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Optimal design of grid-connected hybrid renewable energy systems using multi-objective evolutionary algorithm

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Abstract. The optimal design of grid-connected Hybrid Renewable Energy Systems (HRESs) is studied by using multi-objective evolutionary algorithm in this paper. With the total system cost and fuel emissions to be minimized, a two-objective optimization model of the hybrid system is established. Then, a modified preference-inspired co-evolutionary algorithm is, for the first time, applied to find the optimal configuration of a grid-connected hybrid system. As an example, a grid-connected hybrid system, including PV panels, wind turbines, and diesel generators, has been designed and good results are obtained which show that the proposed method is effective.

1. Introduction

The rising energy consumption, the depletion of limited fossil fuels, and the increasing concern for global warming have enhanced the use of renewable energy sources, such as solar and wind energy. Renewable energy sources can decrease the dependence on conventional resources and reduce the greenhouse gas emissions, making them potential for electric power generation in the future. However, they are also unpredictable and intermittent, hindering their wide application in practice. A good solution to overcome the drawbacks of renewable sources is the appropriate design of a Hybrid Renewable Energy System (HRES), integrating various energy sources. Compared with single-source energy systems that include solar or wind energy alone, HRESs have many advantages, e.g. higher reliability, lower cost, and less fuel emissions.

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An HRES can operate in either Grid-Connected (GC) or Stand-Alone (SA) mode according to the availability of utility grid [1]. Stand-alone systems can generate electricity without utility grid, so that is why they are said to be stand-alone and, hence, they are suitable for remote areas where the grid is not available. Along with the prevalence of HRESs, an increasing number of studies about optimal HRES design have been reported in the literature. The optimal design of an HRES is a Multi-objective Optimization Problem (MOP) [2] in most cases, which is too complex to solve efficiently by traditional optimization methods. Hence, various evolutionary algorithms have been applied to optimally design the HRES with different objectives [3-9]. However, most of the present studies focus on stand-alone hybrid systems without considering the utility grid.

A grid-connected HRES is an independent power system connected to the electricity grid and the grid acts as a storage unit with unlimited capacity [1], so the battery storage device is unnecessary in this system. A grid-connected system is mainly used to cater to the local load demand, and surplus generation will be fed into the grid. Unlike the abundant number of literature reviews on stand-alone systems, there are only a few studies on grid-connected hybrid systems. Caballero et al. [10] proposed a method for the optimal business design of a small grid-connected hybrid PV-wind energy system aiming to minimize the life-cycle cost of the system under a certain level of reliability. In this method, the excess energy generated by the hybrid system is supplied to the grid at a fixed sale price or through a Net Metering scheme. Dalton et al. [11] studied a large-scale grid-connected hotel by an analysis of the technical and financial viability of different types of hybrid power supply configurations. They utilized the HOMER software to assess the net present cost, renewable fraction, and payback time of the system. Based on Particle Swarm Optimization (PSO), Pablo et al. [12] evaluated three Energy Management Systems (EMSs) of a grid-connected hybrid system for long-term optimization. The three EMSs try to seek the optimality of cost, efficiency, and lifetime, respectively. Lashkar et al. [13] proposed a multi-objective optimization methodology to solve the reactive power-planning problem in power system. They combined the ϵ-constraint approach, mixed integer non-linear programming model, and implemented simulation experiments to simultaneously optimize the objectives of total fuel cost, power losses, and system loadability. Bernal and Dufo [14] conducted an economic and environmental research on PV solar energy installations in a grid-connected system.

As a matter of fact, the optimal design of a grid-connected HRES is similar to that of a stand-alone system. The optimization objectives needed to be considered include the economic and environmental indexes, i.e., the cost and fuel emissions. Note that the cost here consists of the initial investment cost and the net cost of purchasing electricity which is equal to the total cost generated by purchasing the deficient energy from the grid minus total benefit from selling excess energy to the grid. In this paper, the total system cost and fuel emissions of one year as two objectives will be taken to establish a grid-connected hybrid system model including PV panels, wind turbines, and diesel generators. To find the optimal configuration of the hybrid system which is a MOP, the modified preference-inspired co-evolutionary algorithm using goal vectors (PICEA-g [15]) is adopted to solve the problem. PICEA-g has better performance than other classical Multi-Objective Evolutionary Algorithm (MOEA), such as NSGA-II [16] and MOEA/D [17]. Meanwhile, the modified PICEA-g has been testified to be effective, especially for bi-objective problems [18], and it is applied to size a grid-connected HRES for the first time in this study.

The rest of the paper is organized as follows. Section 2 describes the problem under consideration. The model of the studied hybrid system is established in Section 3. Section 4 introduces the optimization algorithm, i.e. modified PICEA-g. Experimental study is presented in Section 5, and finally, Section 6 concludes this paper.

2. Problem description

The considered grid-connected hybrid renewable energy system includes PV panels, wind turbines, diesel generators, accessory devices, and utility grid which can act as a back-up system. A particular configuration of the employed system is shown in Figure 1. According to this figure, the system energy flow can be explained as follows. The available energy generated by PV panels and wind turbines is directly used to cater to

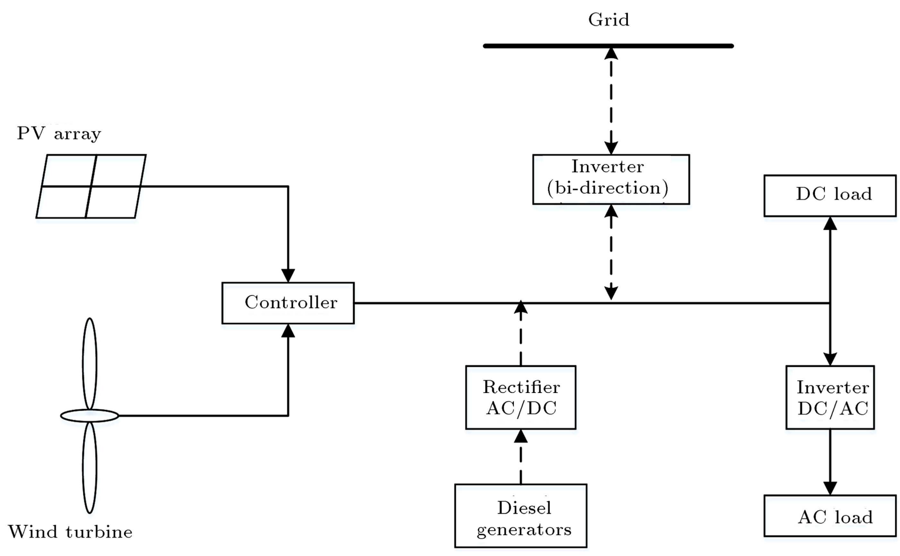

Figure 1. A grid-connected hybrid system configuration.

the load demand. When the power generation exceeds the power demand, the excess power will be fed into the utility grid; thus, it provides additional income for consumers by their surplus energy sales. On the contrary, when the energy from the renewable sources is not enough to satisfy the load demand, the diesel generators start to work. In case the diesel generators cannot meet the surplus load demand, the deficient electricity will be drawn from the grid resulting in an increase of system cost of purchasing electricity.

A grid-connected system may be vulnerable confronted by system abnormalities and a good system design needs to be stable and reliable. In this study, the power balance of the system will always be maintained as the grid faults, disturbances blackouts, or other equipment failures, which are out of consideration.

3. Modeling of the hybrid system

The mathematical model of the hybrid system can be established based on the problem description. It is essential to analyze individual components before constructing the model of their combination. In this section, we first analyze the main system components and establish their individual model including PV panels, wind turbines, and diesel generators, and then the optimization objectives and the system model are presented.

3.1. Mathematical models of system components

The utilization of solar energy includes primarily solar thermoelectric power generation and solar photovoltaic power generation. Although many studies have focused on solar thermoelectric power generation [19,20], photovoltaic generation is becoming prevalent owing to its economic and environmental advantages. Therefore, solar photovoltaic generation is considered in this study. Generally, the output power of PV panels depends mainly on the effective solar radiation, the characteristics, and the slope angle of the PV panel. Mathematically, the output of PV panels at an instant time t, considering that the ambient temperature can be calculated by the following equations [21]:

$$T_{\mathrm{C}}(t)=T_{\mathrm{A}}(t)+\frac{\mathrm{NCOT}-20}{800}S_{\mathrm{p}}(t,\beta), \tag{1}$$

$$I_{\mathrm{SC}}(t)=[I_{\mathrm{SC,STC}}+K_{\mathrm{I}}(T_{\mathrm{C}}(t)-25)]\frac{S_{\mathrm{p}}(t,\beta)}{1000}, \tag{2}$$

$$V_{\mathrm{OC}}(t)=V_{\mathrm{OC,STC}}-K_{\mathrm{V}}\cdot T_{\mathrm{C}}(t), \tag{3}$$

$$P_{\mathrm{M}}(t,\beta)=N_{\mathrm{PV}}\cdot V_{\mathrm{OC}}(t)\cdot I_{\mathrm{SC}},(t,\beta)\cdot FF(t), \tag{4}$$

where $T_C(t)$ and $T_A(t)$ are the cell temperature and ambient temperature at time t, respectively. NCOT is the Nominal Cell Operating Temperature provided by the manufacturer, $I_{\mathrm{SC,STC}}$ and $V_{\mathrm{OC,STC}}$ are the module short-circuit current and open-circuit voltage under Standard Test Conditions, and K_{I} and K_{V} are their corresponding temperature coefficients. $P_{\mathrm{M}}(t)$ is the power of a PV array consisting of N_{PV} PV panels, and FF(t) is the fill factor. β is the slope angle of the panel, S_{p} is the effective solar radiation perpendicular to the tilted panel and it is determined by the horizontal component of solar radiation (S) as follows [22].

$$S_{\mathrm{p}}=\frac{S}{\sin h}\cdot\sin(h+\beta), \tag{5}$$

$$\sin h=\sin\varphi\sin\delta+\cos\varphi\cos\delta\cos\tau, \tag{6}$$

where h is solar elevation angle, φ is geography of the latitude, τ is hour angle, δ is solar declination related to earth's inclination to the plane of its orbit and the daily time [6].

The output power of a wind turbine can be expressed by the following equation:

$$P_{\mathrm{WT}}(\nu,t)=\begin{cases}0, & \nu<V_{\mathrm{c}}\\ \frac{1}{2}C_{\mathrm{P}}\rho A_{\mathrm{WT}}\nu^3, & V_{\mathrm{c}}\leq\nu<V_{\mathrm{r}}\\ P_{\mathrm{WTR}}, & V_{\mathrm{r}}\leq\nu<V_{\mathrm{f}}\\ 0, & \nu\geq V_{\mathrm{f}}\end{cases} \tag{7}$$

where C_{p} is power coefficient of the wind turbine, ρ is the air density, A_{WT} is the rotor swept area, P_{WGR} is the rated power of the wind turbine, and ν is the wind velocity at hub elevation. Cut-in wind speed, V_{c}, and cut-off V_{f} wind speed are set as 4 m/s and 20 m/s, respectively. V_{r} is the rated wind speed taken as 14 m/s in this study [5].

Given wind speed ν_r at reference height H_{r} and the wind speed at the hub elevation of a wind turbine, H_{wg} can be calculated by the power law, which is widely used by the researchers:

$$\nu=\nu_{\mathrm{r}}\left(\frac{H_{\mathrm{wg}}}{H_{\mathrm{r}}}\right)^{\gamma}, \tag{8}$$

where γ is the wind speed power law coefficient and its value is usually set to be one-seventh of relatively flat surfaces.

The diesel generator acts as an emergency in case the power from renewable sources cannot meet the load demand. Its fuel consumption, F_{cons}, can be expressed by a linear function of the power output as follows [5]:

$$F_{\mathrm{cons}}=A_{\mathrm{dg}}P_{\mathrm{r\_dg}}+B_{\mathrm{dg}}P_{\mathrm{dg}}, \tag{9}$$

where $P_{\mathrm{r\text{-}dg}}$ and P_{dg} are the generator's rated and output powers, respectively, A_{dg} and B_{dg} are the coefficients of fuel consumption curve, and their values can be 0.08145 l/kW h and 0.246 l/kW h in this paper according to the references.

3.2. System optimization model

Based on the individual model of each component mentioned above, we can establish a bi-objective system optimization model. The objectives to be minimized in this paper are system total cost and fuel emissions. System total cost, C_{tot}, consists of two parts: the annualized cost (ACS) and net cost of purchasing electricity C_{grid}. ACS is the sum of annualized initial investment cost, (C_{ainv}), operation and maintenance cost (C_{aom}), and replacement cost (C_{arep}) of each component as follows [4]:

$$ACS = C_{\text{ainv}}(comps) + C_{\text{aom}}(comps) + C_{\text{arep}}(comps), \tag{10}$$

$$C_{\text{tot}} = ACS + C_{\text{grid}}, \tag{11}$$

where the components include PV panels, wind turbines, turbine towers, and diesel generators. These components usually have a long lifespan on the average; therefore, they need not to be replaced during the project lifetime of 25 years considered in this study.

As for the fuel emissions, the number of kg CO_2 is utilized as a measure. Both the diesel generators and power generation forming the grid will produce CO_2 in the system. The total fuel emissions are given by:

$$F_{\text{emission}} = \sum_{t=1}^{T} F_{\text{cons}}(t) \cdot Ef + Emission_{\text{grid}}, \tag{12}$$

where E_f is the emission factor depending on the characteristic of the diesel generator and fuel used, and its value is generally 2.5 kg/lit. $Emission_{\text{grid}}$ is the emissions produced by the power generation of the grid to supply the deficient load demand, that is to say, the more electricity is supplied by the grid, the more emissions are produced by the system.

Decision variables are composed of the number of PV panels, N_{pv}, the number of wind turbines, N_{wg}, the number of diesel generators, N_{dg}, PV panel slope angle, β, and turbine tower height, H_{wg}. Considering the constraints of decision variables and the objectives mentioned above, the multi-objective optimization problem, i.e. the system optimization model, can be expressed as follows:

$$\text{Min} \quad F_{\text{obj}} = (C_{\text{total}}, F_{\text{emission}}), \tag{13}$$

subject to

$$(N_{\text{pv}}, N_{\text{wg}}, N_{\text{dg}}) \geq 0, \tag{14}$$

$$H_{\text{low}} \leq H_{\text{wg}} \leq H_{\text{high}}, \tag{15}$$

$$0^\circ \leq \beta \leq 90^\circ, \tag{16}$$

where H_{low} and H_{high} are the wind turbine towers of lower and upper height limits (m). Additionally, the maximum values of N_{pv}, N_{wg}, and N_{dg} in the optimization process are set as 30, 20, and 10, respectively.

4. Optimization algorithm

The optimal design of a grid-connected hybrid system is a multi-objective constraint optimization problem, as shown in Eqs. (13)-(16). Traditional search and optimization approaches, such as Newton method, are no longer effective. Multi-Objective Evolutionary Algorithms (MOEAs) are well-suited for solving MOPs owing to their population-based nature which can find a set of trade-off solutions in a single run. Numerous MOEAs have been proposed over the past two decades and Preference-Inspired Co-Evolutionary Algorithm (PICEA) is one of them. According to the idea of PICEA, different preference sets might lead to different regions of a MOP's Pareto front. Therefore, a promising representative of the trade-off solutions (so-called Pareto front) can be achieved, if multiple specified sets of hypothetical preferences are evolved during the search process [15,23-25].

Preference-Inspired Co-Evolutionary Algorithms using goal vectors (PICEA-g) are instantiation of PICEA [15] and perform well on MOP benchmarks. Like most of evolutionary algorithms, PICEA-g consists of six steps: population initialization, population evaluation, fitness assignment, selection-for-survive, solution reproduction, and selection-for-variation. However, PICEA-g differentiates itself from others by its coevolution features. Specifically, two populations are evolved during the search, i.e. a population of preferences (goal vectors) and the usual population of candidate solutions. The preferences are mainly used to guide candidate solutions effectively towards the entire Pareto optimal front. Such an interaction is specifically realized in the fitness assignment procedure. A candidate solution gains fitness by meeting several goal vectors in objective space, but the fitness contribution has to be shared evenly with other solutions to satisfy the same goal vector. The goal vector will gain fitness only by being satisfied by a candidate solution; therefore, the more it is satisfied, the lower its fitness value is.

Although PICEA-g shows advantages over other evolutionary algorithms, the employed fitness assignment method is only weakly Pareto dominance compliant [15]. Thus, Shi et al. [18] proposed an enhanced fitness assignment method for PICEA-g. The new fitness assignment method considers both the explicit fitness value of goal vectors and the Pareto dominance rank of candidate solutions. This ensures that the dominated solutions will never have higher fitness than non-dominated solutions. The modified PICEA-g with enhanced fitness assignment method (termed as PICEA-ng) has been demonstrated effective and more details can be found in [18].

The PICEA-ng is implemented within a $(\mu + \lambda)$ elitist approach as shown in Figure 2. First, a

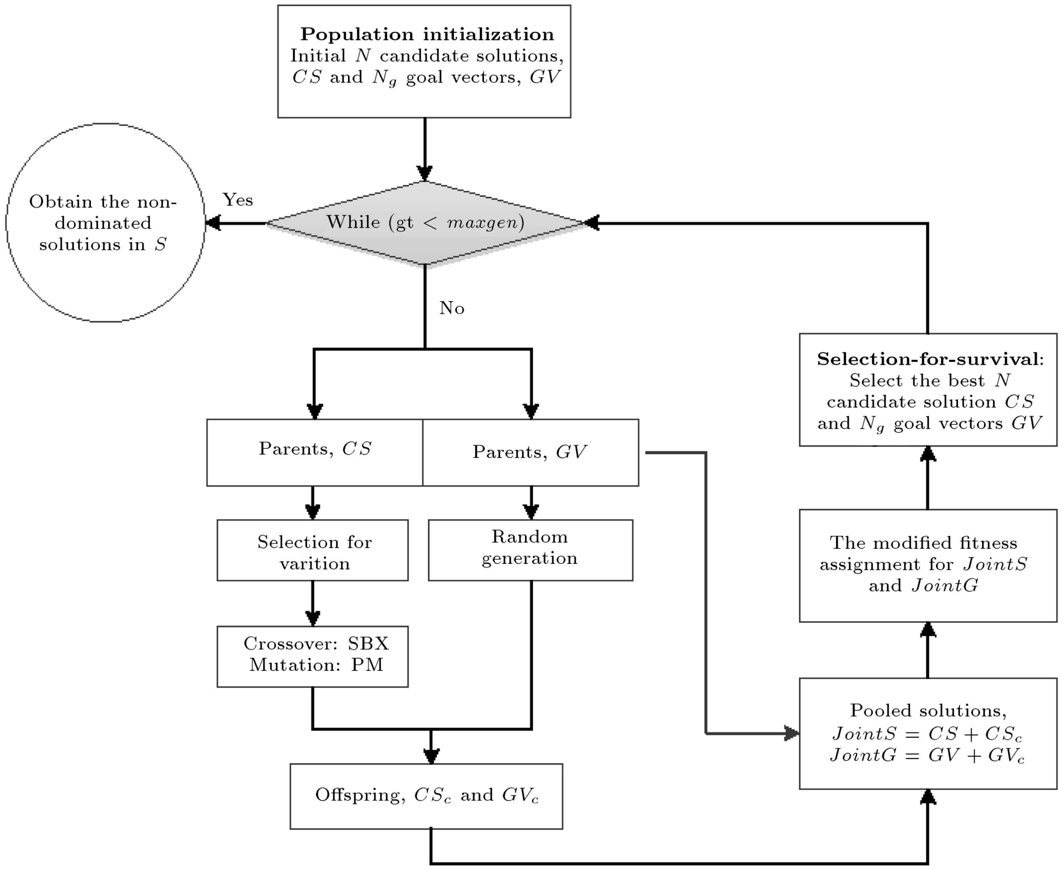

Figure 2. $\mu + \lambda$ elitist approach [13].

population of N candidate solutions, CS, and a set of N_{goal} goal vectors, GV, are initialized. The two populations are then co-evolved for $maxGen$ generations. In each generation, gt and parents CS(gt) will be paired up to produce N offspring, CS_{c}(gt), by genetic operators (specifically, the simulated binary crossover (SBX) and Polynomial Mutation (PM) operators [16]). Meanwhile, N_{g}, new goal vectors, and GV_{c}(gt) are randomly re-generated according to the pre-defined bounds. Since, in the algorithm, all solutions are normalized within [0,1], the goal vector bounds can be set as [1.2,1.2,...,1.2]. Then, CS(gt) and CS_{c}(gt) as well as GV(gt) and GV_{c}(gt) are pooled, respectively. The combined population will be sorted based on their fitness value, respectively. Finally, the same number of individuals with the parent population is selected by the truncation selection as the new parent populations [15].

PICEA-g algorithm is applied to address the MOP mentioned above. The chromosome of a candidate solution is composed of five genes in the form: $[N_{\text{pv}}|N_{\text{wg}}|N_{\text{dg}}|H_{\text{wg}}|\beta]$. In the optimization process, round operation is conducted to keep the number of system devices as integer ones. General parameter settings are given in Table 1, where p_{c} is recombination probability, p_{m} is mutation probability, η_{c} and η_{m} are distribution indices for SBX and PM operators, respectively. $nvar$ is the number of decision variables. In this study, $nvar = 5$. The values of these parameters are set based on previous literature.

Table 1. General parameter settings.

N	N_g	$MaxGen$	p_{c} (SBX)	η_{c} (SBX)	p_{m} (PM)	η_{m} (PM)
50	50	100	1	15	$1/nvar$	20

5. Experimental study

As an example of application, the optimal design of a grid-connected hybrid system to supply power for an area in Spain (latitude 41.65°) is carried out in this section. First, the input data are introduced to conduct the experiment. Then, experimental results and analyses are presented.

5.1. Input data

The input data set includes the hourly solar irradiation on horizontal surface, the hourly mean values of wind speed and ambient temperature, the hourly load demand during one year, and the specifications of system

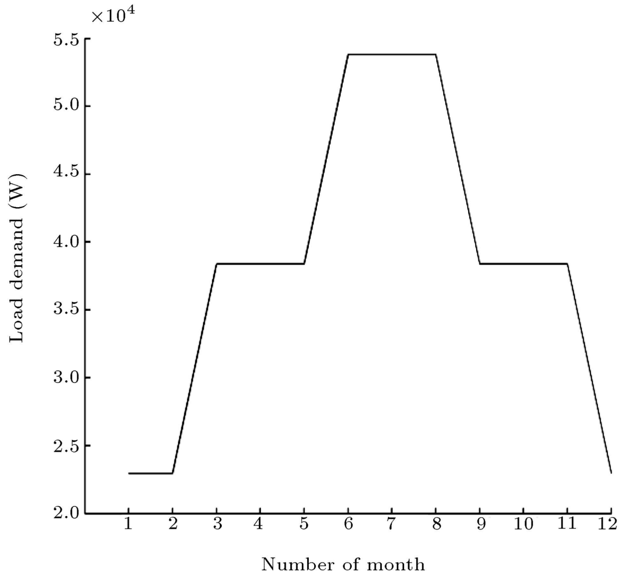

Figure 3. Monthly average load profile.

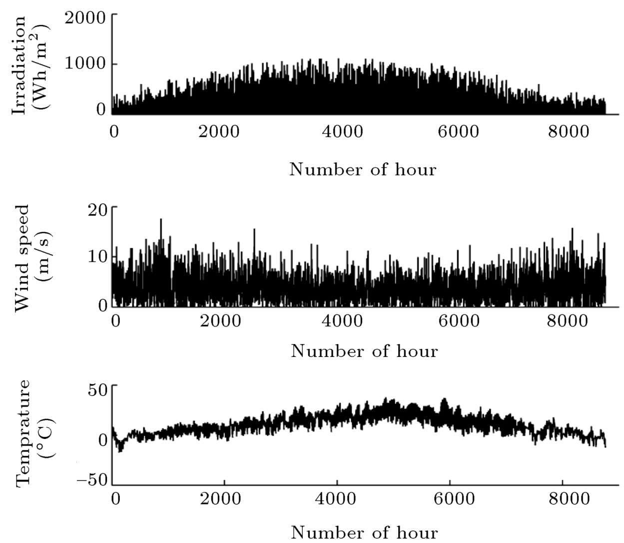

Figure 4. Hourly meteorological data.

components as shown in Figures 3 and 4 and Tables 2 and 3. The load (only DC load is considered here), solar radiation, and wind speed are assumed to be constant during the simulation time step of one hour [26].

The hourly mean values of solar irradiation and wind speed data at 10 meters height as well as the ambient temperature in Figure 4 are the average data of the last ten years [6]. The technical characteristics of system components are given in Tables 2 and 3, where initial investment cost, C_{inv}, and operation and maintenance cost, C_{om}, are used to calculate ACS. WT tower stands for wind turbine tower.

Additionally, the limit of turbine tower height is between 5 and 30 meters, the rotor length is 2 meters, and the rated power is 8892 W. As for the diesel

Table 2. PV panels specifications.

V_{oc} (V)	I_{sc} (A)	$V_{\max}$ (V)	$I_{\max}$ (A)	NCOT (°C)
21	7.22	17	6.47	43

Table 3. The cost specifications of system components.

Item	Initial investment cost C_{inv}	Maintenance cost C_{om}	Lifetime (year)
PV panel	3000 $	30 $	25
Wind turbine	3013 $	50 $	25
WT tower	250 $/m	2.5 $/m	25
Diesel generator	1514 $	0.17 $/h	25

generator, its rated power is 2 kW and its C_{om} is related to the operation time. In addition, the efficiency of the inverter is set to be 90%. The nominal interest rate and annual inflation rate considered are 3.75% and 1.5%, respectively. The fuel price used by the diesel generator is 1.2 $/lit [26]. The prices of selling electricity back to the grid and buying electricity from it are assumed to be equal and they are both 0.1/$kW h. The produced equivalent CO_2 emissions are set as 0.5 kg per unit power, when we purchase electricity from the grid in this study.

5.2. Results

With the input data, the PICEA-ng algorithm has been applied to address the optimization problem. The optimization result is shown in Figure 5, which is the representation of the last generation in objective space. As can be observed from the result, the total system cost and fuel emissions have a significant

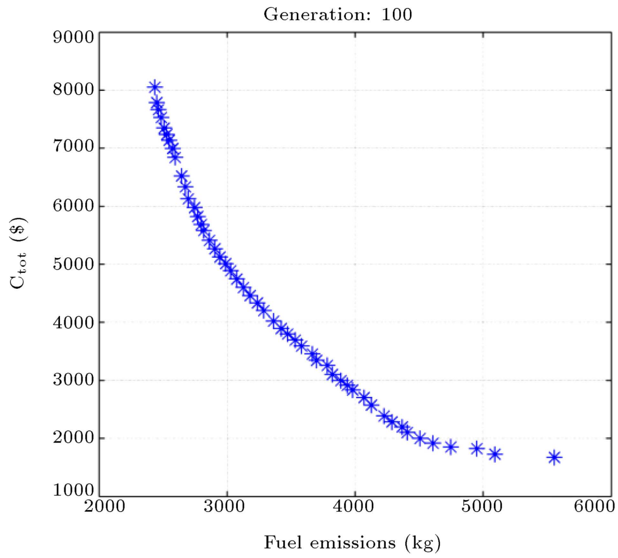

Figure 5. Pareto front of the last generation.

Table 4. Three typical optimal solutions.

Solution	N_{pv}	N_{wg}	N_{dg}	H_{wg}	β	F_{emission}(kg)	C_{tot} ($)
1	30	10	0	26.10	47.29	2434.79	8051.49
2	3	7	0	19.83	57.63	3978.92	2835.72
3	0	1	0	25.53	56.10	5555.77	1675.14

negative relationship, i.e. a more cost-effective system will produce more fuel emissions.

Along with the obtained Pareto set, a decision-maker has to select a suitable solution by incorporating his/her *a posteriori* preference information. As an example, three typical solutions are selected from the Pareto set according to the fuel emissions objective (the minimal, medium, and maximum one) as shown in Table 4.

Compared with the previous work [26], this paper studied a grid-connected hybrid renewable energy system using the modified PICEA-g algorithm. In the grid-connected hybrid system, the utility grid serves as the storage device, so that the battery bank can be excluded. Although the system model and objectives are different, good results of the problems by means of the preference-inspired co-evolutionary approach are obtained. It is worthy to note that the number of diesel generators is zero in the grid-connected system configurations, i.e. there is no diesel generators in the optimal configurations. The reason may be that the cost of diesel generators is high, and they emit too many greenhouse gases compared with acquiring the same electricity from the grid.

6. Conclusions

The modified Preference-Inspired Co-Evolutionary Algorithm (PICEA-ng), which has high performance and simplicity compared with other evolutionary algorithms, has been used for the first time to the optimal design of grid-connected hybrid renewable energy systems in this article. With simultaneous minimization of total system cost and fuel emissions, we established the grid-connected system model, which is a two-objective optimization problem. As a case study, a grid-connected hybrid system, including PV panels, wind turbines, and diesel generators, has been designed to find the optimal configuration and good results are obtained by the proposed method.

It is worth mentioning that the optimization model is limited to a static environment, where some noisy parameters can be considered in the input data or objective functions to describe uncertain problems for future research. Moreover, various prices of selling the excess power back to the grid and buying the electricity from the grid might be considered to study their influence on the optimal design of a grid-connected hybrid system. Lastly, other advanced evolutionary algorithms, e.g. [27,28,29], can be employed to solve the optimal design of HRES. In another aspect, the problem itself can be formulated as a standard multi-objective problem to benchmark the performance of different multi-objective evolutionary algorithms.

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