Development and Implementation of a Novel Optimization Algorithm for Reliable and Economic Grid-Independent Hybrid Power System

Mohammed Kharrich 1, Omar Hazem Mohammed 2, Salah Kamel 3, Ali Selim 3,4, Hamdy M. Sultan 5, Mohammed Akherraz 1 and Francisco Jurado 4,*

1 Department of Electrical Engineering, Mohammadia School of Engineers, Mohammed V University, Ibn Sina Street P.B 765, Rabat 10090, Morocco; mohammedkharrich@research.emi.ac.ma (M.K.); akherraz@emi.ac.ma (M.A.)
2 Department of Technical Power Engineering, Technical College, Northern Technical University, Mosul 41002, Iraq; omar.hazem@ntu.edu.iq
3 Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan 81542, Egypt; skamel@aswu.edu.eg (S.K.); ali.selim@aswu.edu.eg (A.S.)
4 Department of Electrical Engineering, University of Jaén, 23700 EPS Linares Jaén, Spain
5 Electrical Engineering Department, Faculty of Engineering, Minia University, Minia 61111, Egypt;
   hamdy.soltan@mu.edu.eg
* Correspondence: fjurado@ujaen.es

Abstract: Recently, fast uptake of renewable energy sources (RES) in the world has introduced new difficulties and challenges; one of the most important challenges is providing economic energy with high efficiency and good quality. To reach this goal, many traditional and smart algorithms have been proposed and demonstrated their feasibility in obtaining the optimal solution. Therefore, this paper introduces an improved version of Bonobo Optimizer (BO) based on a quasi-oppositional method to solve the problem of designing a hybrid microgrid system including RES (photovoltaic (PV) panels, wind turbines (WT), and batteries) with diesel generators. A comparison between traditional BO, the Quasi-Oppositional BO (QOBO), and other optimization techniques called Harris Hawks Optimization (HHO), Artificial Electric Field Algorithm (AEFA) and Invasive Weed Optimization (IWO) is carried out to check the efficiency of the proposed QOBO. The QOBO is applied to a stand-alone hybrid microgrid system located in Aswan, Egypt. The results show the effectiveness of the QOBO algorithm to solve the optimal economic design problem for hybrid microgrid power systems.

Keywords: economic energy; Bonobo Optimizer; hybrid renewable energy system; microgrid; PV panels; wind turbine; energy storage

1. Introduction

Despite the steady increase in electric power production, it is still below the required level, due to the increase in load demand caused by the population increase as well as the increased use of technology in the residential, industrial and agricultural fields. According to the International Energy Agency (IEA), the global electricity demand will grow at an annual rate of 2.1% until 2040. This increases electricity’s share in the total energy consumption to 24% in 2040. It is expected that renewable energy sources (RES) will face a significant increase in global investment in the coming years, to cover more than half of the energy consumption in the world by 2040. These energies will
make up for the shortfall in electrical energy production and contribute to a reduction in carbon dioxide emissions in the atmosphere, thereby reducing pollution significantly [1–3].

In order to invest in RES to optimize electrical energy production and raise the efficiency of the systems, many studies in the world recommend combining different technologies to form hybrid renewable energy systems (HRES) [4,5]. Consequently, these sources complement each other, support the national grid, and reduce the use of traditional power plants depending on fossil fuels that release greenhouse gases and pollute the environment [6]. However, the design of these hybrid systems needs sophisticated programs and smart algorithms capable of reaching the optimal solution taking into consideration all the conditions and constraints such as reliability aspects, economic cost, sensitivity factors, availability of RES, etc. [1,2,7,8].

Several studies have been conducted on the technical and economic feasibility of hybrid systems in past years to determine their viability. Many of these studies have used different modeling of HRES, and they have applied different algorithms and various software tools to achieve their goals. According to the literature, these challenges still exist and are the focus of a lot of research, especially on finding the best algorithms and modern techniques in reaching the optimal solutions of the optimization problem of finding the optimal sizing of the installed capacities of the components of HRES [9–15].

In [16], the pre-feasibility analysis of a stand-alone energy system using HRES including renewable and conventional energy sources was applied using HOMER software in Newfoundland, Canada. In one of the earlier studies [17], the authors conducted a feasibility study of generating electricity using RES for a hybrid system in a stand-alone village in Chhattisgarh, India. In [18], the authors introduce a realistic solution for energy demand from a hybrid power system consists of wind turbines (WT), photovoltaics (PV), and battery energy storage systems (BESS). Through a real measurement of meteorological data in 2017, concerning especially the wind speed, solar radiation and temperature, the output power of the proposed hybrid system is calculated. Load satisfaction is considered to evaluate the feasibility of the system. The optimum solution is found using the linear TORSCHE optimization technique, while a comparative study between PV/WT/battery and PV/WT has been accomplished and an economic analysis was presented. As a result, the hybrid PV/WT/battery is proved more economical than using each system individually.

Xiao Xu et al. [19] designed and investigated a hybrid PV/WT/hydropower/pump storage as a case of study. The optimal configuration of the HRES is found using a techno-economic index that respects the maximum Loss of Power Supply Probability (LPSP) and minimum investment cost. The Multi-Objective Particle Swarm Optimization (MOPSO) is used to trade off analysis between two objectives. Besides, the curtailment rate (CR) of the WT and PV are taken into consideration due to policy requirements. The authors in [20] proposed an optimized design of an energy system featuring the highest penetration of renewable energy. This system is composed of WT, PV, geothermal, diesel, and BESS; otherwise, the system is obtained respecting the technological and financial feasibility constraints. The model developed is based on weather and electric demand data measured to reach the optimal sizing of the hybrid system. Three objective functions are conflicting, which are the Net Present Cost (NPC), renewable energy fraction and the energy index of reliability.

In [21], the authors implemented and compared three algorithms to find the optimal design of a hybrid WT/PV/Biomass/BESS energy system. Based on the obtained results, the Harmony Search Algorithm (HSA) was faster and efficient in the convergence, compared to Jaya and PSO optimization algorithms. The techno-economic study has been implemented to have the optimal unit sizing of the HRES, which guaranteed a cost-effective, efficient, and reliable power supply for the customers of electric energy. The constraints are chosen to enhance the reliability and efficiency of the hybrid system, using the LPSP and the energy fraction factors.

In this paper, a new smart algorithm named Bonobo Optimizer [22] was employed and improved using a quasi-oppositional method, and the modified Quasi Oppositional BO (QOBO) was utilized for optimal economic designing of a stand-alone microgrid hybrid system in Aswan, Egypt, where the hybrid system consists of RES (PV panels, WT and BESS) with diesel generators. Then, the results were
compared between the traditional and improved BO. This proved the ability of the QOBO algorithm to reach the optimal solution in a shorter time and with better efficiency compared to the traditional BO algorithm. Other algorithms, namely Harris Hawks Optimization, Artificial Electric Field Algorithm and Invasive Weed Optimization are applied, and the results are compared where the efficiency of the QOBO algorithm has been proved. Additionally, a sensitivity analysis of the proposed systems scenarios was performed to obtain the optimal solution.

2. Mathematical Description of the Proposed Hybrid System Components

The schematic diagram of the suggested HRES is shown in Figure 1. Four scenarios are applied, which include the PV power plant, WT power plant, diesel generator, Biomass, BESS and inverter.

![Configuration of the proposed microgrid hybrid energy system.](image)

Figure 1. Configuration of the proposed microgrid hybrid energy system.

Two strategies are adopted in this paper; the first is the biomass/PV as shown in Figure 2 and the second uses the PV or WT or both as in Figure 3. The main strategy steps for the operation of the proposed system can be explained as follows:

- The PV and WT are used first as a principal power source and served the load needs.
- The battery is used when the PV and WT cannot serve it.
- The diesel system is working when the battery storage system is empty and starts when the need is higher than 30% of its nominal power.

2.1. PV System

The PV system is considered as a number of cells connected in series. The output power of the PV system is presented based on many parameters as introduced in Equation (1) [23]:

\[
P_{pv} = I(t) \times \eta_{pv}(t) \times A_{pv}
\]  

(1)

where \( I \) represents the solar irradiation, \( A_{pv} \) represents the area covered with PV modules and \( \eta_{pv} \) is the efficiency of the PV system that can be calculated as follows:

\[
\eta_{pv}(t) = \eta_r \times \eta_t \times \left[ 1 - \beta \times (T_a(t) - T_r) - \beta \times I(t) \times \left( \frac{NOCT - 20}{800} \right) \times (1 - \eta_r \times \eta_l) \right]
\]

(2)
where NOCT is the nominal operating cell temperature (°C), \( \eta_r \) is the reference efficiency, \( \eta_t \) is the efficiency of the maximum power point tracking (MPPT) equipment, \( \beta \) is the temperature coefficient, \( T_a \) is the ambient temperature (°C), and \( T_r \) is the solar cell reference temperature (°C).

![Flowchart Diagram](image-url)

**Figure 2.** Power management of the PV/Biomass hybrid renewable energy sources (RES).
Figure 3. Power management of the PV/WT/diesel/battery energy storage system (BESS), PV/diesel/BESS and WT/diesel/BESS hybrid RES.

2.2. Wind Energy System

Based on the basics of aerodynamics, wind power can be presented as [24]:

\[
P_{\text{wind}} = \begin{cases} 
0, & V(t) \leq V_{ci}, \quad V(t) \geq V_{co} \\
a \times V(t)^3 - b \times P_r, & V_{ci} < V(t) < V_r \\
P_r, & V_r \leq V(t) < V_{co} 
\end{cases}
\] (3)
where $V$ represents wind speed, $P_r$ is the rated power of wind, $V_{ci}, V_{co}$ and $V_r$ are the cut-in, cut-out, and rated wind speed, respectively. $a$ and $b$ are two constants, which can be expressed as:

$$
\begin{align*}
    a &= \frac{P_r}{(V_r^3 - V_{co}^3)} \\
    b &= \frac{V_{ci}^3}{(V_r^3 - V_{ci}^3)}
\end{align*}
$$

(4)

The rated power of wind is calculated as given in the following equation:

$$
P_r = \frac{1}{2} \times \rho \times A_{wind} \times C_p \times V_r^3
$$

(5)

where $\rho$ represents the air density, $A_{wind}$ is the swept area of the wind turbine, $C_p$ is the maximum power coefficient ranging from 0.25% to 0.45%.

### 2.3. Biomass System

The biomass system is a renewable energy system, which produces power as given in Equation (6) [23].

$$
P_{BM} = \frac{Total_{bio} \times 1000 \times CV_{bio} \times \eta_{bio}}{8760 \times O_{time}}
$$

(6)

where $Total_{bio}$ is the total organic material of biomass, $CV_{bio}$ is the calorific value of the organic material (20 MJ/kg), $\eta_{bio}$ is the biomass efficiency, which is taken as 24% and $O_{time}$ presents the operating hours each day.

### 2.4. Diesel System

The diesel generator is used as a back-up, working just in case there is a need, is connected directly with the load, and starts when the battery is fully discharged and the load is more than 30% of its rated capacity. The model of the diesel generator regarding its output power is presented by the following Equation [25]:

$$
P_{dg} = \frac{F_{dg}(t) - A_g \times P_{dg,\text{out}}}{B_g}
$$

(7)

where $F_{dg}$ is fuel consumption, $P_{dg,\text{out}}$ is the output power of diesel generator, $A_g$ and $B_g$ are the constants of the linear consumption of the fuel.

### 2.5. BESS System

The battery energy storage system (BESS) is a mandatory element for the isolated hybrid systems. BESS is charged in the periods of power excess and discharged when the load increases. The capacity of the BESS is expressed as follows [25]:

$$
C_{bat} = \frac{E_l \times AD}{DOD \times \eta_{inv} \times \eta_b}
$$

(8)

where $E_l$ is the load demand, $AD$ represents the autonomy daily of the battery, $DOD$ is the depth of discharge of the battery system, $\eta_{inv}$ and $\eta_b$ are the battery and inverter efficiency, respectively.

### 3. Formulation of the Optimization Problem

#### 3.1. Net Present Cost

The objective function in the optimization model is the minimization for the Net Present Cost (NPC) which is the pillar factor considered for any project design; it is counted as a sum of all components costs including the capital ($C$), operation and maintenance ($OM$) and replacement costs ($R$), considering also the fuel cost of the diesel ($FC_{dg}$), taking into account the interest rate ($i_r$), inflation
rate ($\delta$), and escalation rate ($\mu$) and the predefined project lifetime ($N$). The NPC modeling is expressed as follows [23,24]:

$$NPC = C + OM + R + FC_{dg}$$  \hspace{1cm} (9)

3.1.1. PV and WT Costs

The costs of PV and WT are presented in a similar concept, their capital cost is expressed based on its initial cost ($\lambda_{PV,WT}$) and its area ($A_{PV,WT}$), the capital cost is as follows [26]:

$$C_{PV,WT} = \lambda_{PV,WT} \times A_{PV,WT}$$  \hspace{1cm} (10)

The operation and maintenance costs are expressed as [26]:

$$OM_{PV,WT} = \theta_{PV,WT} \times A_{PV,WT} \times \sum_{i=1}^{N} \left( \frac{1 + \mu}{1 + \delta} \right)^i$$  \hspace{1cm} (11)

where $\theta_{PV,WT}$ is the annual operation and maintenance costs for any components. The replacement costs are considered null because the project lifetime and the PV or WT lifetime are the same.

3.1.2. Diesel Generator Costs

The costs of the diesel generator are presented as follows [27]:

$$C_{dg} = \lambda_{dg} \times P_{dg}$$  \hspace{1cm} (12)

$$OM_{dg} = \theta_{dg} \times N_{run} \times \sum_{i=1}^{N} \left( \frac{1 + \mu}{1 + \delta} \right)^i$$  \hspace{1cm} (13)

$$R_{diesel} = R_{dg} \times P_{dg} \times \sum_{i=7,14}^{1} \left( \frac{1 + \delta}{1 + \delta} \right)^i$$  \hspace{1cm} (14)

$$C_f(t) = p_f \times F_{dg}(t)$$  \hspace{1cm} (15)

$$FC_{dg} = \sum_{t=1}^{8760} C_f(t) \times \sum_{i=1}^{N} \left( \frac{1 + \mu}{1 + \delta} \right)^i$$  \hspace{1cm} (16)

where $C_{dg}$ is the capital cost, $\lambda_{dg}$ is the initial cost of the diesel generator for each KW, $OM_{dg}$ represent the actual O&M cost, $\theta_{dg}$ is the annual O&M cost of diesel, $N_{run}$ is the number of operating hours of diesel generator per year, $R_{diesel}$ is the diesel generator replacement cost, $R_{dg}$ represents the annual replacement cost of diesel generator, $p_f$ is the fuel cost, $F_{dg}$ is the annual consumption of fuel and $FC_{dg}$ is the total fuel cost.

3.1.3. BESS Costs

The capital and O&M (containing the replacement) costs of the BESS are expressed as follows [26]:

$$C_{BESS} = \lambda_{bat} \times C_{bat}$$  \hspace{1cm} (17)

$$OM_{BESS} = \theta_{bat} \times C_{bat} \times \sum_{i=1}^{T_b} \left( \frac{1 + \mu}{1 + \delta} \right)^{(i-1)N_{bat}}$$  \hspace{1cm} (18)

where $\lambda_{bat}$ is the BESS initial cost and $\theta_{bat}$ is the annual O&M cost of BESS.

3.1.4. Biomass Costs

The biomass costs are presented as follows [28]:

$$C_{bg} = \lambda_{bg} \times P_{bg}$$  \hspace{1cm} (19)
\[ OM_{bg} = \theta_1 \times P_{bg} \times \sum_{i=1}^{N} \left( 1 + \frac{\mu}{1 + i_r} \right)^i + \theta_2 \times P_w \times \sum_{i=1}^{N} \left( 1 + \frac{\mu}{1 + i_r} \right)^i \] (20)

where \( \lambda_{bg} \) is the biomass initial cost, \( \theta_1 \) is the annual fixed O&M cost and \( \theta_2 \) is the variable O&M cost of the biomass system, and \( P_w \) is the annual energy generated by the Biomass system (kWh/Year).

3.1.5. Inverter Costs

The inverter capital and O&M costs are presented as follows [27]:

\[ C_{inv} = \lambda_{inv} \times P_{inv} \] (21)

\[ OM_{inv} = \theta_{inv} \times \sum_{i=1}^{N} \left( 1 + \frac{\mu}{1 + i_r} \right)^i \] (22)

where \( \lambda_{inv} \) is the inverter initial cost and \( \theta_{inv} \) is the annual O&M cost of the inverter.

3.2. Levelized Cost of Energy

The Levelized Cost of Energy (LCOE) is a critical factor. The consumers do not care about project cost or its lifetime, but their interest is to know how much to pay for each kilowatt-hour of consumption. Therefore, the LCOE is a measure of the average NPC over its lifetime, its equation is expressed as follows [25]:

\[ LCOE = \frac{NPC \times CRF}{\sum_{t=1}^{8760} P_{load}(t)} \] (23)

where \( P_{load} \) is the load demand; \( CRF \) is the capital recovery factor used to convert the initial cost to an annual capital cost, and is expressed as follow:

\[ CRF(ir, R) = \frac{i_r \times (1 + i_r)^R}{(1 + i_r)^R - 1} \] (24)

where \( R \) denotes the lifetime of the hybrid system.

3.3. Loss of Power Supply Probability

The loss of power supply probability (LPSP) is a technical factor used to express the reliability of the system. The LPSP is expressed as follows [25]:

\[ LPSP = \frac{\sum_{t=1}^{8760} (P_{load}(t) - P_{pv}(t) - P_{awd}(t) + P_{dg, out}(t) + P_{bmin})}{\sum_{t=1}^{8760} P_{load}(t)} \] (25)

3.4. Renewable Energy Fraction

The transfer from classical electricity production to renewable energy projects was not easy. The majority introduced RES partially, while the objective is to use all projects with 100% renewable energy. Therefore, the renewable energy factor is dedicated to calculating the percentage of the renewable energy used. The renewable energy fraction (RF) is expressed as follows [25]:

\[ RF = \left( 1 - \frac{\sum_{t=1}^{8760} P_{dg, out}(t)}{\sum_{t=1}^{8760} P_{re}(t)} \right) \times 100 \] (26)

where \( P_{re} \) represents the total power from RES.
3.5. Availability Index

The availability index \( (A) \) is calculated to predict customer satisfaction. The availability index measures the energy converted to the load while confirming the ability of the designing system of the project. The availability index is calculated as follows [23]:

\[
A = 1 - \frac{DMN}{\sum_{t=1}^{8760} P_{\text{load}}(t)}
\]  
(27)

\[
DMN = P_{\text{min}}(t) - P_b(t) - \left( P_{\text{pv}}(t) + P_{\text{wind}}(t) + P_{\text{dg, out}}(t) - P_{\text{load}}(t) \right) \times u(t)
\]  
(28)

while, \( u \) will be equal to 1 when the load is not satisfied, and 0 when the load is satisfied.

3.6. Constraints

The constraints are presented to achieve the desired system design. In this microgrid system, the constraints are shown as follows:

\[
\begin{align*}
0 & \leq A_{\text{pv}} \leq A_{\text{pv}}^{\text{max}}, \\
0 & \leq A_{\text{wind}} \leq A_{\text{wind}}^{\text{max}}, \\
0 & \leq P_{\text{dg}} \leq P_{\text{dg}}^{\text{max}}, \\
0 & \leq P_{\text{cap, bat}} \leq P_{\text{cap, bat}}^{\text{max}}, \\
LPSP & \leq LPSP^{\text{max}}, \\
RF^{\text{min}} & \leq RF, \\
A^{\text{min}} & \leq A \\
AD^{\text{min}} & \leq AD
\end{align*}
\]  
(29)

4. Algorithms

In this section, the conventional BO and proposed QOBO are illustrated. In addition, both algorithms are compared with well-known optimization techniques (HHO, AEFA and IWO) which are briefly described in Appendix A.

4.1. Bonobo Optimizer

Bonobo optimizer is a new optimization algorithm that was proposed in [22]. In BO, the social reproductive behavior of the bonobo is modeled based on four mating strategies: promiscuous, restrictive, consortship, and extra-group mating. These mating strategies are subjected to the living condition of the bonobo, hence two terms named positive phase (PP) and negative phase (NP) have been used to present the situations of this life. In this framework, PP describes the peaceful living in which the mating can be done. On the contrary, NP expresses a hard life. In the BO, each solution is called \( X_B \) and the best solution is \( X_B^\alpha \). The mathematical modeling of the BO algorithm is presented in the following subsections.

4.1.1. Bonobo Selection Using Fission–Fusion Strategy

The solutions update of the BO algorithm depends on the mating strategies subjected to the current phase. However, a bonobo should be selected before each mating based on the fission–fusion social group strategy. As noted, the bonobo community lives in small groups with different sizes (random and unpredictable) for a few days and the communities rejoined again to the main community. Hence, based on this behavior, a bonobo for mating can be selected. The mathematical formulation for the maximum number of these temporary subgroups \( N_{\text{sub}} \) can be expressed as follows:

\[
N_{\text{sub}} = \max \left( 2, (\varepsilon_{\text{sub}} \times N) \right)
\]  
(30)
where \( N \) is the total number of the population and \( \varepsilon_{\text{sub}} \) denotes the sub-group size factor. To find the selected bonobo \( X_i^p \) for mating with \( X_i^s \) to create a new bonobo \( X_i^{\text{new}} \), if the best bonobo in the subgroup in terms of the fitness function is better than the \( X_i^s \), then it is selected as \( X_i^p \) else a random one should be selected form the subgroup.

4.1.2. Creation of New Bonobo

After achieving the selected bonobo \( X_i^p \), four mating strategies are used in the BO algorithm to create a new bonobo \( X_i^{\text{new}} \) based on the current phase (PP or NP). For the PP case, promiscuous and restrictive mating have higher probabilities \( (\rho_{\text{ph}}) \) for occurrence. On the contrary, in NP, the probabilities \( (\rho_{\text{ph}}) \) of consortship mating and extra-group mating are higher.

Promiscuous and Restrictive Mating

In this mating strategy, the new bonobo can be created using the following equation:

\[
X_i^{\text{new}} = X_i^p + r_1 \times S_i^{\alpha,\text{coeff}} \times (X_i^s - X_i^p) + (1 - r_2) \times S_i^{\beta,\text{coeff}} \times C_{\text{flag}} \times (X_i^x - X_i^p) \tag{31}
\]

where \( r_1 \) is a random number between \([0, 1]\). \( S_i^{\alpha,\text{coeff}} \) and \( S_i^{\beta,\text{coeff}} \) are the sharing coefficients for the alpha bonobo \( X_i^a \) and the selected bonobo \( X_i^p \) respectively. \( C_{\text{flag}} \) is a flag value that equals \(-1\) or \(1\) for restrictive and promiscuous mating, respectively. A controlling parameter in terms of the phase probability \( \rho_{\text{ph}} \) is used to adopt the mating strategy. Initially, \( \rho_{\text{ph}} \) is set to 0.5. Hence, if a random number \( r \) is found to be less than or equal to \( \rho_{\text{ph}} \), a new bonobo is created based on promiscuous and restrictive mating, otherwise, consortship mating and extra-group mating can be used.

Consortship and Extra-Group Mating

If \( r \) is greater than \( \rho_{\text{ph}} \), consortship and extra-group mating can occur. However, a new random number \( r_2 \) between \([0, 1]\) is used with a probability of extra-group mating \( \rho_{xg} \) to represent the occurrence of extra-group mating when \( r_2 \) is less than or equal to \( \rho_{xg} \) as follows [22, 29]:

\[
X_i^{\text{new}} = \begin{cases} 
X_i^a + \beta_1 \times (X_i^{\text{max}} - X_i^a), & X_i^a \geq X_i^s, \text{and } r_4 \leq \rho_d \\
X_i^a - \beta_2 \times (X_i^a - X_i^{\text{min}}), & X_i^a \geq X_i^s, \text{and } r_4 > \rho_d \\
X_i^a - \beta_3 \times (X_i^{\text{min}} - X_i^s), & X_i^a < X_i^s, \text{and } r_4 \leq \rho_d \\
X_i^a + \beta_4 \times (X_i^{\text{max}} - X_i^s), & X_i^a < X_i^s, \text{and } r_4 > \rho_d 
\end{cases} \tag{32}
\]

\[
\beta_1 = e^{(r_2^2+r_4-\frac{r_4}{4})} \\
\beta_2 = e^{(r_2^2+2r_4-\frac{r_4}{4})} \tag{33}
\]

where \( r_3 \) and \( r_4 \) are random numbers between \([0, 1]\) and \( r_4 \neq 0 \). \( \rho_d \) is a directional probability with initial value which equals 0.5. \( \beta_1 \) and \( \beta_2 \) are intermediate parameters between \([0, 1]\). \( X_i^{\text{min}} \) and \( X_i^{\text{max}} \) are the values of the upper and lower boundary.

If \( r_2 \) is greater than \( \rho_{xg} \), a new bonobo can be created using the consortship mating strategy as follows:

\[
X_i^{\text{new}} = \begin{cases} 
X_i^a + C_{\text{flag}} \times e^{-r_5} \times (X_i^x - X_i^p), & C_{\text{flag}} = 1 \text{ or } r_6 \leq \rho_d \\
X_i^p, & \text{Otherwise} 
\end{cases} \tag{34}
\]

where \( r_5 \) and \( r_6 \) are two random numbers.

4.1.3. Parameter Updating

The BO’s parameters are updated during the iterative process based on the best solution \( X_g^s \) at each iteration, where if there is an improvement in the final solution compared to the previous iteration, the BO’s parameters can be updated in the following way.
The negative phase count is set to zero \( (NP_{\text{cont}} = 0) \) and the positive phase count grows by increments of one \( (PP_{\text{cont}} = PP_{\text{cont}} + 1) \). In addition, \( \rho_{\text{gg}} = \rho_{\text{gg, initial}} \) and \( \rho_{\text{ph}} = 0.5 + Cp \) where \( Cp \) is the amount of the change in the phase, and can be calculated as \( Cp = \min(0.5, PP_{\text{cont}} \times rcp) \) where \( rcp \) is the rate of the change in the phase. Moreover \( \rho_{\text{d}} = \rho_{\text{ph}} \) and

\[
\epsilon_{\text{sub}} = \min (\epsilon_{\text{sub, max}}, (\epsilon_{\text{sub, initial}} + PP_{\text{cont}} \times rcp^2))
\]

where \( \epsilon_{\text{sub, initial}} = 0.5 \times \epsilon_{\text{sub, max}} \).

On the other hand, if there is no improvement, the BO’s parameters are updated as follows:

\[
NP_{\text{cont}} = NP_{\text{cont}} + 1 \text{ and } PP_{\text{cont}} = 0,
\]

\[
Cp = \min(0.5, NP_{\text{cont}} \times rcp),
\]

\[
\rho_{\text{gg}} = \rho_{\text{gg, initial}} \min(0.5, \rho_{\text{gg, initial}} + NP_{\text{cont}} \times rcp^2),
\]

and

\[
\epsilon_{\text{sub}} = \min (\epsilon_{\text{sub, max}}, (\epsilon_{\text{sub, initial}} - NP_{\text{cont}} \times rcp^2)).
\]

The overall steps of the BO algorithm are presented in Algorithm 1.

**Algorithm 1: BO**

1. Initialize a set of random search bonobo \( X_B^i = (X_B^{i1}, X_B^{i2}, \ldots, X_B^{iN}) \) within the limits \( X_B^{i\text{min}} \leq X_B^i \leq X_B^{i\text{max}} \).
2. Initialize the BO’s parameters.
3. Evaluate the objective function for all bonobos.
4. Identify the alpha bonobo \( X_B^\alpha \).
5. While \( (k < K_{\text{max}}) \):
   - Determine the actual size of the temporary sub-group.
   - Choose a bonobo using fission-fusion society strategy.
   - Create a new bonobo \( X_B^{new} \) as follows:
     - if \( r \leq \rho_{\text{ph}} \)
       - Create new bonobo using promiscuous or restrictive mating strategy.
     - else \( r > \rho_{\text{ph}} \)
       - Create new bonobo using consortship or extra-group mating strategy.
   - end if
   - Calculate the objective function.
   - Update alpha bonobo \( X_B^\alpha \) and the BO’s parameters.
   - \( K = K + 1 \).
   - end while
7. Return the final best solution \( X_B^\alpha \).

### 4.2. Improved Quasi-Oppositional BO (QOBO) Algorithm

As with any population-based algorithm, BO has some problems such as falling in the local optima. However, in this work, an improved BO based on three leaders’ selection and quasi-opposition-based learning is developed.

#### 4.2.1. Three Leaders

In this method, instead of using the best solution (alpha bonobo \( X_B^{\alpha} \)) for updating the new bonobo \( X_B^{new} \) and ignoring the other best solutions, three leaders can be used to increase the diversity of the solutions as follows

\[
X_B^{\alpha} = w_1 \times X_{\text{best}1} + w_2 \times X_{\text{best}2} + w_3 \times X_{\text{best}3}
\]

where

\[
w_1 = \frac{r_7}{r_7 + r_8 + r_9}, \quad w_2 = \frac{r_8}{r_7 + r_8 + r_9}, \quad \text{and} \quad w_3 = \frac{r_9}{r_7 + r_8 + r_9}
\]

\( r_7, r_8, \) and \( r_9 \) are random values between \([0, 1]\).
4.2.2. Quasi-Oppositional

Opposition-based learning (OBL) [30] has been widely used to improve many optimization techniques such as quasi-oppositional teaching-learning (QOTLBO) [31,32], Quasi-oppositional swine influenza model-based optimization with quarantine (QOSIMBO-Q) [33] and Oppositional Jaya Algorithm [34]. In the OBL, improvements can be achieved by using the candidate solution and its opposite at the same time. Hence, in this work, the opposite solution of the BO algorithm \( X^i_B \) can be expressed as presented in [35]:

\[
X^{\text{qnew}}_B = C + r_{10}(C - X^{\text{new}}_B)
\]

(37)

where \( r_{10} \) is a random number between [0, 1], and \( C \) is a middle point between \( X^{i}_{\min} \) and \( X^{i}_{\max} \) which can be calculated as follows:

\[
C = \frac{X^{i}_{\min} + X^{i}_{\max}}{2}
\]

(38)

Additionally, \( X^{\text{qnew}}_B \) is the opposite solution which can be calculated as

\[
X^{\text{qnew}}_B = X^{i}_{\min} + X^{i}_{\max} - X^{\text{new}}_B
\]

(39)

The overall steps of the improved BO based on three leaders and the quasi-oppositional method are presented in Algorithm 2.

**Algorithm 2: QOBO**

1. Initialize a set of random search bonobo \( X^i_B = (X^1_B, X^2_B, ..., X^N_B) \) within the limits \( X^{i}_{\min} \leq X^i_B \leq X^{i}_{\max} \).
2. Initialize the BO’s parameters.
3. Evaluate the objective function for all bonobos.
4. Determine the alpha bonobo \( X^\alpha_B \) using three-leader method.
5. While \( (k < K_{\max}) \):
   1. Determine the actual size of the temporary sub-group.
   2. Choose a bonobo using fission-fusion society strategy.
   3. Create a new bonobo \( X^{\text{new}}_B \) as follows:
      1. if \( r \leq \rho_{ph} \):
         1. Create new bonobo using promiscuous or restrictive mating strategy.
      2. else \( r > \rho_{ph} \):
         1. Create new bonobo using consortship or extra-group mating strategy.
   end if
   4. Calculate the objective function for all new bonobos \( X^{\text{new}}_B \).
   5. Find quasi-oppositional model for all new bonobos \( X^{\text{qnew}}_B \).
   6. Calculate the objective function for all new bonobos \( X^{\text{qnew}}_B \).
   7. if \( f(X^{\text{qnew}}_B) \leq f(X^{\text{new}}_B) \), \( X^{\text{new}}_B = X^{\text{qnew}}_B \).
   Else \( X^{\text{new}}_B = X^{\text{new}}_B \).
   end if
   8. Update alpha bonobo \( X^{\alpha}_B \) using three leader method and the BO’s parameters.
   9. \( K = K + 1 \).
end while
10. Return the final best solution \( X^{\alpha}_B \).

5. Case Study

To validate the robustness of the QOBO algorithm, it has been applied for addressing the studied problem of optimal configuration of the proposed multiple scenarios HRES, i.e., the PV/WT/diesel generator/BESS, PV/biomass, PV/diesel generator/BESS and WT/diesel generator/BESS. The proposed hybrid systems have been introduced in the isolated mode for satisfying the load requirements in the proposed site.
The project is applied in Aswan, Egypt as shown in Figure 4. The annual load curve over a time interval of one hour is shown in Figure 5. Figures 6–9 present solar irradiation, temperature, wind speed and atmospheric pressure in the studied region. Four standalone scenarios of the hybrid system will be evaluated for covering the load demand in that site. These configurations are: (1) PV/WT/diesel/BESS, (2) PV/biomass, (3) PV/diesel/BESS and (4) WT/diesel/BESS. The proposed QOBO is validated on optimal sizing of these four hybrid systems and the optimization results are comprehensively compared with the corresponding ones obtained from BO, HHO, AEFA and IWO algorithms.

Figure 4. Location of the case study (Aswan) on the world map.

Figure 5. Annual load curve over a time interval of one hour with a peak demand of 70 kW.
Figure 4. Location of the case study (Aswan) on the world map.

Figure 5. Annual load curve over a time interval of one hour with a peak demand of 70 kW.

Figure 6. Solar irradiation over the studied region.

Figure 7. Temperature variation in Aswan.

Figure 8. Annual variation of wind speed over the year in Aswan.

Figure 9. Atmospheric pressure variation in Aswan.
6. Results

The main object of this research paper is to find the optimal design of the proposed hybrid system and to validate the accuracy of the proposed QOBO optimization method. The optimal sizing is based on the objective functions introduced in (9) and the parameters of optimization are: (i) the area of PV system, (ii) the area swept by the WT, (iii) the rated power of diesel generator, (iv) the nominal capacity of the battery, (v) the consumption of the biomass fuel. To confirm the suitability of the QOBO in addressing such optimization problem, QOBO, BO, HHO, AEFA and IWO were launched 100 times for each configuration and statistical study was conducted based on the best minimum value of the fitness function. For a deep analysis of the obtained results and to ensure the sensitivity analysis, four indices were chosen, namely, NPC, LCOE, LPSP and the availability index. In the next subsections, the optimization results are provided for the standalone system with multiple scenarios. Modelling and simulation of the optimization problem were accomplished using MATLAB 2015a program, while the adjusting parameters for the three algorithms are the same, i.e., the number of maximum iterations is taken as 100 iterations and the search agents’ number is 30 agents. The input technical and economic data for the system components are presented in Table 1. The results of the statistical measurements for the modified QOBO and the conventional BO with HHO, AEFA and IWO algorithms are listed in Tables 2 and 3. From the previously mentioned tables, the reader can conclude that the QOBO technique generates the best minimum value of the fitness function in all cases. The convergence curves of the 100 iterations implemented for all the studied configurations using QOBO, BO, HHO, AEFA and IWO are presented in Figure 10a–d.
Table 1. Units for magnetic properties.

| Symbol | Quantity            | Conversion |
|--------|---------------------|------------|
| N      | Project lifetime    | 20 years   |
| i<sub>r</sub> | Interest rate   | 13.25%     |
| µ      | Escalation rate     | 2%         |
| δ      | Inflation rate      | 12.27%     |

### PV system

| Symbol | Quantity            | Conversion |
|--------|---------------------|------------|
| λ<sub>pV</sub> | PV initial cost | 300 $/m² |
| θ<sub>pV</sub> | Annual O&M cost of PV | 0.01 * λ<sub>pV</sub> $/m²/year |
| η<sub>r</sub> | Reference efficiency of the PV | 25% |
| η<sub>η</sub> | Efficiency of MPPT | 100% |
| T<sub>r</sub> | PV cell reference temperature | 25 °C |
| β     | Temperature coefficient | 0.005 °C |
| NOCT  | Nominal operating cell temperature | 47 °C |
| N<sub>pV</sub> | PV system lifetime | 20 years |

### WT system

| Symbol | Quantity            | Conversion |
|--------|---------------------|------------|
| λ<sub>wind</sub> | Wind initial cost | 125 $/m² |
| θ<sub>wind</sub> | Annual O&M cost of wind | 0.01 * λ<sub>wind</sub> $/m²/year |
| C<sub>p, wind</sub> | Maximum power coefficient | 48% |
| V<sub>ci</sub> | Cut-in wind speed | 2.6 m/s |
| V<sub>co</sub> | Cut-out wind speed | 25 m/s |
| V<sub>r</sub> | Rated wind speed | 9.5 m/s |
| N<sub>wind</sub> | Wind system lifetime | 20 years |

### Diesel generator

| Symbol | Quantity            | Conversion |
|--------|---------------------|------------|
| λ<sub>dg</sub> | Diesel initial cost | 250 $/kW |
| θ<sub>dg</sub> | Annual O&M cost of diesel | 0.05 $/h |
| R<sub>dg</sub> | Replacement cost | 210 $/kW |
| p<sub>f</sub> | Fuel price in Egypt | 0.43 $/L |
| N<sub>diesel</sub> | Diesel system lifetime | 7 years |

### BESS

| Symbol | Quantity            | Conversion |
|--------|---------------------|------------|
| λ<sub>bat</sub> | Battery initial cost | 100 $/kWh |
| θ<sub>bat</sub> | Annual operation and maintenance cost of battery | 0.03 * λ<sub>bat</sub> $/m²/year |
| DOD   | Depth of discharge | 80%         |
| η<sub>b</sub> | Battery efficiency | 97%         |
| SOC<sub>min</sub> | Minimum state of charge | 20% |
| SOC<sub>max</sub> | Maximum state of charge | 80% |
| N<sub>bat</sub> | Battery system lifetime | 5 years |

### Inverter

| Symbol | Quantity            | Conversion |
|--------|---------------------|------------|
| λ<sub>inv</sub> | Inverter initial cost | 400 $/m² |
| θ<sub>inv</sub> | Annual O&M cost of inverter | 20 $/year |
| η<sub>inv</sub> | Inverter efficiency | 97%         |

6.1. Validation of QOBO Algorithm

The results of the statistical measurements for the modified QOBO, the conventional BO, HHO, AEFA and IWO algorithms are listed in Tables 2 and 3. From Table 2, the reader can find the results of the optimal sizing for the multiple scenarios studied, as well as the convergence time of each simulation, and conclude that the QOBO algorithm finds the best results with a short time compared with the other algorithms. From Table 3, the reader can compare between algorithms and the different scenarios of the proposed hybrid system using multiple factors. Briefly, it is noticed that the hybrid PV/biomass system is highly competitive, mainly using the developed QOBO algorithm, the optimized system is calculated with $110,807, which means an LCOE of 0.1053 $/kWh, the constraints are satisfied and the project is 100% supplied by renewable energy sources. In this scenario, the performances of the QOBO and the BO are almost equal, while in other scenarios, the difference is clearly noticed.
Table 2. Sizing results of different scenarios obtained from different optimization methods.

| Hybrid Power System | Algorithm | PV (m²) | Wind (m²) | Diesel (kW) | Battery (kWh) | Biomass (t/year) | Time(s) |
|---------------------|-----------|---------|-----------|-------------|---------------|-----------------|---------|
| PV/WT/Diesel/BESS   | QOBO      | 484.765 | 0         | 1.2142      | 13.4390       | //              | 51,507  |
|                     | BO        | 484.765 | 0         | 1.2142      | 13.4390       | //              | 51,507  |
|                     | HHO       | 513.105 | 305.293   | 0.5204      | 14.6552       | //              | 30,655  |
|                     | AEFA      | 329.159 | 176.277   | 5.4696      | 18.6552       | //              | 10,531  |
|                     | IWO       | 830.791 | 136.557   | 10.296      | 5.8224        | //              | 57,938  |
| PV/Biomass          | QOBO      | 293.971 | //        | //          | //             | 1020.18        | 32,104  |
|                     | BO        | 293.972 | //        | //          | //             | 1020.31        | 122,417 |
|                     | HHO       | 482.756 | //        | //          | //             | 2040.47        | 10,453  |
|                     | AEFA      | 386.692 | //        | //          | //             | 1185.76        | 3855    |
|                     | IWO       | 748.387 | //        | //          | //             | 2739.00        | 36,098  |
| PV/Diesel/BESS      | QOBO      | 376.011 | //        | 1.3402      | 58.9083       | //              | 16,799  |
|                     | BO        | 336.253 | //        | 2.9170      | 52.1928       | //              | 33,009  |
|                     | HHO       | 482.756 | //        | 1.7843      | 13.7590       | //              | 13,983  |
|                     | AEFA      | 386.692 | //        | 1.6713      | 55.7583       | //              | 6237    |
|                     | IWO       | 748.387 | //        | 4.0111      | 51.4565       | //              | 24,630  |
| WT/Diesel/BESS      | QOBO      | 2726.29 | 91.141    | 72.375      | //              | 26,510         |
|                     | BO        | 2823.34 | 42.637    | 72.371      | //              | 66,514         |
|                     | HHO       | 2808.76 | 74.565    | 73.230      | //              | 135,097        |
|                     | AEFA      | 3015.08 | 72.963    | 72.653      | //              | 78,697         |
|                     | IWO       | 4318.76 | 78.218    | 82.7987     | //              | 26,960         |

Table 3. Factor results for all scenarios.

| Hybrid Power System | Algorithm | NPC ($) | LCOE ($/kWh) | LPSP (%) | Availability (%) | Renewable Energy (%) | Battery Daily Autonomy (day) |
|---------------------|-----------|---------|--------------|----------|-----------------|----------------------|-----------------------------|
| PV/WT/Diesel/BESS   | QOBO      | 175,651 | 0.1669       | 0.019    | 98.87           | 98.15                | 0.5826                      |
|                     | BO        | 209,096 | 0.1986       | 0.050    | 96.99           | 99.75                | 0.6418                      |
|                     | HHO       | 201,109 | 0.1910       | 0.025    | 99.23           | 99.88                | 0.6353                      |
|                     | AEFA      | 183,284 | 0.1741       | 0.026    | 99.33           | 98.88                | 0.8087                      |
|                     | IWO       | 347,523 | 0.3301       | 0.014    | 99.68           | 97.72                | 0.2524                      |
| PV/Biomass          | QOBO      | 110,807 | 0.1053       | 0.050    | 96.03           | 100                  | //                          |
|                     | BO        | 110,808 | 0.1053       | 0.050    | 96.03           | 100                  | //                          |
|                     | HHO       | 114,098 | 0.1084       | 0.046    | 96.94           | 100                  | //                          |
|                     | AEFA      | 113,410 | 0.1077       | 0.040    | 96.93           | 100                  | //                          |
|                     | IWO       | 130,491 | 0.1240       | 0.018    | 98.70           | 100                  | //                          |
| PV/Diesel/BESS      | QOBO      | 153,401 | 0.1457       | 0.049    | 98.63           | 97.25                | 2.5536                      |
|                     | BO        | 167,981 | 0.1596       | 0.050    | 98.72           | 92.88                | 2.2625                      |
|                     | HHO       | 183,501 | 0.1743       | 0.017    | 97.94           | 97.27                | 0.5964                      |
|                     | AEFA      | 160,774 | 0.1527       | 0.042    | 98.74           | 96.70                | 2.4171                      |
|                     | IWO       | 287,730 | 0.2733       | 0.026    | 99.16           | 96.12                | 2.2306                      |
| WT/Diesel/BESS      | QOBO      | 1,095,270| 1.0405       | 0.014    | 99.85           | 70.03                | 3.9509                      |
|                     | BO        | 1,098,685| 1.0437       | 0.003    | 99.97           | 71.3527              | 1.8483                      |
|                     | HHO       | 1,123,579| 1.0673       | 0.008    | 99.92           | 70.2407              | 3.1745                      |
|                     | AEFA      | 1,119,533| 1.0635       | 0.008    | 99.92           | 73.6967              | 3.1494                      |
|                     | IWO       | 1,319,108| 1.2531       | 0.008    | 99.92           | 81.8292              | 3.3907                      |

6.2. Combinations of the Studied System Components

In this section, the results obtained in the convergence simulation of the NPC as a fitness function using the QOBO are presented. The optimized parameter results (i.e., \( A_{\text{pv}}, A_{\text{wind}}, P_{\text{dgn}}, P_{\text{Cap,bat}}, P_{\text{BM}} \)) for all suggested combinations are listed in Table 3 with the rating of the inverter that takes the value of the peak load demand. From Figure 10, the reader can notice that using QOBO, BO, HHO, AEFA and IWO algorithms, the best minimum values of fitness function (NPC) is obtained for the second configuration, i.e., hybrid PV/biomass energy system. From the table, it is obvious that QOBO generates the minimum value of LCOE in all cases.
The reliability of the proposed scenarios of the proposed HRES are respected and the availability of power is highly assured, the penetration RES is considered in this paper, while different results are obtained. The minimum penetration of 70% is obtained for the WT/Diesel/Battery scenario while the maximum penetration of 99.75% is obtained for the PV/WT/Diesel/BESS scenario. The daily battery autonomy is also influenced by the configuration of the HRES, the best autonomy is achieved for the WT/Diesel/BESS scenario taking nearly 4 days, while the minimum autonomy is obtained in PV/WT/Diesel/BESS case with only 6 h. The last system is composed of the different energy resource which explains the independence for a specific resource. Table 4 presents a detailed overview of all costs needed, for all scenarios presented and for all proposed algorithms.

![Figure 10. Cont.](image-url)
Figure 10. Convergence of the objective function of all algorithms for different scenarios; (a) PV/WT/Diesel/BESS, (b) PV/Biomass, (c) PV/Diesel/BESS, (d) WT/Diesel/BESS.
Table 4. Convergence of objective function of different scenarios.

| Hybrid Power System | Algorithm | PV Costs | Wind Inv | O&M Rep | Diesel Inv | O&M Rep | Battery Fuel | Inverter Inv | Rep | Invert Rep | Rep | Invert O&M Fuel |
|---------------------|-----------|----------|----------|----------|------------|----------|--------------|-------------|-----|------------|-----|----------------|
|                     |           |          |          |          |            |          |              |              |     |            |     |                |
| Scenario I          | QOBO      | 145,429  | 11,558   | 0        | 0          | 0        | 303          | 1792        | 465 | 17,080     | 1343| 28,400        |
|                     | BO        | 74,400   | 5913     | 0        | 124,813    | 9920     | 162          | 526         | 248 | 5244       | 1480| 28,400        |
|                     | HHO       | 153,931  | 12,234   | 0        | 38,161     | 3033     | 130          | 330         | 199 | 3729       | 1465| 28,400        |
|                     | AEFA      | 98,747   | 7848     | 0        | 22,034     | 1751     | 1367         | 537         | 2097| 44,542     | 1865| 28,400        |
|                     | IWO       | 249,237  | 19,809   | 0        | 17,069     | 1356     | 2574         | 470         | 3949| 80,625     | 582 | 28,400        |
| Scenario II         | QOBO      | 88,191   | 7009     | 0        | //         | //       | //            | //          | //  | //         | //  | //            |
|                     | BO        | 88,191   | 7009     | 0        | //         | //       | //            | //          | //  | //         | //  | //            |
|                     | HHO       | 89,658   | 7126     | 0        | //         | //       | //            | //          | //  | //         | //  | //            |
|                     | AEFA      | 90,894   | 7224     | 0        | //         | //       | //            | //          | //  | //         | //  | //            |
|                     | IWO       | 109,654  | 8715     | 0        | //         | //       | //            | //          | //  | //         | //  | //            |
| Scenario III        | QOBO      | 112,803  | 8965     | 0        | //         | //       | //            | 335         | 1869| 514         | 19,339| 5890       |
|                     | BO        | 100,873  | 8017     | 0        | //         | //       | //            | 729         | 1994| 1118       | 43,812| 5219       |
|                     | HHO       | 144,826  | 11,510   | 0        | //         | //       | //            | 446         | 1792| 684         | 25,102| 1375       |
|                     | AEFA      | 116,007  | 9224     | 0        | //         | //       | //            | 417         | 1855| 641         | 24,008| 5575       |
|                     | IWO       | 224,516  | 17,844   | 0        | //         | //       | //            | 1002        | 1756| 1538       | 55,745| 5145       |
| Scenario IV         | QOBO      | //       | //       | //       | 340,787    | 27,085   | 0            | 18,093      | 921 | 27,759     | 720,800| 9114       |
|                     | BO        | //       | //       | //       | 352,917    | 28,050   | 0            | 18,092      | 912 | 27,757     | 717,633| 4263       |
|                     | HHO       | //       | //       | //       | 351,094    | 27,905   | 0            | 18,641      | 915 | 28,599     | 740,365| 7323       |
|                     | AEFA      | //       | //       | //       | 376,885    | 29,955   | 0            | 18,240      | 887 | 27,985     | 714,885| 7265       |
|                     | IWO       | //       | //       | //       | 539,845    | 42,907   | 0            | 20,699      | 774 | 31,757     | 766,838| 7821       |
6.3. Sensitivity Analysis

RES is intermittent which can be affected by any variation of sizing, meteorological or economic data. The sensitivity analysis is a method that helps to select and/or to expect the optimal configuration of the hybrid system. The sensitivity analysis in this paper is implemented on the best scenario of the proposed, i.e., the PV/Biomass in the Aswan region. The selection of the sensitivity variables is based on the sizing of components in order to analyze the effect of sizing variation on four factors which are NPC, LCOE, LPSP and the Availability index.

Figure 11 shows the effect of variation in the sizing of PV and biomass units on the NPC. The PV sizing is highly impacted by the total cost of the hybrid PV/Biomass system, which means that in the case of reducing the area of PV units the NPC is reduced too. On the other hand, if the area covered by PV modules is increased, the NPC increases too. The variation in the sizing of biomass unit is increased throughout the interval −20 to 20 slowly and it has no noticeable impact on the NPC anyway. Figure 12 shows the effect of variation of PV and biomass sizing on the LCOE. The NPC and the LCOE are linked with a linear equation which means that they have the same shape. The LCOE reached 0.08 $/kWh when the area of the PV system is reduced by 20%. Figure 13 shows the impact of variation in the sizing of PV and biomass systems on the LPSP. The impact of PV size is very important for the LPSP, because when the size of the PV system is increased the LPSP is enhanced, mainly in the −20% to 0% interval. When the PV size is changed in the interval of 0% to +20%, the LPSP is increased to 2% while when the PV size is changed to −20%, the change in LPSP equals 16.4% which is a very bad sign for system building. The Biomass system does not affect the value of the LPSP and the transition between −4% to 0% is explained as the obtained sizing of the system is optimum. Figure 14 shows the impact of the variation of PV and Biomass sizing on the availability index. The availability index enhanced exponentially with the increase in the PV sizing. In the interval between −20% and 0, availability progresses quickly, while after zero, the availability begins to be stabilized and it is clearly shown in the interval between +12% and +20%.

![Figure 11. Sensitivity analysis application for net present cost (NPC).](image-url)
Figure 12. Sensitivity analysis application for Levelized Cost of Energy (LCOE).

Figure 13. Sensitivity analysis application for Loss of Power Supply Probability (LPSP).
Among these dilemmas, the economic cost and feasibility of installing systems in different locations is considered the most important challenge. Therefore, this research proposes a developed algorithm called Quasi-Oppositional Bonobo Optimizer (QOBO) for the optimal economic design of a stand-alone hybrid microgrid system in Aswan, Egypt. Four configurations of the hybrid system have been implemented, which consist of RES (PV panels, WT and biomass) with diesel generators and battery storage systems. The obtained results showed that the PV/Biomass scenario is the most cost-effective system with an NPC of $110,807 and LCOE of 0.1053 $/kWh; otherwise, the best configuration of the microgrid system contained 293.971 m² of PV and 1020.18 ton/year consumed by the biomass system; the PV/Diesel/BESS scenario is also cost-effective with NPC of $153,401 and LCOE of 0.1457 $/kWh. On the other side, the LPSP and availability index are satisfied and without the need for traditional resources. Additionally, the results showed the ability of the QOBO algorithm to reach the optimal solution in a shorter time and with better efficiency compared to the traditional BO, HHO, AEFA and IWO algorithms in all cases studies. Furthermore, a sensitivity analysis of the proposed systems scenarios was performed to obtain the impact of unit size on the performance of the hybrid system, where it has been emphasized that PV system sizing is very important and has a great impact on the overall performance of the system. The obtained results from this study would be useful material for decision makers working on the development of the renewable energy sector in Egypt. In future studies, it is suggested to apply the proposed QOBO in other engineering problems.

**7. Conclusions**

With the increased penetration level of RES into electrical energy production in the microgrid systems, new challenges have emerged on the international scene. These challenges are represented in finding ways to optimize the design of the hybrid system by using smart algorithms and software. Among these dilemmas, the economic cost and feasibility of installing systems in different locations in the world is considered the most important challenge. Therefore, this research proposes a developed algorithm called Quasi-Oppositional Bonobo Optimizer (QOBO) for the optimal economic design of a stand-alone hybrid microgrid system in Aswan, Egypt. Four configurations of the hybrid system have been implemented, which consist of RES (PV panels, WT and biomass) with diesel generators and battery storage systems. The obtained results showed that the PV/Biomass scenario is the most cost-effective system with an NPC of $110,807 and LCOE of 0.1053 $/kWh; otherwise, the best configuration of the microgrid system contained 293.971 m² of PV and 1020.18 ton/year consumed by the biomass system; the PV/Diesel/BESS scenario is also cost-effective with NPC of $153,401 and LCOE of 0.1457 $/kWh. On the other side, the LPSP and availability index are satisfied and without the need for traditional resources. Additionally, the results showed the ability of the QOBO algorithm to reach the optimal solution in a shorter time and with better efficiency compared to the traditional BO, HHO, AEFA and IWO algorithms in all cases studies. Furthermore, a sensitivity analysis of the proposed systems scenarios was performed to obtain the impact of unit size on the performance of the hybrid system, where it has been emphasized that PV system sizing is very important and has a great impact on the overall performance of the system. The obtained results from this study would be useful material for decision makers working on the development of the renewable energy sector in Egypt. In future studies, it is suggested to apply the proposed QOBO in other engineering problems.

**Author Contributions:** Conceptualization, S.K. and M.K.; Data curation, O.H.M., H.M.S. and A.S.; Formal analysis, F.J., M.A. and H.M.S.; Methodology, M.K., A.S. and S.K.; Resources, O.H.M., S.K. and H.M.S.; Software,
A.S., M.K.; Supervision, F.J.; Validation, H.M.S. and O.H.M.; Visualization, S.K., A.S. and M.A.; Writing—original draft, M.K., O.H.M., A.S. and H.M.S.; Writing—review & editing, S.K., M.A. and F.J. All authors together organized and refined the manuscript in the present form. All authors have approved the final version of the submitted paper. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported in part by the NSFC, China-ASRT, Egypt, Joint Research Fund, under Grant 51861145406.

**Acknowledgments:** The authors gratefully acknowledge the contribution of the NSFC (China)-ASRT (Egypt) Joint Research Fund, Project No. 51861145406 for providing partial research funding to the work reported in this research.

**Conflicts of Interest:** The authors declare no conflict of interest.

**Nomenclature**

**Symbols**

- $A$: Availability index
- $A_d$: Coefficient of consumption curve (a = 0.246 L/kW)
- $AD$: Daily autonomy of the battery (day)
- $A_{pr}$: Area covered by PV panels (m²)
- $A_{tt}$: Cross-sectional area of the tidal (m²)
- $A_{wind}$: Swept area by the wind turbine (m²)
- $C$: Capital Cost ($)
- $C_{Battery}$: Capacity of the Battery (kWh)
- $C_P$: Maximum power coefficient (%)
- $CV_{org}$: Calorific value of the organic material (MJ/kg)
- $DOD$: Depth of Discharge (%)
- $E_t$: Load demand (kWh)
- $F_{dg}$: Fuel consumption of the diesel generator (L/h)
- $FC_{dg}$: Fuel Cost for one year ($/Year)
- $I$: Solar irradiation (kW/m²)
- $i_r$: Interest rate (%)
- $N$: project lifetime (year)

- NOCT: Nominal operating cell temperature (°C)
- NPC: Net Present Cost ($)
- OM: Maintenance and Operation ($) $\eta_b$: Efficiency of the battery (%)
- $\eta_{batt}$: Efficiency of the biomass system (%)
- $\eta_{inv}$: Efficiency of the inverter (%)
- $\eta_{pv}$: Efficiency of the PV system (%)
- $\eta_r$: Reference efficiency of PV panels (%)

- $P_{wind}$: Output power of the wind turbine (kW)
- $R$: Replacement Cost ($)
- $T$: Temperature (°C)
- $T_a$: Ambient temperature (°C)
- $T_r$: Reference temperature of solar cell (°C)
- $V$: Wind speed (m/s)
- $V_{ci}$: Cut-in wind speed (m/s)
- $V_{co}$: Cut-out wind speed (m/s)
- $V_r$: Rated wind speed (m/s)

- $B_g$: Coefficient of consumption curve (b = 0.08415 L/kW)

- $\eta_{MPPT}$: Efficiency MPPT system (%)
- $\rho$: Temperature coefficient (0.004 to 0.006 °C)
- $\rho$: Air density (Kg/m³)
- $\lambda_{bat}$: Initial cost of the battery system ($/kWh)
- $\lambda_{bio}$: Initial cost of biomass system ($/kWh)
- $\lambda_{dg}$: Initial cost of diesel generator ($/kWh)
- $\lambda_{PV,WT}$: Initial cost of PV and WT ($/m²$)
- $\delta$: Inflation rate (%)
- $\mu$: Escalation rate (%)
- $\theta_1$: Biomass annual fixed O&M cost ($/kWh/year)
- $\theta_2$: Biomass variable O&M cost ($/kWh h$

**Acronyms**

- AEFA: Artificial Electric Field Algorithm
- ACS: Annualized cost of the system
- BESS: Battery Energy Storage System
- BO: Bonobo Optimizer Algorithm
- BOQO: Improved Quasi Oppositional BO Algorithm
- COE: Cost of Energy
- CRF: Capital Recovery Factor
- HOMER: Hybrid Optimization of Multiple Energy Resources
- HRES: Hybrid Renewable Energy Systems
- HHO: Harris Hawks Optimization

- HSA: Harmony Search Algorithm
- IWO: Invasive Weed optimization Algorithm
- LCOE: Levelized Cost of Energy
- LPSP: Loss of Power Supply Probability
- MOPOSO: Multiple Objective Particle Swarm Optimization
- NPC: Net present cost
- PSO: Particle Swarm Optimization
- PV: Photovoltaic
- RF: Renewable Fraction
- WT: Wind Turbine

**Appendix A. Algorithms**

**Appendix A.1. Harris Hawks Optimization Algorithm**

Heidari and et al. [36] proposed a new nature-inspired optimization algorithm called Harris Hawks Optimizer. They were inspired by the cooperative behavior and chasing style of Harris hawks. The modeling of this technique is based firstly on an exploration phase; afterwards, the transition from exploration to exploitation, then the...
exploitation phase and, finally, the soft besiege. The modeling is taken on for all strategies for exploring a prey, surprise pounce and different attacking methods of Harris hawks. The pseudo-code of the HHO algorithm is proposed below.

**Algorithm A1**: Pseudo code of HHO

| Initialize the population size and max iteration \( K_{\text{max}} \) |
|-------------------------------------------------------------|
| Initialize a set random rabbit location, within the limits \( X_{\text{min}} \leq X_{\text{rabbit}} \leq X_{\text{max}} \). |
| Evaluate the objective function for all rabbits |
| While \( (k < K_{\text{max}}) \) |
| Calculate the fitness of hawks |
| Set \( x_{\text{rabbit}} \) in the best location |
| for each hawk do |
| Update the initial energy \( E_0 \), energy \( E \) and jump strength \( J \); |
| \( E_0 = 2 \text{rand}() - 1, E = 2E_0(1 - \frac{t}{T}), J = 2(1 - \text{rand}()) \) |
| if \( (|E| \geq 1) \) then |
| Exploration phase |
| if \( (|E| < 1) \) then |
| Exploitation phase |
| if \( (r \geq 0.5 \text{ and } |E| \geq 0.5) \) then |
| Soft besiege |
| else if \( (r \geq 0.5 \text{ and } |E| < 0.5) \) then |
| Hard besiege |
| else if \( (r < 0.5 \text{ and } |E| \geq 0.5) \) then |
| Soft besiege with progressive rapid dives |
| else if \( (r < 0.5 \text{ and } |E| < 0.5) \) then |
| Hard besiege with progressive rapid dives |
| Return \( x_{\text{rabbit}} \) |

| Appendix A.2. Artificial Electric Field Algorithm |
|------------------------------------------------|
| Anita and Yadav [37] were inspired by Coulomb’s law of electrostatic force to create a novel artificial electric field algorithm. The concepts of electric field and charged particles provide us a strong theory for the working force of attraction or repulsion between two charged particles. The pseudo code of the AEFA algorithm is proposed in Algorithm A2. |

**Algorithm A2**: Pseudo code of AEFA

| Initialize a set of random population \( X^i_B = \{ X^1_B, X^2_B, \ldots, X^N_B \} \) of N size, within the limits |
|-------------------------------------------------------------|
| \( X^i_{\text{min}} \leq X^i_B \leq X^i_{\text{max}} \). |
| Initialize the velocity to a random value |
| Evaluate the fitness of whole population |
| Set the iteration to zero |
| Reproduction and Updating |
| While criteria not satisfied do |
| Calculate \( K(t) \), best (t) and worst (t) |
| for \( i = 1: N \) do |
| Calculate the fitness values |
| Calculate the total force in each direction |
| Calculate the acceleration |
| \( V_i(t + 1) = \text{rand}() \times V_i(t) + a_i(t) \) |
| \( X_i(t + 1) = X_i(t) + V_i(t + 1) \) |
| end for |
| end while |

| Appendix A.2.1. Invasive Weed Optimization Algorithm |
|------------------------------------------------|
| Invasive weed optimization is a numerical stochastic optimization algorithm inspired by colonizing weeds, which was introduced in 2006 by Mehrabian and Lucas [38]. In IWO, a certain number of weeds make up the |
whole population, and each weed comprises a set of decision variables. Weeds are a serious threat to desirable plants because they are plants that are invasive and hardy.

Weeds are plants which are vigorous and invasive; they pose a serious threat to desirable, cultivated plants in agriculture. Weeds have shown to be very robust and adaptive to change in the environment. The IWO optimization algorithm has been modeled based on four steps: initialization, reproduction, spatial dispersal and competitive exclusion.

- **Initialization and Production**

Firstly, the population is spread over the research space randomly; afterwards, each plant is allowed to produce seeds depending on its own fitness; the production of seeds is not only allowed for the better plants’ fitness as in the other evolutionary algorithms, but the reproduction step of IWO is also proposed to give a chance to infeasible individuals to survive and reproduce similar to the mechanism which occurs in nature. The weeds producing seeds can be formulated as follows:

\[
\text{Weed}_n = \frac{f - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}} (s_{\text{max}} - s_{\text{min}}) + s_{\text{min}} \quad (A1)
\]

where in each iteration, \( f \) is the current weed’s fitness. \( f_{\text{max}} \) and \( f_{\text{min}} \) represent the max and min fitness values, respectively. \( s_{\text{max}} \) and \( s_{\text{min}} \) represent the max and min values of the weeds, respectively.

- **Spatial Dispersal**

The generated seeds are being randomly distributed over the search space such that they abode near the parent plant. However, the standard deviation (\( \sigma \)) of the random function will be reduced in every iteration, the nonlinear alteration equation of the standard deviation at each iteration is presented as follows:

\[
\sigma_{\text{inter}} = \left( \frac{\text{iter}_{\text{max}} - \text{iter}}{\text{iter}_{\text{max}}} \right)^n (\sigma_{\text{initial}} - \sigma_{\text{final}}) + \sigma_{\text{final}} \quad (A2)
\]

where \( \text{iter}_{\text{max}} \) is the maximum iteration, \( n \) is the nonlinear modulation index, \( \sigma_{\text{initial}} \) and \( \sigma_{\text{final}} \) are the initial and final values of standard deviation, respectively.

- **Competitive Exclusion**

In a colony, the maximum number allowed of plants is limited; for that, competitive exclusion is applied. The plant that leave no offspring would go extinct; otherwise, they can survive. After some iterations, the number of plants in a colony will reach its maximum through the reproduction step, the seeds and their parents are ranked together, and all plants in the research space are considered as weeds; afterwards, weeds with lower fitness are eliminated.

The overall steps of the IWO algorithm are presented in Algorithm A3.

---

**Algorithm A3**: Pseudo code of IWO

- Initialize a set of random weeds, \( \text{weed}_B = (\text{weed}_B^1, \text{weed}_B^2, \ldots, \text{weed}_B^N) \) within the limits
  \( \text{weed}_{\text{min}}^B \leq \text{weed}_B^i \leq \text{weed}_{\text{max}}^B \).
- Set the IWO’s parameters
- Evaluate the objective function for all weeds
- While (\( \text{iter} < \text{iter}_{\text{max}} \))
  - Calculate the best and worst fitness in the colony
  - Calculate the \( \sigma \)
    - for each weed in the colony
  - Calculate the number of seeds following the fitness of each weed
  - Add the seeds to their parents in the colony
  - if \( \text{Size}_{\text{max}} \leq \text{N}_{\text{population}} \)
    - Sort the new population according to their fitness
    - Eliminate the worst fitness in order to achieve the \( \text{Size}_{\text{max}} \) allowed
  - end if
- Update iteration \( \text{iter} = \text{iter} + 1 \)
- end while
- Return the final best solution
References

1. Kharrich, M.; Mohammed, O.H.; Mohammed, Y.S.; Akherraz, M. A Review on Recent Sizing Methodologies for Hybrid Microgrid Systems. *Int. J. Energy Convers.* 2019, 7, 230–240. [CrossRef]

2. Babatunde, O.M.; Munda, J.L.; Hamam, Y. A Comprehensive State-of-the-Art Survey on Hybrid Renewable Energy System Operations and Planning. *IEEE Access* 2020, 8, 75313–75346. [CrossRef]

3. Khatib, H. IEA world energy outlook 2011—A comment. *Energy Policy* 2012, 48, 737–743. [CrossRef]

4. Zhang, W.; Maleki, A.; Rosen, M.A.; Liu, J. Optimization with a simulated annealing algorithm of a hybrid system for renewable energy including battery and hydrogen storage. *Energy* 2018, 163, 191–207. [CrossRef]

5. Diab, A.A.Z.; Sultan, H.M.; Mohamed, I.S.; Kuznetsov, O.N.; Do, T.D. Application of different optimization algorithms for optimal sizing of PV/wind/diesel/battery storage stand-alone hybrid microgrid. *IEEE Access* 2019, 7, 119223–119245. [CrossRef]

6. Diab, A.A.Z.; Sultan, H.M.; Kuznetsov, O.N. Optimal sizing of hybrid solar/wind/hydroelectric pumped storage energy system in Egypt based on different meta-heuristic techniques. *Environ. Sci. Pollut. Res.* 2019, 27, 1–23. [CrossRef]

7. Mohammed, O.; Amirat, Y.; Benbouzid, M.; Feld, G. Optimal Design and Energy Management of a Hybrid Power Generation System Based on Wind/Tidal/Pv Sources: Case Study for the Ouessant French Island. In *Smart Energy Grid Design for Island Countries*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 381–413.

8. Lian, J.; Zhang, Y.; Ma, C.; Yang, Y.; Chaina, E. A review on recent sizing methodologies of hybrid renewable energy systems. *Energy Convers. Manag.* 2019, 199, 112027. [CrossRef]

9. Rezk, H.; Al-Dhaifallah, M.; Hassan, Y.B.; Ziedan, H.A. Optimization and Energy Management of Hybrid Photovoltaic-Diesel-Battery System to Pump and Desalinate Water at Isolated Regions. *IEEE Access* 2020, 8, 102512–102529. [CrossRef]

10. Nandi, S.K.; Ghosh, H.R. Prospect of wind–PV-battery hybrid power system as an alternative to grid extension in Bangladesh. *Energy* 2010, 35, 3040–3047. [CrossRef]

11. Alshammari, N.; Asumadu, J. Optimum Unit Sizing of Hybrid Renewable Energy System Utilizing Harmony Search, Jaya and Particle Swarm Optimization Algorithms. *Sustain. Cities Soc.* 2020, 60, 102255. [CrossRef]
22. Das, A.K.; Pratihar, D.K. A New Bonobo Optimizer (BO) for Real-Parameter Optimization. In Proceedings of the 2019 IEEE Region 10 Symposium (TENSYMP), Kolkata, India, 7–9 June 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 108–113.

23. Kharrich, M.; Mohammed, O.H.; Akherraz, M. Assessment of Renewable Energy Sources in Morocco using Economical Feasibility Technique. Int. J. Renew. Energy Res. 2019, 9, 1856–1864.

24. Kharrich, M.; Mohammed, O.H.; Akherraz, M. Design of Hybrid Microgrid PV/Wind/Diesel/Battery System: Case Study for Rabat and Baghdad. EAI Endorsed Trans. Energy Web 2020, 7. [CrossRef]

25. Ramli, M.A.M.; Bouchekara, H.R.E.H.; Alghamdi, A.S. Optimal sizing of PV/wind/diesel hybrid microgrid system using multi-objective self-adaptive differential evolution algorithm. Renew. Energy 2018, 121, 400–411. [CrossRef]

26. Ghiasi, M. Detailed study, multi-objective optimization, and design of an AC-DC smart microgrid with hybrid renewable energy resources. Energy 2019, 169, 496–507. [CrossRef]

27. Movahediyan, Z.; Askarzadeh, A. Multi-objective optimization framework of a photovoltaic-diesel generator hybrid energy system considering operating reserve. Sustain. Cities Soc. 2018, 41, 1–12. [CrossRef]

28. Heydari, A.; Askarzadeh, A. Optimization of a biomass-based photovoltaic power plant for an off-grid application subject to loss of power supply probability concept. Appl. Energy 2016, 165, 601–611. [CrossRef]

29. Sultan, H.M.; Menesy, A.S.; Kamel, S.; Tostado-Véliz, M.; Jurado, F. Parameter Identification of Proton Exchange Membrane Fuel Cell Stacks Using Bonobo Optimizer. In Proceedings of the 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPES Europe), Madrid, Spain, 9–12 June 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–7.

30. Tizhoosh, H.R. Opposition-Based Learning: A New Scheme for Machine Intelligence. In Proceedings of the International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC’06), Vienna, Austria, 28–30 November 2005; IEEE: Piscataway, NJ, USA, 2005; pp. 6957–6961.

31. Roy, P.K.; Bhui, S. Multi-objective quasi-oppositional teaching learning based optimization for economic emission load dispatch problem. Int. J. Electr. Power Energy Syst. 2013, 53, 937–948. [CrossRef]

32. Sultana, S.; Roy, P.K. Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems. Int. J. Electr. Power Energy Syst. 2014, 63, 534–545. [CrossRef]

33. Sharma, S.; Bhattacharjee, S.; Bhattacharya, A. Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine for optimal allocation of DG in radial distribution network. Int. J. Electr. Power Energy Syst. 2016, 74, 348–373. [CrossRef]

34. Yu, J.; Kim, C.-H.; Rhee, S.-B. Oppositional Jaya Algorithm With Distance-Adaptive Coefficient in Solving Directional Over Current Relays Coordination Problem. IEEE Access 2019, 7, 150729–150742. [CrossRef]

35. Abd Elaziz, M.; Mirjalili, S. A hyper-heuristic for improving the initial population of whale optimization algorithm. Knowl. Based Syst. 2019, 172, 42–63. [CrossRef]

36. Heidari, A.A.; Mirjalili, S.; Faris, H.; Aljarah, I.; Mafarja, M.; Chen, H. Harris hawks optimization: Algorithm and applications. Future Gener. Comput. Syst. 2019, 97, 849–872. [CrossRef]

37. Yadav, A. AEFA: Artificial electric field algorithm for global optimization. Swarm Evol. Comput. 2019, 48, 93–108.

38. Mehrabian, A.R.; Lucas, C. A novel numerical optimization algorithm inspired from weed colonization. Ecol. Inform. 2006, 1, 355–366. [CrossRef]