}$$

where ε is the box's width and i$\in$ [1,2.....,N].

Each box can be filled with only one solution, which helps to preserve the divergence of F(x*). For a specific solution, the $box_i(x)$ is defined by:

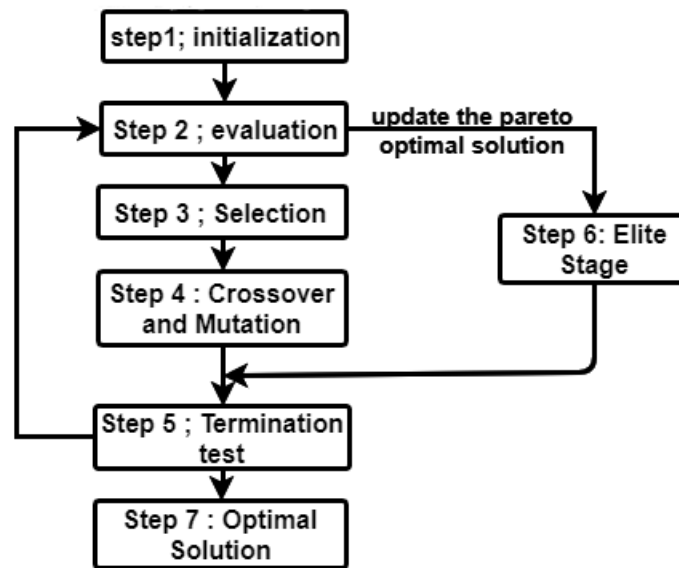$$box_i(x) = \frac{F_i(x) - F_i^{min}}{F_i^{max} - F_i^{min}} * N_{box} \tag{5.2}$$

Figure 4. MOGA operation flow chart.

A solution with x_1 ε-dominates x_2 where $x_1 < \varepsilon x_2$, when and only if

$$(box(x_1) < box(x_2)) \vee (box(x_1) = box(x_2) \quad and \quad x_1 < x_2) \tag{5.3}$$

Thus, a set $x^* \in x$ is ε-pareto when and only if

$$\forall x_1, \quad x_2 \in x^*, \quad x_1 \neq x_2, \quad box(x_1) \neq box(x_2) \wedge box(x_1) > \varepsilon box(x_2) \tag{5.4}$$

A(t) is always updated by ε-dominant solutions which do not share the same box. The remaining solution always occupies the center of the box to accomplish the prevention of solutions belonging to neighboring boxes and increase the solution variety [54, 55]. ε's goal is to reach X^* with as many solutions as possible to adequately characterize the pareto front, which is bounded by:

$$Ns_{max} = \frac{\Pi_{i=1}^N N_{box_i} + 1}{N_{box}^{max} + 1}, \quad N_{box}^{max} = max[N_{box_i}] \tag{5.5}$$

Three populations are generated To ensure solution variance. P(t) is the main population, Q(t) is the auxiliary population, and A(t) represents the archive of the best solutions. The proposed algorithm's principal steps are as follows:

- Step 1: Begin with creating empty A(t).
- Step 2: Initializing the base population at random P(0).
- Step 3: Calculate the corresponding function value P(t).
- Step 4: Test the applicable values to be included in A(t).
- Step 5: Generate Q(t) by using two random individuals from P(t) and A(t).
- Step 6: Calculate the corresponding function value for each individual in Q(t).
- Step 7: According to the objective space location, test which individual can be added to A(t).
- Step 8: Update P(t) with individuals from G(t) by randomly comparing each value of G(t) with selected individuals of P(t).
- Step 9: Eventually, the pareto front's smart characterisation is formed by individuals from A(t).

6. Uncertainties modelling

Because of weather effects on renewable energy, it became increasingly difficult to guarantee the system's reliability. Therefore, it is necessary to solve this issue by introducing PV and wind sources' uncertainty that primarily depend on weather conditions. Monte-Carlo Simulation (MCS) or Monte-Carlo approach provides an appropriate solution to quantitative issues by carrying out statistical sampling procedures.

A variety of random configurations may be used in this case to produce data and samples to reflect the solar radiation and wind speed variation. Each input is independently sampled to construct a random sequence $\{x_i\}_{i=1}^{N}$ from $U_d(0,1)$ with estimated mean of [56]:

$$\overline{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \qquad (6.1)$$

The general approach of solving stochastic formulations is to transform stochastic models into deterministic problems. Monte Carlo approach succeeds in representing uncertainties by inputs sampling and defining them through the probabilities distribution functions [57, 58].

MCS is conducted to generate a finite number of possible scenarios based on the probability distributions for all stochastic parameters [59], as shown in Figure 5. The microgrid sizing procedures with MCS used the same parameters of the deterministic problem formulation and can be described as follows [38]:

- Step 1: Initialize algorithm parameters.
- Step 2: Apply Monte-Carlo simulation techniques to produce plentiful different scenarios with the same probability.
- Step 3: In each scenario, the optimum size is calculated by operating strategy.
- Step 4: Test the constraint satisfaction to create the next generation and jump to step 5.
- Step 5: Repeat step 2 to 4 till the specific iteration step is completed, or other termination conditions are met.
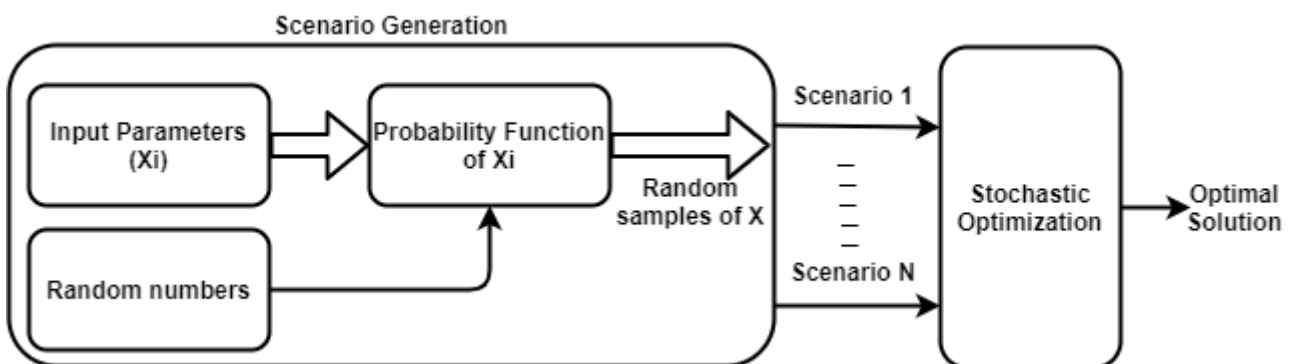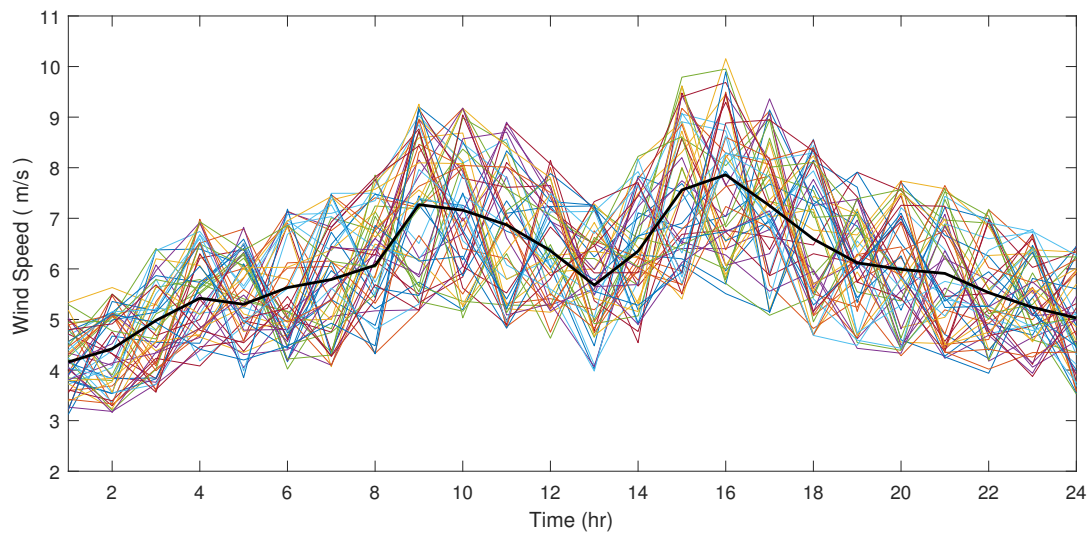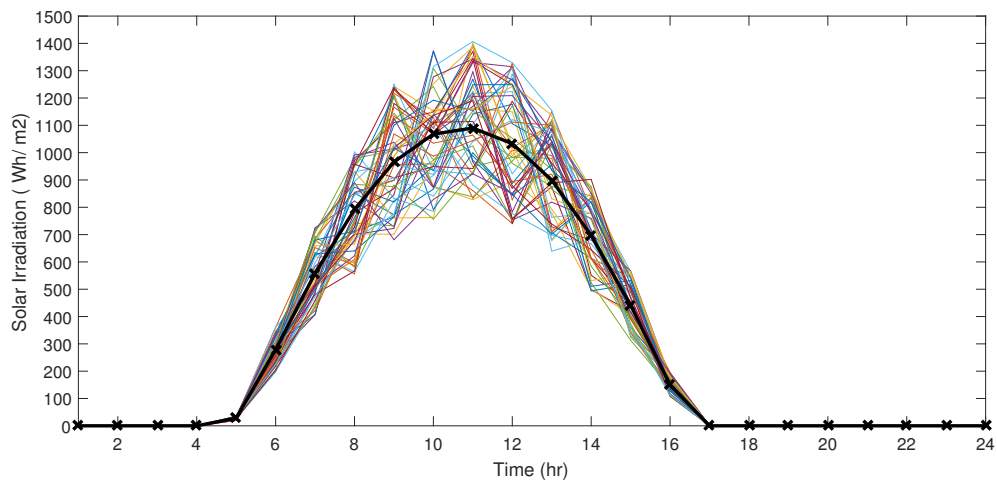

Figure 5. Scenario based stochastic optimization.

Figure 6 shows fifty uncertain-based scenarios for wind speed and solar radiation.

(a) Wind Speed Scenarios (50 Scenarios).

(b) Solar Irradiation (50 Scenarios).

Figure 6. Uncertain scenarios of renewable energies.

7. Simulation and results

Two optimization techniques are applied for nine scenarios of the microgrid to ensure load satisfactions. The comparison between these techniques is shown in Table 1. For comparison, the same systems are also studied in deterministic and stochastic cases to show the uncertainties effects in selecting the appropriate capacities of generating units, storage systems, and proper biomass generation implementation. Table 2 shows the stochastic results. The economic and technical specifications of the proposed system's components are listed in Table 3. In this work, the optimization and Monte Carlo simulation have been coded in MATLAB software.

Table 1. Deterministic results.

		Cost ($)	PV (KW)	WG (KW)	No of Batteries	Pbiomass (max) KW
		Category A				
Scenario 1	MOGA	$1.787 * 10^8$	100.072	0	0	321.810
($PV + Biomass$)	$\epsilon - MOGA$	$1.789 * 10^8$	99.883	0	0	328.254
Scenario 2	MOGA	$1.539 * 10^8$	0	705.943	0	277.906
($WG + Biomass$)	$\epsilon - MOGA$	$1.540 * 10^8$	0	705.770	0	278.426
Scenario 3	MOGA	$1.480 * 10^8$	21.118	678.794	0	279.669
($PV + WG + Biomass$)	$\epsilon - MOGA$	$1.479 * 10^8$	20.052	684.906	0	280.355
		Category B				
Scenario 4	MOGA	$3.455 * 10^7$	462.114	0	23	94.150
($PV + Biomass + BESS$)	$\epsilon - MOGA$	$2.647 * 10^7$	488.195	0	22	328.917
Scenario 5	MOGA	$6.649 * 10^7$	0	1883.090	14	95.797
($WG + Biomass + BESS$)	$\epsilon - MOGA$	$2.953 * 10^7$	0	2297.645	14	303.548
Scenario 6	MOGA	$6.030 * 10^7$	413.147	292.798	24	88.689
($PV + WG + Biomass + BESS$)	$\epsilon-$ MOGA	$3.236 * 10^7$	0	2500	17	330
		Category C				
Scenario 7	MOGA	$4.040 * 10^6$	535.060	0	22	0
($PV + BESS$)	$\epsilon - MOGA$	$3.359 * 10^6$	474.495	0	18	0
Scenario 8	MOGA	$9.397 * 10^6$	0	2469.141	13	0
($WG + BESS$)	$\epsilon - MOGA$	$9.397 * 10^6$	0	2469.182	13	0
Scenario 9	MOGA	$5.599 * 10^6$	562.579	272.012	27	0
($PV + WG + BESS$)	$\epsilon - MOGA$	$5.204 * 10^6$	634.020	0	29	0

Table 2. Stochastic results.

Configuration		Cost ($)	PV (KW)	WG (KW)	No of Batteries	Pbiomass (max) KW
		Category A				
Scenario 1	$PV + Biomass$	$1.911 * 10^8$	77.534	0	0	322.528
Scenario 2	$WG + Biomass$	$1.933 * 10^8$	0	317.317	0	329.821
Scenario 3	$PV + WG + Biomass$	$1.890 * 10^8$	42.377	182.208	0	320.965
		Category B				
Scenario 4	$PV + Biomass + BESS$	$8.979 * 10^7$	501.204	0	33	191.922
Scenario 5	$WG + Biomass + BESS$	$1.246 * 10^8$	0	1698.970	30	155.320
Scenario 6	$PV + WG + Biomass + BESS$	$7.533 * 10^7$	458.217	701.070	42	103.754
		Category C				
Scenario 7	$PV + BESS$	$4.327 * 10^6$	504.755	0	25	0
Scenario 8	$WG + BESS$	$1.007 * 10^7$	0	2166.951	25	0
Scenario 9	$PV + WG + BESS$	$7.912 * 10^6$	773.901	9.108	47	0

Table 3. Simulation parameters [60].

Component and Economic Specification		
Discount rate (r)	5%	
Escalation rate	7%	
PV Module		
Investment cost	1690	$/KW
Maintenance	26	$/KW/yr
(PV) reduction factor	84%	
lifetime	25	years
Wind Generator		
Investment cost	2030	$/KW
Operating and Maintenance	75	$/KW/yr
lifetime	25	years
Cut-in wind speed	4	m/s
Cut-out wind speed	25	m/s
Rated wind speed	14.5	m/s
Shear coefficient	0.14	
Turbine hub height	50	m
BESS		
Investment cost	200	$/KWh
Replacement cost	200	$/KWh
Self discharge rate	0.01%	
Efficiency	90%	
Life time	5	years
Biomass generator		
Investment cost(γ_{bg})	6200	$/KWh
Annual fixed operation and maintenance cost of biomass system($\theta 1_{bg}$)	$0.05*\gamma_{bg}$	$/Kw/year
Variable operation and maintenance cost of biogas system($\theta 2_{bg}$)	0.0042	$/Kw/year
Biomass fuel cost of biogas system($\theta 2_{bg}$)	35	($/t/year)
Biomass system resale price(λ_{bg})	$0.3*\gamma_{bg}$	($/Kw)
Electrical conversion efficiency(η_{bm})	0.21	

7.1. Category (A)

In this category, there is no storage system. All available generated power is used directly to fulfil load requirements. Three combinations of generating units are studied in this category. Scenario (1) consists of PV with biomass, while scenario (2) consists of WG with biomass, and scenario (3) consists of a combination of PV and WG with biomass generator.

Figures 7–9 show the generation load mismatch and the energy share of each generating unit for each scenario. The total cost of each scenario is plotted in Figure 10 to show the comparison between scenarios and show the percentages of capital cost with running cost.
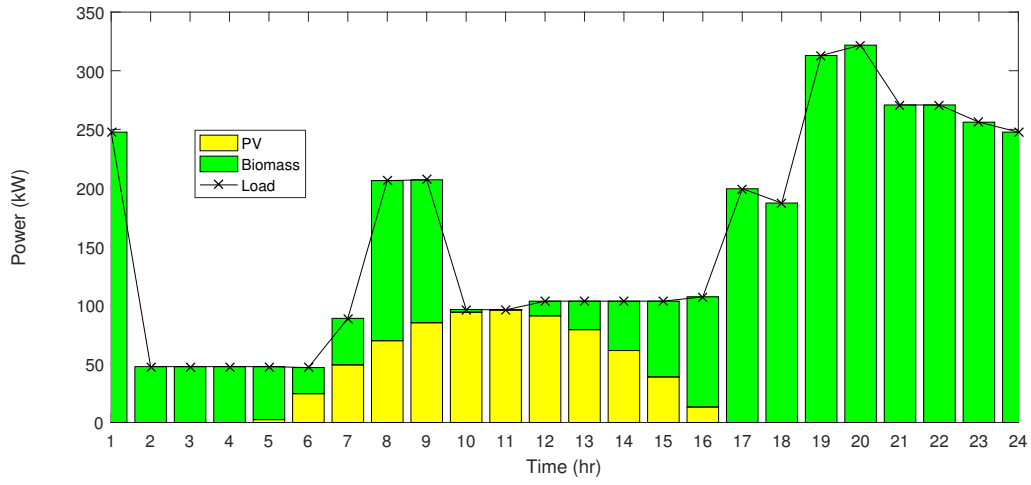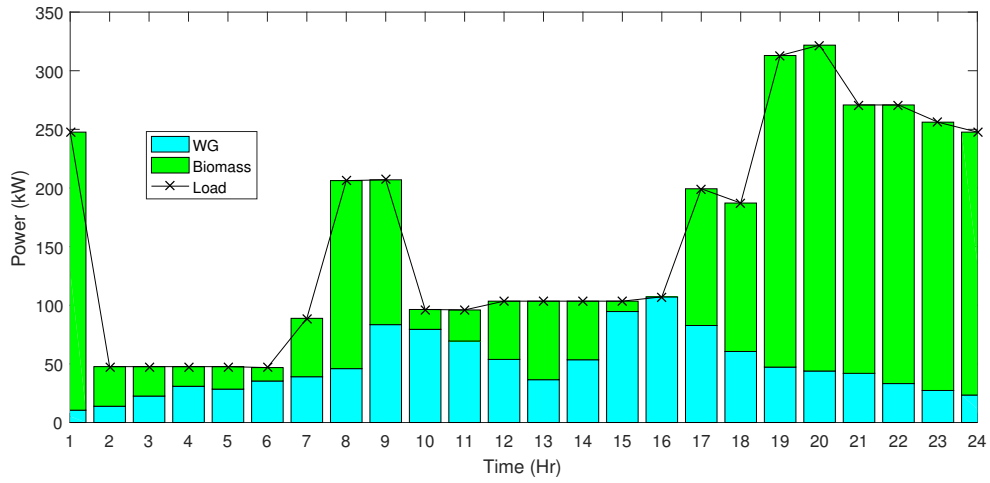
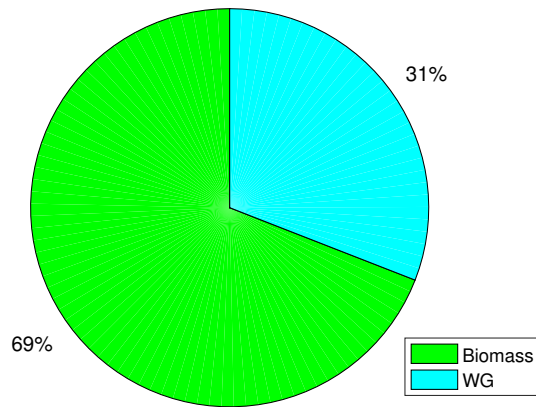(a) Load-generation mismatch of scenario 1.
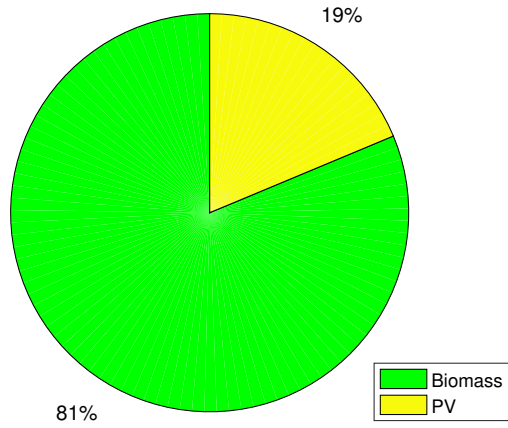
(b) Percentage Share of Renewable Energy of Scenario 1.
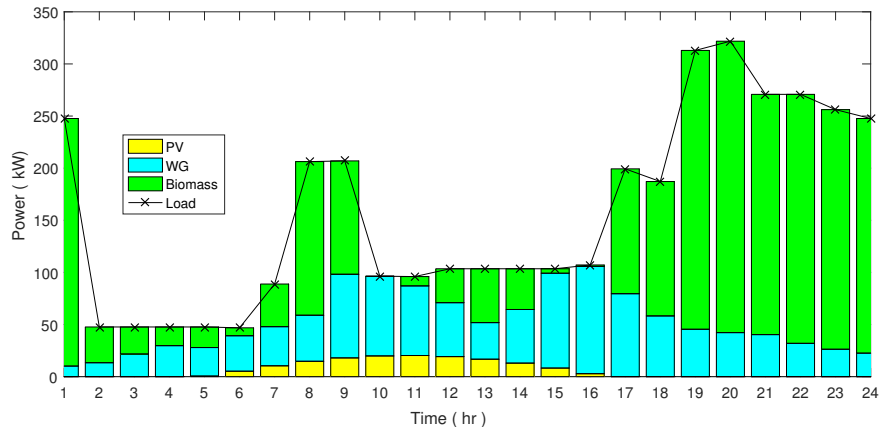
Figure 7. Scenario 1 results.

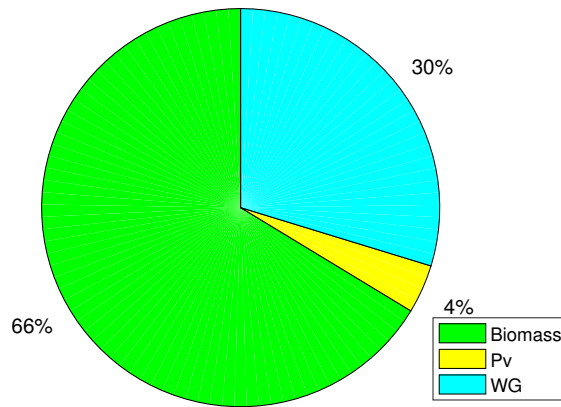(a) Load-generation mismatch of scenario 2.

(b) Percentage Share of Renewable Energy of Scenario 2.

Figure 8. Scenario 2 results.

(a) Load-generation mismatch of scenario 3.

(b) Percentage Share of Renewable Energy of Scenario 3.
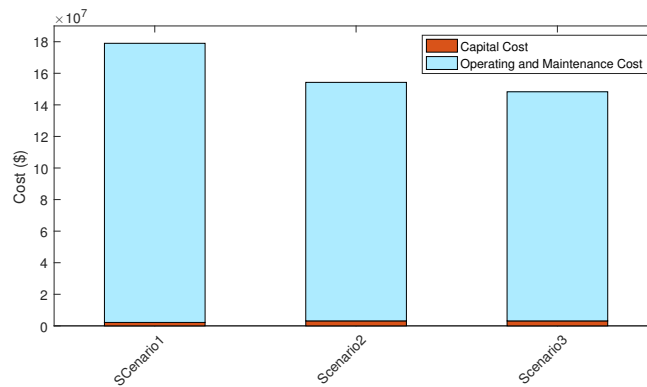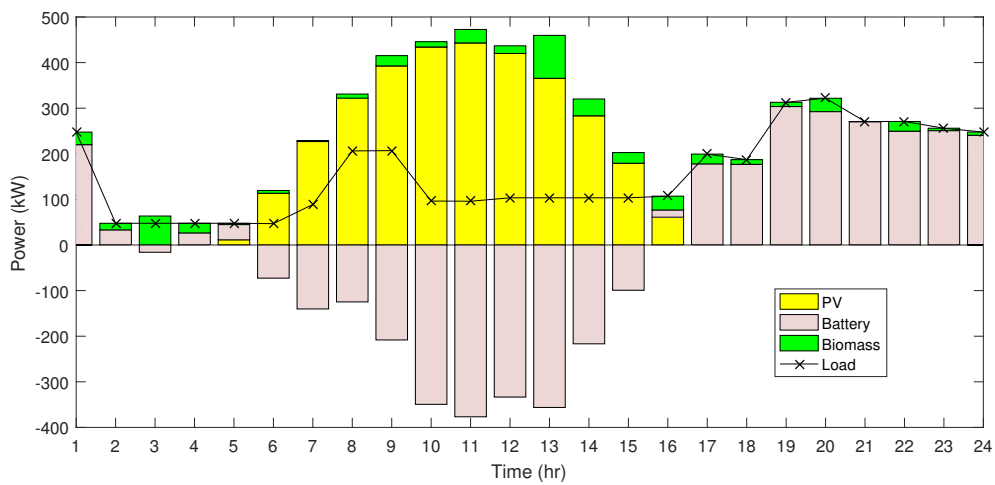
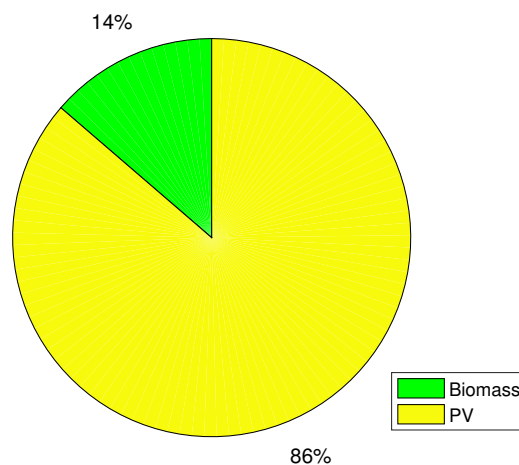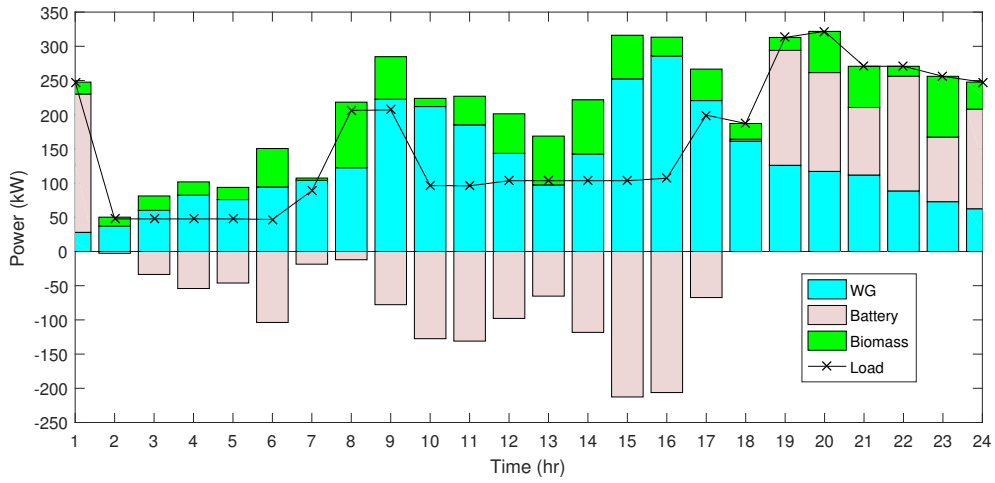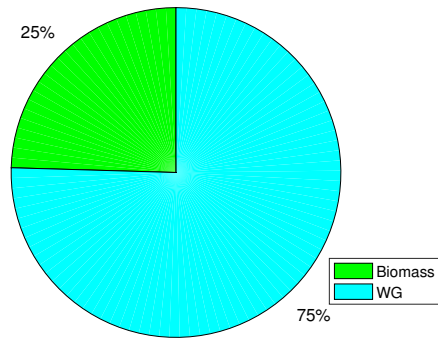**Figure 9.** Scenario 3 results.

Figure 10. Category A cost.

7.2. Category (B)

Category (B) represents batteries and biomass generation's participation in the same configuration with other renewable sources. Scenario (4) consists of PV with biomass and BESS units. Scenario (5) integrates batteries with WG and biomass generators. Scenario (6) represents the share of all available system components (PV, WG, BESS and biomass).

Figures 11–13 show the generation load mismatch and each generating unit's energy share for scenarios 4–6, respectively. Figure 14 shows the total system cost for each of category B' scenarios.

(a) Load-generation mismatch of scenario 4.

(b) Percentage Share of Renewable Energy of Scenario 4.
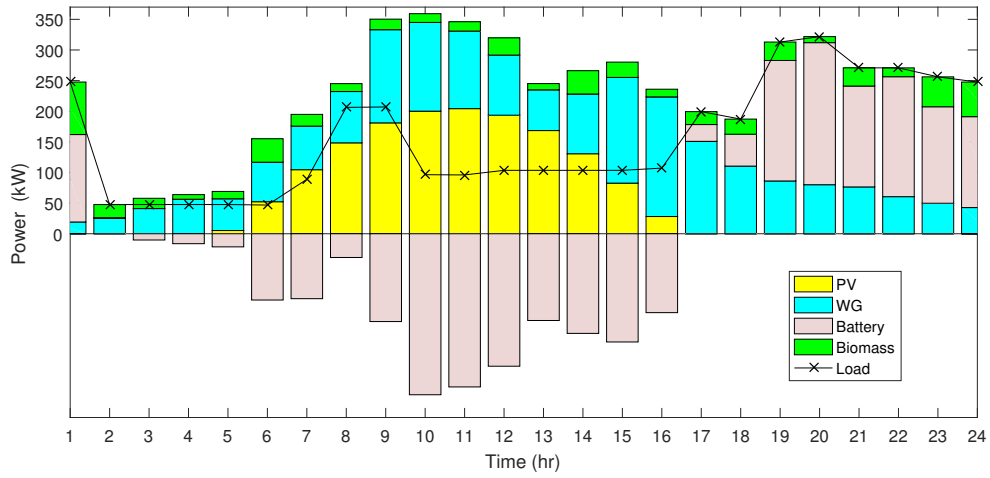
Figure 11. Scenario 4 results.

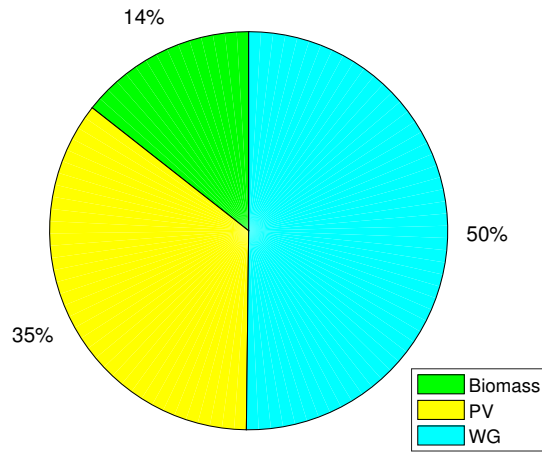(a) Load-generation mismatch of scenario 5.

(b) Percentage Share of Renewable Energy of Scenario 5.

Figure 12. Scenario 5 results.

(a) Load-generation mismatch of scenario 6.

(b) Percentage Share of Renewable Energy of Scenario 6.
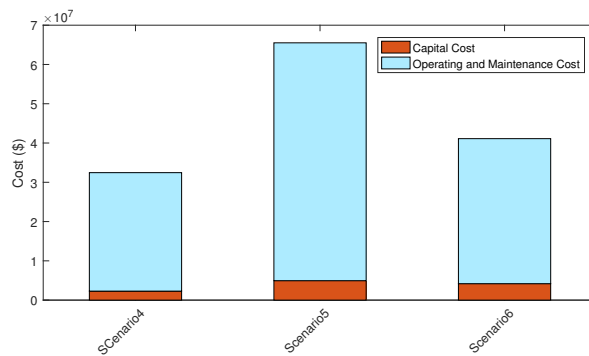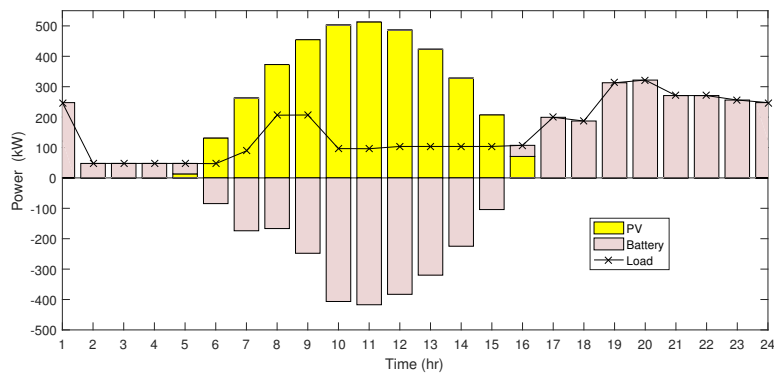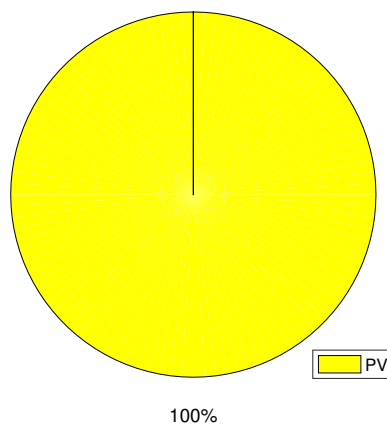
Figure 13. Scenario 6 results.

Figure 14. Category B cost.

7.3. Category (c)

This category is considered the most simple and economical category, but it has the lowest environmental concern of CO_2 emissions and rice straw problems. In this kind of systems, there is no existence of biomass technology. The power generation depends mainly on a combination of PV and WG. Figures 15–17 show the generation load mismatch and each generating unit's energy share for scenarios 7–9, respectively. The capital cost and operating with maintenance cost of this category are shown in Figure 18.
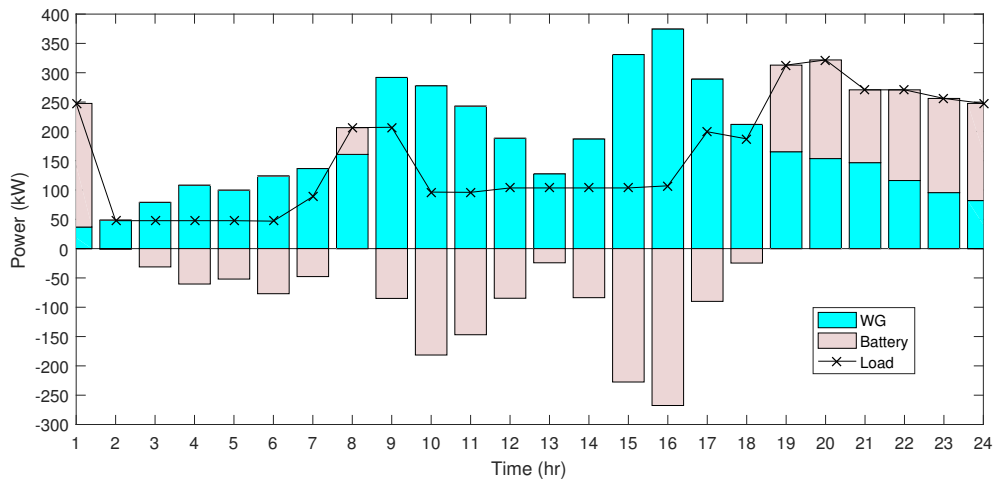

(a) Load-generation mismatch of scenario 7.

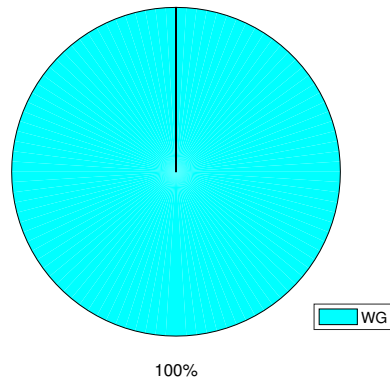100%

(b) Percentage Share of Renewable Energy of Scenario 7.
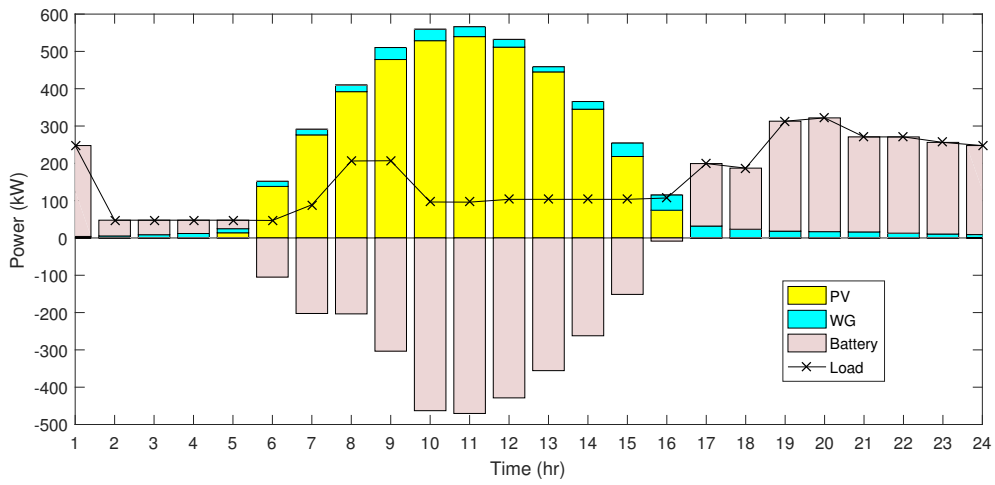
Figure 15. Scenario 7 results.

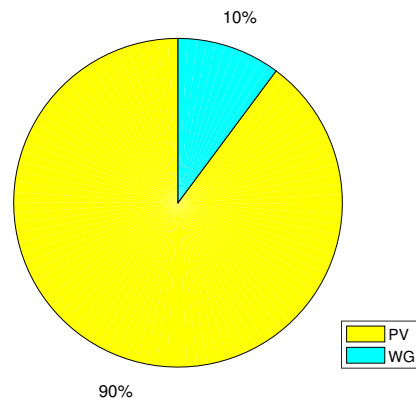(a) Load-generation mismatch of scenario 8.

100%

(b) Percentage Share of Renewable Energy of Scenario 8.

Figure 16. Scenario 8 results.

(a) Load-generation mismatch of scenario 9.

(b) Percentage Share of Renewable Energy of Scenario 9.
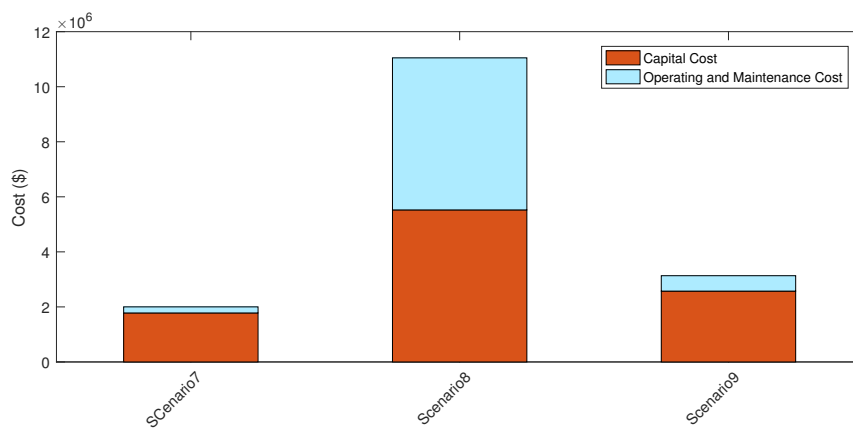
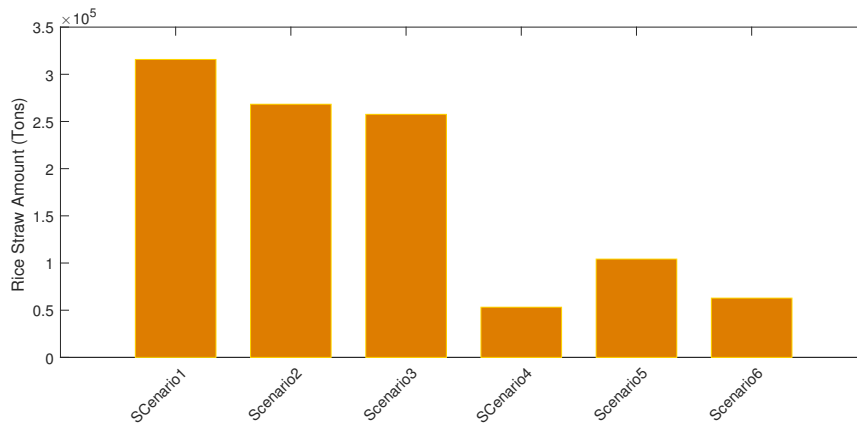**Figure 17.** Scenario 9 results.

Figure 18. Category C cost.

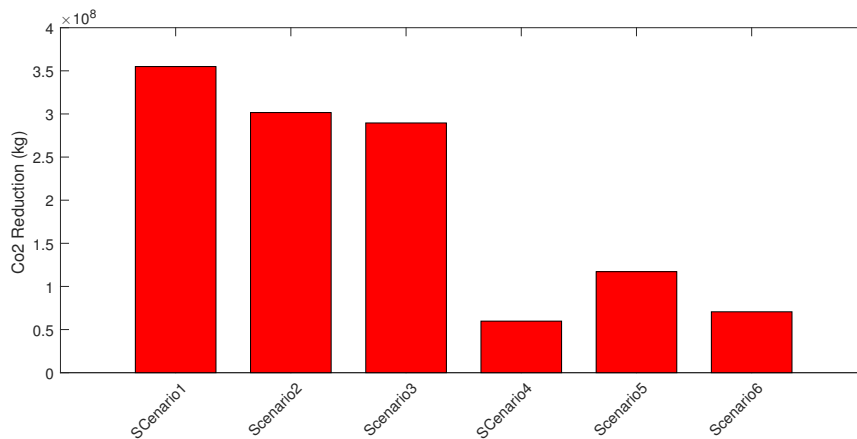**Figure 19.** The amount of required rice Straw of each scenario.

Figure 20. The amount of Co_2 reduction.

8. Discussion

In all scenarios, the load is met with optimal system size using two multi-optimization techniques. It is found that the results of the two optimization techniques have some similarities in some cases and differences in other scenarios. Thus, the simulation results for the nine scenarios confirm the following features:

1. Scenario 7 is the cheapest scenario between all discussed scenarios by a total system cost of $ 4.040 million with a PV capacity of 535.060 kWh and a total number of 22 battery sets. In contrast, PV without BESS scenario is not recommended because it is the highest cost scenario. It does not use the available capabilities of solar energy due to the lack of energy storage systems. However, it would be applicable in case of applying load demand control strategies.

2. ε-MOGA gives almost nearly equal results as MOGA for category A and C, but it gives different results for category B. It uses biomass generators with high capacity in category B, but it is used for a limited no of hours during the day, which causes the low cost of fuel and low corresponding total cost. Although the results of ε-MOGA for category B seems to be better than MOGA, it is

not accepted as biomass generator is planned to be used for a limited number of hours during the day. It can not be used as a backup generator because biomass units take time to be inserted to the system.

3. Without using BESS as in category A, the amount of biomass share is very high. It reaches 81% in scenario 1 as the PV is the only generating system with biomass. Besides, PV does not work for more than thirteen hours of the all-day hours, as seen in Figure 7a. Introducing wind generators in category (A) is noticed to be more dependable as it exists during all-day hours. Although wind speed is not high at all times, its existence is better than solar existence. Biomass share is reduced to around 69% in scenario 2 and 3, which reduces the cost and increases the share of other generating units like WG in scenario (2) and both PV and WG in Scenario 3.

4. Category (B) is considered a mix between category (A) and (C). Both BESS and biomass are considered in this category. It is the most reliable category as BESS enhances the system performance in fluctuated weather conditions. In addition, bio-gas can be considered a backup generation in case of load increase or other generating unit outages. In this category, the percentage of biomass's share is decreased, and the percentage share of other renewable sources is increased. Wind generation share is about 75% and 50% in scenarios 5 and 6, respectively. While PV energy share is about 86% and 35% in Scenarios 4 and 5. Biomass energy share in scenario 4 is the same as scenario 6 by a value of 14%. This percentage increases in the case of PV absence, as in scenario 5.

5. From deterministic results, PV and wind power capacities increased by the integration of BESS. By comparing category A with category B, PV increased by (3.6%) from scenario 1 to scenario 4. Also, WG capacity increased by (1.6%) from scenario 2 to scenario 4. In scenario 3, BESS integration increases PV capacity by (392.029 kWh) and decreases WG capacity by (386.004 kWh) as noticed from scenario 6's results.

6. From shown results in table 1, if BESS replaces biomass units in category A as in Category C, the cost of scenarios 1–3 will be decreased by ($ 174.66 million), ($ 144.503 million) and ($ 142.401 million) respectively. Removing biomass generators from category B reduces the total system cost and increases other renewable sources' share. By comparing scenario 4 with 7 and 5 with 8, PV power increased by (72.9 kWh), and wind power increased by (586.051 kWh). Also, by comparing scenario 6 with scenario 9, PV power is increased, and WG power is decreased like what happened in comparing scenarios 3 and 6.

7. PV energy share represents 100% in scenario 7, and WG represents the same amount in scenario 8. It is found that category c is the most economically effective category as it recorded the least cost between other categories with about total cost of ($ 4.040 million), ($ 9.397 million) and ($ 5.599 million) for scenarios 7–9, respectively.

8. In scenario 9, the power share of PV is nine times the power share of wind. In the case of no storage, it is not economical to use a high PV amount.

9. When comparing scenario 7 with scenario 8, PV introduction is better than WG, with a cost reduction of about (57%). In comparison, (PV+WG+BESS) scenario is noticed to have ($ 1.559 million) over cost compared to scenario 7.

10. Biomass generation cost is high due to the high operating cost, including fuel, operating and maintenance costs. The high cost of Categories A and B illustrates the high use of biomass generation, as shown in Figures 10 and 14. Differently, the capital cost in category C's scenarios

represents a significant percentage of the total system's cost, including the installation and establishment of the system, as seen in Figure 18.

11. (PV + BESS) is the best economical choice for sizing, but it is still unreliable if the weather changes as there is only a single generating source. In contrast, applying (PV with Biomass) is the highest cost scenario due to the storage system absence, so all power is fed at night from the biomass system, which is costly.

12. Biomass is an expensive choice for electricity generation, but it is an environmentally friendly choice that increases system reliability, especially in critical situations. It can be used as a backup in case of generation shortage. It is not economically recommended to use biomass generators alone without other generation sources. Hybrid renewable energy is the best energy choice for planning isolated microgrid as it leans on different types of sources. Moreover, renewable sources with storage systems are considered the best reliable option.

13. Using biomass for electrical generation is not effective only as a power source. It is considered a recycling process to get rid of unwanted waste. Rice straw using as biomass fuel helps in different environmental trends like clean electricity production, recycling process and CO_2 emission reduction instead of burning after harvest. The amount of rice straw satisfies the CO_2 emissions reduction.

14. Category (A) has the highest amount of biomass share, so it has the highest value of CO_2 reduction. Still, it is not economically to be applied, although it is the most eco-friendly category to reduce rice straw burning's threats. This category does not enhance or make the best benefits of renewable energy sources (PV and WG) due to the lack of storage systems.

15. Scenario 1 represents the highest dependence on rice straw of about ($3.1 * 10^5$ tons). Scenario 2's amount is near to scenario 3's amount with around ($2.6 * 10^5$ tons). The amount of rice straw for category (B) is less than category (A). Scenario 4 is the least dependant scenario on the biomass of category B's scenarios.

16. Category (C) is the cheapest microgrid sizing strategy, especially using (PV only with BESS). Due to the absence of biomass in this strategy, there is no CO_2 emission reduction from agricultural waste recycling.

17. The rating of biomass gasifiers is increased in all scenarios when comparing deterministic and stochastic results except scenario (1), which is almost the same as this scenario depends mainly on biomass generation. In addition, the number of battery sets increased in all scenarios by ratios between (0.13%) and (1.14%). It helps to overcome the uncertainties of renewable energies through the use of reserved power during unexpected bad weather periods.

18. Besides the increase in the energy storage or biomass capacities in most scenarios, PV and WG capacities are decreased as the sources uncertainties affect their productivity. Systems depend mainly on using extra power during good weather conditions or low load periods for charging batteries to enable its reuse during unexpected periods of low PV or WG generation capability. Furthermore, biomass generation guarantees more system reliability by having backup or controllable power sources in the worst conditions.

19. All scenarios cost increased by applying Monte-Carlo simulation to all scenarios to consider renewable energy uncertainties in the sizing process. The minimum cost increase is in scenario 7 by ($ 0.287 million). Whereas Scenario 5 has a maximum increase of about ($ 58.11 million) due to the increase of batteries and biomass share.

20. By taking into consideration renewable energy uncertainty, the cost increased by ($ 12.4 million), ($ 39.4 million) and ($ 41 million) for scenarios 1–3 respectively. Moreover, the solar and wind power capacities decreased by (22.538 kWh), (388.626 kWh) and (475.324 kWh). In contrast, the biomass share increased to handle the shortage of power. WG's use in scenario 9 is highly decreased, and the scenario depends mainly on PV power and storing it for low radiation periods. Furthermore, scenario 8's cost increased by ($ 0.673 million), the number of batteries is almost doubled, and the wind generation rating decreased by 302.19 kWh.

9. Conclusions

This paper proposed a 100 % clean microgrid from renewable resources. Multi-objective optimization techniques are utilized for sizing the system with minimizing load-generation mismatch and total system cost minimization as objective functions. Nine scenarios classified into three categories are presented to meet the load requirements. The first category is considered the basic case study with biomass generation implementation and without storage systems. BESS is presented in category B. Category C is considered the cheapest category without biomass generation integration and without consideration to the environmental impacts of biomass use.

Renewable energy is the prospective key for reducing the dependence on harmful fossil fuels in power sectors. Also, biomass is considered the future of recycling and energy production. The on-site generation will be cost-effective to reduce the operating and transportation cost of biomass fuel, so it is preferred for small-scale ranges in isolated microgrids. Biomass generation is costly compared to other generation units. Still, it has two fundamental preferences: it provides reliable generation, especially in considering solar and wind uncertainties. It also presents a recycling option for solving the threatening environmental problem of rice straw disposal in agricultural communities instead of open-air burning. Simulation results confirm that solar energy with a storage system is the best-preferred economical option. Moreover, the hybrid system of scenario 6 gives the reasonable ecological configuration of (PV/WG/BESS/Biomass), especially for sources uncertainties consideration. Applying demand response programs with a detailed feasibility study of its effect on enhancing the energy use and optimal generation sizing is the planned future work.

Conflict of interest

The authors declare no conflicts of interest.

References

1. Bakr N, Bahnassy MH (2019) Egyptian Natural Resources. *The Soils of Egypt, Springer* 33–49.

2. Yoldaş Y, Önen A, Muyeen S, Vasilakos AV, et al. (2017) Enhancing smart grid with microgrids: Challenges and opportunities. *Renewable Sustainable Energy Rev* 72: 205–214.

3. Abdulgalil MA, Khalid M, Alismail F (2019) Optimal sizing of battery energy storage for a grid-connected microgrid subjected to wind uncertainties. *Energies* 12: 2412.

4. Beshr E (2013) Comparative study of adding PV/wind energy systems to autonomus micro grid. *IEEE* 3rd International Conference on Electric Power and Energy Conversion Systems: 1–6.

5. Krepl V, Shaheen HI, Fandi G, et al. (2020) The Role of Renewable Energies in the Sustainable Development of Post-Crisis Electrical Power Sectors Reconstruction. *Energies* 13: 6326.

6. Ullah S, Haidar AM, Hoole P, et al. (2020) The current state of Distributed Renewable Generation, challenges of interconnection and opportunities for energy conversion based DC microgrids. *J Cleaner Prod* 122777.

7. International renewable energy agency (2018) Renewable Energy Outlook: Egypt.

8. Abdo T, EL-Shimy M (2013) Estimation of global solar radiation (gsr) over egypt, The Future of New and Renewable Energy in Arab World. February 12th 14th, 2013, Assiut, EGYPT.

9. Sarkar T, Bhattacharjee A, Samanta H, et al. (2019) Optimal design and implementation of solar PV-wind-biogas-VRFB storage integrated smart hybrid microgrid for ensuring zero loss of power supply probability. *Renewable Sustainable Energy Rev* 191: 102–118.

10. Situmorang YA, Zhao Z, Yoshida A, et al. (2020) Small-scale biomass gasification systems for power generation (< 200 kW class): A review. *Renewable Sustainable Energy Rev* 117: 109486.

11. Torigoe K, Hasegawa S, Numata O, et al. (2000) Influence of emission from rice straw burning on bronchial asthma in children. *Pediatr Intl* 42: 143–150.

12. Röder M, Jamieson C, Thornley P (2020) (Stop) burning for biogas. Enabling positive sustainability trade-offs with business models for biogas from rice straw. *Biomass Bioenergyy* 138: 105598.

13. Zhao XG, Zhang ZQ, Xie YM, et al. (2020) Economic-environmental dispatch of microgrid based on improved quantum particle swarm optimization. *Energy* 195: 117014.

14. Castillo-Calzadilla T, Macarulla AM, Kamara-Esteban, O, et al. (2020) A case study comparison between photovoltaic and fossil generation based on direct current hybrid microgrids to power a service building. *J Cleaner Prod* 244: 118870.

15. Alsaidan I, Alanazi A, Gao W, et al. (2017) State-of-the-art in microgrid-integrated distributed energy storage sizing. *Energies* 10: 1421.

16. Cuesta MA, Castillo-Calzadilla T, Borges C (2020) A critical analysis on hybrid renewable energy modeling tools: An emerging opportunity to include social indicators to optimise systems in small communities. *Renewable Sustainable Energy Rev* 122: 109691.

17. Aguilar-Jiménez J, Velázquez N, Acuña A, et al. (2018) Techno-economic analysis of a hybrid PV-CSP system with thermal energy storage applied to isolated microgrids. *Solar Energy* 174: 55–65.

18. Charabi Y, Abdul-Wahab S (2020) The optimal sizing and performance assessment of a hybrid renewable energy system for a mini-gird in an exclave territory. *AIMS Energy* 8: 669–685.

19. Zamani MH, Riahy GH (2008) Introducing a new method for optimal sizing ofa hybrid (wind/pv/battery) system considering instantaneous wind speedvariations. *Energy Sustainable Develop* 12: 27–33.

20. Ghazvini AM, Olamaei J (2019) Optimal sizing of autonomous hybrid PV system with considerations for V2G parking lot as controllable load based on a heuristic optimization algorithm. *Solar Energy* 184: 30–39.

21. Syed IM (2017) Near-optimal standalone hybrid PV/WE system sizing method. *Solar Energy* 157: 727–734.

22. Bukar AL, Tan CW, Lau KY (2019) Optimal sizing of an autonomous photovoltaic/wind/battery/diesel generator microgrid using grasshopper optimization algorithm. *Solar Energy* 188: 685–696.

23. Ho WS, Hashim H, Muis ZA (2012) Integrated biomass power plant and storage for peak load management. *Comput Aided Chem Eng* 31: 1000–1004.

24. Sufyan M, Abd Rahim N, Tan C, et al. (2019) Optimal sizing and energy scheduling of isolated microgrid considering the battery lifetime degradation. *Plos One* 14: e0211642.

25. Guerra G, Martinez-Velasco JA (2018) Optimal sizing and operation of energy storage systems considering long term assessment. *AIMS Energy* 6: 70–96.

26. Lehtveer M, Fridahl M (2020) Managing variable renewables with biomass in the European electricity system: Emission targets and investment preferences. *Energy* 213: 118786.

27. Jimenez O, Curbelo A, Suarez Y (2012) Biomass based gasifier for providing electricity and thermal energy to off-grid locations in Cuba. Conceptual design. *Energy Sustainable Develop* 16: 98–102.

28. Ghenai C, Janajreh I (2016) Design of solar-biomass hybrid microgrid system in Sharjah. *Energy Procedia* 103: 357–362.

29. Wincy WB, Edwin M, Sekhar SJ (2020) Energy and exergy evaluation of rice processing mills working with biomass gasifier in parboiling process. *Fuel* 259: 116255.

30. Cao L, Iris K, Xiong X, et al. (2020) Biorenewable hydrogen production through biomass gasification: A review and future prospects. *Environ Res* 186: 109547.

31. Dasappa S (2011) Potential of biomass energy for electricity generation in sub-Saharan Africa. *Energy Sustainable Develop* 15: 203–213.

32. Liu Z, Xu A, Long B, et al. (2011) Energy from combustion of rice straw: status and challenges to China. *Energy Power Eng* 3: 325.

33. Abdelhady S, Borello D, Shaban A, et al. (2014) Viability study of biomass power plant fired with rice straw in Egypt. *Energy Procedia* 61: 211–215.

34. Borges CE, Kamara-Esteban O, Castillo-Calzadilla T, et al. (2020) Enhancing the missing data imputation of primary substation load demand records. *Sustainable Energy Grids Networks* 23: 100369.

35. Mehrjerdi H, Rakhshani E (2019) Correlation of multiple time-scale and uncertainty modelling for renewable energy-load profiles in wind powered system. *J Cleaner Prod* 236: 117644.

36. Mohammadi S, Soleymani S, Mozafari B (2014) Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices. *Int J Electr Power Energy Syst* 54: 525–535.

37. Qiao X, Zou Y, Li Y, et al. (2019) Impact of uncertainty and correlation on operation of micro-integrated energy system. *Int J Electr Power Energy Syst* 112: 262–271.

38. Li L, Yang L (2012) A chance-constrained programming based energy storage system sizing model considering uncertainty of wind power. *International Conference on Sustainable Power Generation and Supply*, Hangzhou, 1–6.

39. Lennard M, Date A, Yu X (2017) Islanded microgrid energy system parameter estimation using stochastic methods. *Solar Energy* 147: 300–313.

40. Ansari MM, Guo C, Shaikh M, et al. (2020) Considering the uncertainty of hydrothermal wind and solar-based DG. *Alexandria Eng J* 59: 4211–4236.

41. Luo L, Abdulkareem SS, Rezvani A, et al. (2020) Optimal scheduling of a renewable based microgrid considering photovoltaic system and battery energy storage under uncertainty. *J Energy Storage* 28: 101306.

42. Thang V, Ha T (2019) Optimal siting and sizing of renewable sources in distribution system planning based on life cycle cost and considering uncertainties. *AIMS Energy* 7: 211–226.

43. Shouman ER (2017) International and national renewable energy for electricity with optimal cost effective for electricity in Egypt. *Renewable Sustainable Energy Rev* 77: 916–923.

44. Kiptoo MK, Adewuyi OB, Lotfy ME, et al. (2019) Assessing the techno-economic benefits of flexible demand resources scheduling for renewable energy–based smart microgrid planning. *Future Internet* 11: 219.

45. Ramli MA, Bouchekara H, Alghamdi AS (2018) Optimal sizing of PV/wind/diesel hybrid microgrid system using multi-objective self-adaptive differential evolution algorithm. *Renewable Energy* 121: 400–411.

46. Singh S, Singh M, Kaushik SC (2016) Feasibility study of an islanded microgrid in rural area consisting of PV, wind, biomass and battery energy storage system. *Energy Convers Manage* 128: 178–190.

47. Heydari A, Askarzadeh A (2016) Optimization of a biomass-based photovoltaic power plant for an off-grid application subject to loss of power supply probability concept. *Appl Energy* 165: 601–611.

48. Talaat M, Alsayyari AS, Alblawi A, et al. (2020) Hybrid-cloud-based data processing for power system monitoring in smart grids. *Sustainable Cities Soc* 55: 102049.

49. Sediqi MM, Furukakoi M, Lotfy ME, et al. (2017) Optimal economical sizing of grid-connected hybrid renewable energy system. *J Energy Power Eng* 11: 244–53.

50. Gamil MM, Sugimura M, Nakadomari A, et al. (2020) Optimal Sizing of a Real Remote Japanese Microgrid with Sea Water Electrolysis Plant Under Time-Based Demand Response Programs *Energies* 13: 3666.

51. Sugimura M, Gamil MM, Akter H, et al. (2020) Optimal sizing and operation for microgrid with renewable energy considering two types demand response. *J Renewable Sustainable Energy* 12: 065901.

52. Tobaru S, Shigenobu R, Sharma A, et al. (2016) Optimal operation method with fuel cells in plural regional power systems. *IEEE Int Conf Evol Comput* IEEE: 442–447.

53. Murata T, Ishibuchi H (1995) MOGA: Multi-objective genetic algorithms. *IEEE Int Conf Evol Comput* 1: 289–294.

54. Lotfy ME, Senjyu T, Farahat MA, et al. (2017) A frequency control approach for hybrid power system using multi-objective optimization. *Energies* 10: 80.

55. Afzalan E, Joorabian M (2013) Emission, reserve and economic load dispatch problem with non-smooth and non-convex cost functions using epsilon-multi-objective genetic algorithm variable. *Int J Electr Power Energy Syst* 52: 55–67.

56. Philipson P, Hickey GL, Crowther MJ, et al. (2020) Faster Monte Carlo estimation of joint models for time-to-event and multivariate longitudinal data. *Comput Stat Data Anal* 151: 107010.

57. Maleki A, Khajeh MG, Ameri M (2016) Optimal sizing of a grid independent hybrid renewable energy system incorporating resource uncertainty, and load uncertainty. *Int J Electr Power Energy Syst* 83: 514–524.

58. Fioriti D, Poli D (2019) A novel stochastic method to dispatch microgrids using Monte Carlo scenarios. *Electr Power Syst Res* 175: 105896.

59. Zheng Y, Jenkins BM, Kornbluth K, et al. (2018) Optimization of a biomass-integrated renewable energy microgrid with demand side management under uncertainty. *Appl Energy* 230: 836–844.

60. Kiptoo MK, Lotfy ME, Adewuyi OB, et al. (2020) Integrated approach for optimal techno-economic planning for high renewable energy-based isolated microgrid considering cost of energy storage and demand response strategies. *Energy Convers Manage* 215: 112917.