PSO-Based Multi-Criteria Optimum Design of A Grid-Connected Hybrid Power System With Multiple Renewable Sources of Energy

Lingfeng Wang and Chanan Singh

Department of Electrical and Computer Engineering Texas A&M University College Station, TX 77843-3128 Emails: l.f.wang@ieee.org, singh@ece.tamu.edu

Abstract—With the stricter environmental regulation and diminishing fossil-fuel reserve, various renewable sources of energy are being exploited recently. These alternative sources of energy are usually environmentally friendly and emit no pollutants. However, the capital investments for those renewable sources of energy are normally high and there are also maintenance cost differences to be considered. Furthermore, due to the variability of these power sources, reliability issues should be addressed when integrating different power sources. In this paper, a grid-connected hybrid generating system comprising wind turbine generators, photovoltaic panels, and storage batteries is designed. In this multi-source generation system design, three design objectives are considered, that is, costs, reliability, and pollutant emissions. Considering the complexity of this problem, we have developed a multi-objective particle swarm optimization (MOPSO) algorithm to derive a set of non-dominated solutions, each of which represents a candidate system design. A numerical example is discussed to illustrate the design procedure and the simulation results are analyzed.

I. INTRODUCTION

Distributed generation (DG) differs significantly from the conventional large-scale, centrally located power plants [9, 12, 27]. DG is usually located near the point of power consumption while central generation system is most often away from where the power is used. DG is generally operated as a complement to the conventionally supplied power and it defers investments on the expansion of existing transmission and distribution capacity. DG using renewables is also able to help to reduce the pollutant emissions from power industry and improve the security of the global energy supply [1-8, 10, 19, 22, 24, 25, 28]. However, they also have certain drawbacks. They need high capital investments and also bring about reliability concerns due to their undispatchability. For instance, the generation of both wind power and solar power is very dependent on the weather conditions, which are difficult to be precisely forecasted. Since no single source of energy is capable of supplying cost-effective, clean, and reliable power so far, the combined use of multiple power sources can be a viable way to achieve tradeoff solutions in terms of costs, emissions, and reliability. Proper integrated resource planning (IRP) is crucial to achieve a cost-effective, clean, and reliable generation system. Hybrid power generation is a promising solution for this purpose and several such hybrid systems have already been built and are now in stable practical operations [13-15, 23]. In this study, we intend to design a grid-connected hybrid generating system which includes renewable sources of energy such as wind turbine generators, solar photovoltaic panels, and storage batteries. The power of utility grid is dispatchable and may also be relatively inexpensive, but will cause significant pollutant emissions and thus incur environmental concerns. On the contrary, the renewable sources of power are clean but they cannot be accurately predicted and are not always available due to their intermittent nature [21, 29]. The adoption of renewable generation technologies poses risks of compromising system reliability if the multiple power sources cannot be managed in an appropriate manner. Thus, through utilization of their respective merits, a reasonably designed system may be obtained. Furthermore, to achieve a reasonable compromise between these three design objectives, we propose a multi-objective particle swarm optimization (MOPSO) algorithm to handle the problem. PSO is especially suited to deal with complex engineering designs due to its fast convergence performance and simple operations. The standard PSO is extended to solve the multi-objective optimization problem.

The remainder of the paper is organized as follows. Section II introduces the characteristics of different energy resources. Section III formulates the hybrid system design problem including its multiple objectives coupled with a set of design constraints. The operation strategy is discussed in Section IV. Section V introduces the mechanism of particle swarm optimization algorithms. The proposed MOPSO algorithm is detailed in Section VI. Simulation results and analysis are presented in Section VII. Finally, conclusions are drawn and future research directions are outlined.

II. GRID-CONNECTED HYBRID GENERATION SYSTEMS

As shown in Figure 1, the grid-connected hybrid generation system comprises different power sources including the traditional fuel-fired generators (FFGs), wind turbine generators (WTGs), PV panels (PVs), and storage batteries (SBs). These power sources have different impacts on cost, environment, and reliability. In a hybrid generation system, they are integrated together and complement one another in order to serve the load while satisfying certain economical, environmental, and reliability criteria.

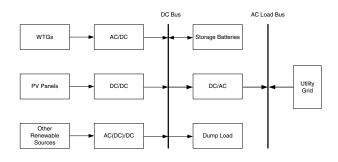


Fig. 1. Configuration of a typical grid-linked hybrid generation system.

A. Fuel-Fired Generators (FFGs)

In the traditional fuel-fired generators (FFGs), pollutant emissions are the major drawback. For instance, coal has been a reliable, abundantly available, and relatively inexpensive fuel source, but coal-fired power generation is facing increasing pressure since environmental regulations are becoming more stringent than ever around the world. Affordable control scheme for air pollution reduction is a deciding factor in fossil fuels' continued role as a major power source in power generation industry. As a result, combined use of fuel sources and other cleaner sources may be a viable way to abate pollutant emissions while still fulfilling certain cost and reliability requirements. In the restructured power market, distributed generation using renewable sources of energy is being connected to the utility grid at the distribution level attempting to diminish the demerits in traditional central generation plants. Renewable power sources are promising to play an important role in complementing the fossil-fuel-fired generation by reducing its negative environmental impacts.

B. Wind Turbine Generators (WTGs)

The average US wind energy growth rate for the past five years is 24%. Wind turbine generators (WTGs) are powered by windmills and they are usually operated by utilities and independent power producers (IPPs). They are located in areas with rich wind resources (both onshore and offshore), and wind power is a type of clean energy. Thus, effective utilization of wind energy is particularly attractive in spurring the reduction of pollutant emissions, which is a major drawback in the traditional fossil-fuel-based generation. However, the availability of wind power is primarily determined by the weather conditions and thus it is quite fluctuating in a year or even in a day. The volatility of wind power should be addressed when designing a renewable-based power plant. In our investigation, other power sources are also used in order to mitigate or even out the fluctuations caused by the intermittency of wind power.

C. Photovoltaic cells (PVs)

Sunlight can be directly converted into electric energy by PV panels. Like the wind power, the production of a solar system is also influenced considerably by the varying meteorological conditions. Because of its nature of intermittency, to continuously supply power, other supplemental power sources such as storage batteries are usually needed. PV panels produce no direct emissions and can be considered as environmentally friendly. The advance of manufacturing technologies has made the cost of PV system significantly reduced and PVs also have lower maintenance demands.

D. Storage Batteries (SBs)

Since both wind and PVs are intermittent sources of power, it is highly desirable to incorporate energy storage into such hybrid power systems. Energy storage can smooth out the fluctuation of wind and solar power and improve the load availability [2]. In a certain sense, storage batteries can be deemed as a buffer to balance the supply and demand relationship. When the power generated by WTGs and PVs exceeds the load demand, the surplus power will be stored in the batteries for future use. On the contrary, when there is any deficiency in the overall power generation, the stored power will be used to supply the load so as to enhance the system reliability. Energy storage reduces the power dumped and thus helps to minimize the operational cost.

Optimum generation mix is crucial to achieve an economically viable, environmentally friendly, and operationally reliable hybrid generation system.

III. PROBLEM FORMULATION

The objective of this study is to achieve a grid-linked hybrid generation system, which should be appropriately designed in terms of economic, reliability, and environmental measures subject to physical and operational constraints/strategies [4, 5, 14, 15].

A. Design objectives

• Objective 1: Costs [4, 5, 14, 15]

The total cost COST(\$/year) includes initial cost, operational and maintenance (OM) cost for each type of power source, and the salvage value of each equipment should be deducted:

$$COST = \frac{\sum_{i=w,s,b} (I_i - S_{P_i} + OM_{P_i})}{N_p} + C_g \quad (\text{III.1})$$

where w, s, b indicate the wind power, solar power, and battery storage, respectively; I_i , S_{P_i} , OM_{P_i} are the initial cost, present worth of salvage value, and present worth of operation and maintenance cost for equipment *i*, respectively; $N_p(year)$ is the life span of the project; and C_g is the annual costs for purchasing power from the utility grid. Here we assume that the life time of the project does not exceed those of both WTGs and PV arrays. 1) For the WTGs,

$$I_w = \alpha_w A_w \tag{III.2}$$

where $\alpha_w(\$/m^2)$ is the initial cost of WTGs; the present worth of the total salvage value is

$$S_{P_w} = S_w A_w (\frac{1+\beta}{1+\gamma})^{N_p} \tag{III.3}$$

where $S_w(\$/m^2)$ is the salvage value of WTGs per square meter, β and γ are the inflation rate and interest rate, respectively; the present worth of the total operation and maintenance cost (OM) in the project life time is

$$OM_{P_w} = \alpha_{OM_w} * A_w * \sum_{i=1}^{N_p} (\frac{1+\nu}{1+\gamma})^i$$
 (III.4)

where $\alpha_{OM_w}(\$/m^2/year)$ is the yearly OM cost per unit area and ν is the escalation rate.

2) For the PV panels, the initial cost is

$$I_s = \alpha_s A_s \tag{III.5}$$

where $\alpha_s(\$/m^2)$ is the initial cost; the present worth of the total salvage value is

$$S_{P_s} = S_s A_s (\frac{1+\beta}{1+\gamma})^{N_p} \tag{III.6}$$

where $S_s(\$/m^2)$ is the salvage value of PVs per square meter of PV panels; the present worth of the total operation and maintenance cost (OM) in the project life time is

$$OM_{P_s} = \alpha_{OM_s} * A_s * \sum_{i=1}^{N_p} (\frac{1+\nu}{1+\gamma})^i$$
 (III.7)

where $\alpha_{OM_s}(\$/m^2/year)$ is the yearly OM cost per unit area and ν is the escalation rate.

3) For the storage batteries, since their life span is usually shorter than that of the project, the total present worth of capital investments can be calculated as follows:

$$I_b = \alpha_b * P_{b_{cap}} * \sum_{i=1}^{X_b} (\frac{1+\nu}{1+\beta})^{(i-1)N_b}$$
(III.8)

where N_b is the life span of SBs; X_b is the number of times to purchase the batteries during the project life span N_p ; the salvage value of SBs is ignored in this study; and the present worth of the total OM cost in the project life time is calculated as follows:

$$OM_{p_b} = \alpha_{OM_b} * P_{b_{cap}} * \sum_{i=1}^{N_p} (\frac{1+\nu}{1+\gamma})^i$$
(III.9)

where $\alpha_{OM_b}(\$/kWh/year)$ is the yearly OM cost per kilowatthour.

4) The annual cost for purchasing power from the utility grid can be calculated as follows:

$$C_g = \sum_{t=1}^{T} P_{g,t} * \varphi \tag{III.10}$$

where $P_{g,t}(kW)$ is the power purchased from the utility at hour t; $\varphi(\$/kWh)$ is the grid power price; and T (8760 hours) is the operational duration under consideration. Objective 2: Reliability

Reliability is used to assess the quality of load supply. Here Energy Index of Reliability (EIR) is used to measure the reliability of each candidate hybrid system design [4, 5, 14, 15]. EIR can be calculated from Expected Energy Not Served (EENS) as follows:

$$EIR = 1 - \frac{EENS}{E}$$
(III.11)

The EENS(kWh/year) for the duration under consideration T(8760hours) can be calculated as follows:

$$EENS = \sum_{t=1}^{T} (P_{b_{min}} - P_{b_{soc}}(t) - P_{sup}(t)) * U(t)$$
(III 12)

where U(t) is a step function, which is zero when the supply exceeds or equals to the demand, and equals to one if there is insufficient power in period t; $P_d(t)$ is the load demand during hour t, $P_{sup}(t) = P_{total}(t) - P_d(t)$ is the surplus power in hour t, $P_{total}(t)$ is the total power from WTGs, PVs, and FFGs during hour t:

$$P_{total}(t) = P_w(t) + P_s(t) + P_q(t)$$
 (III.13)

 $P_{b_{soc}}(t)$ is the battery charge level during hour t, and $P_{b_{min}}$ is the minimum permitted storage level, the term $P_{b_{soc}}(t) - P_{b_{min}}$ indicates the available power supply from batteries during hour t; and provided that there is insufficient power in hour t,

$$P_g(t) = \kappa * (P_d(t) - P_w(t) - P_s(t) - P_b(t)) \quad \text{(III.14)}$$

where $\kappa \in [0, 1]$ indicates the portion of purchased power with respect to the hourly insufficient power; or else, $P_g(t) = 0$. Note that no generator failures and unexpected load deviations are considered in calculating the EENS, which in this study is all contributed by the fluctuations of renewable power generation.

• Objective 3: Pollutant emissions

With the increasing concerns on environment protection, there are stricter regulations on pollutant emissions. The most important emissions considered in the power generation industry due to their highly damaging effects on the ecological environment are sulfur dioxide (SO_2) and nitrogen oxides (NO_x) . These emissions can be modeled through functions that associate emissions with power production for generating units. They are dependent on fuel consumption and take the quadratic form:

$$PE = \alpha + \beta * \sum_{t=1}^{T} P_{g,t} + \gamma * (\sum_{t=1}^{T} P_{g,t})^2 \quad \text{(III.15)}$$

where α , β , and γ are the coefficients approximating the generator emission characteristics.

B. Design constraints

Due to the physical or operational limits of the target system, there is a set of constraints that should be satisfied throughout system operations for any feasible solution [4, 5, 14, 15].

• Constraint 1: Power balance constraint

For any period t, the total power supply from the hybrid generation system must supply the total demand P_d with a certain reliability criterion. This relation can be represented by

$$P_w(t) + P_s(t) + P_b(t) + P_g(t) \ge (1 - R)P_d(t) \quad \text{(III.16)}$$

$$P_w(t) + P_s(t) + P_b(t) + P_g(t) - P_{dump}(t) \le P_d(t) \quad \text{(III.17)}$$

where P_w , P_s , P_b , P_g , $P_{dump}(t)$, and P_d are the wind power, solar power, charged/discharged battery power, power bought from grid, dumped power, and total load demand, respectively; R is the ratio of the maximum permissible unmet power with respect to the total load demand in each time instant. The transmission loss is not considered in this investigation.

The output P_{WTG} (kW/m^2) from WTGs for wind speed V can be calculated as

$$P_{WTG} = \begin{cases} 0, & V < V_{ci} \\ a * V^3 - b * P_r, & V_{ci} \le V < V_r \\ P_r, & V_r \le V \le V_{co} \\ 0 & V > V_{co} \end{cases}$$
(III.18)

where $a = \frac{P_r}{V_r^3 - V_{ci}^3}$, $b = \frac{V_{ci}^3}{V_r^3 - V_{ci}^3}$, P_r is the rated power, V_{ci} , V_r , and V_{co} are the cut-in, rated, and cut-out wind speed, respectively. The real electric power from WTGs can be calculated as follows:

$$P_w = P_{WTG} * A_w * \eta_w \tag{III.19}$$

where A_w is the total swept area of WTGs and η_w is the efficiency of WTGs.

The output power ${\cal P}_s(kW)$ from PV panels can be calculated as follows:

$$P_s = H * A_s * \eta_s \tag{III.20}$$

where $H(kW/m^2)$ is the horizontal irradiance, A_s is the PV area, and η_s is the efficiency of PV panels.

Constraint 2: Bounds of design variables

The swept area of WGTs should be within a certain range:

$$A_{w_{min}} \le A_w \le A_{w_{max}} \tag{III.21}$$

Likewise, the area of PV arrays also has its upper and lower bounds:

$$A_{s_{min}} \le A_s \le A_{s_{max}} \tag{III.22}$$

The state of charge (SOC) of storage batteries $P_{b_{soc}}$ should not exceed the capacity of storage batteries $P_{b_{cap}}$ and should be larger than the minimum permissible storage level $P_{b_{min}}$; the total SB capacity should not exceed the allowed storage capacity $P_{b_{cap}max}$; and the hourly charge or discharge power P_b should not exceed the hourly inverter capacity $P_{b_{max}}$. As a result,

$$P_{b_{min}} \le P_{b_{soc}} \le P_{b_{cap}} \tag{III.23}$$

$$0 \le P_{b_{cap}} \le P_{b_{cap}max} \tag{III.24}$$

$$P_b \le P_{b_{max}} \tag{III.25}$$

The amount of power bought from utility grid annually should be within a certain range:

$$P_{g_{min}} \le \sum_{t=1}^{T} P_{g,t} \le P_{g_{max}} \tag{III.26}$$

where $P_{g_{min}}$ and $P_{g_{max}}$ are the minimum and maximum annual power allowed to be bought from the utility grid, respectively.

The coefficient κ indicates the portion of purchased power from utility grid with respect to the insufficient power:

$$0 \le \kappa \le 1 \tag{III.27}$$

C. Problem statement

In summary, the objective of optimum design for renewable hybrid generation system is to simultaneously minimize $COST(A_w, S_w, P_{b_{cap}}, \kappa)$ and $PE(A_w, S_w, P_{b_{cap}}, \kappa)$, as well as maximize $EIR(A_w, S_w, P_{b_{cap}}, \kappa)$, subject to the constraints (III.16)–(III.27). The design parameters that should be derived include WTG swept area $A_w(m^2)$, PV area $A_s(m^2)$, total battery capacity $P_{b_{cap}}(kWh)$, and the portion of the power purchased from grid with respect to the insufficient power κ .

IV. OPERATION STRATEGY

The power outputs from WTGs and PVs have the highest priorities to feed the load. Only if the total power from wind and solar systems is insufficient to satisfy the load demand, the storage batteries can be discharged a certain amount of energy to supply the load. If there is still no enough power to supply the load, a certain amount of power will be purchased from the utility grid. That is, the grid power has the lowest priority to feed the load. Furthermore, if there is any excess power from WTGs and PVs, the batteries will be charged to store a certain permissible amount of energy for future use.

V. MECHANISM OF PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a population-based stochastic optimization procedure inspired by certain social behaviors in bird groups and fish schools [16, 18]. First a population of particles is randomly generated with initial speeds and positions. By utilizing the best positions encountered by itself and its neighbors, each particle updates its position according to its own flight experience and that of its companions.

Assume x and v denote a particle position and its speed in the search space. Therefore, the *i*-th particle can be represented as $x_i = [x_{i_1}, x_{i_2}, \dots, x_{i_d}, \dots, x_{i_M}]$ in the *M*-dimensional space. Each particle continuously records the best solution it has achieved thus far during its flight. This fitness value of the solution is called *pbest*. The best previous position of the *i*-th particle is memorized and represented as $pbest_i =$ $[pbest_{i_1}, pbest_{i_2}, \ldots, pbest_{i_d}, \ldots, pbest_{i_M}]$. The global best *gbest* is also tracked by the optimizer, which is the best value achieved so far by any particle in the swarm. The best particle of all the particles in the swarm is denoted by *gbest_d*. The velocity for particle *i* is represented as $v_i =$ $(v_{i_1}, v_{i_2}, \ldots, v_{i_d}, \ldots, v_{i_M})$. The velocity and position of each particle can be continuously adjusted based on the current velocity and the distance from $pbest_{i_d}$ to $gbest_d$:

$$\begin{aligned} v_{i_d}^{(t+1)} &= \chi * (w * v_{i_d}^{(t)} + c_1 * \operatorname{rand}() * (pbest_{i_d} - x_{i_d}^{(t)}) \\ &+ c_2 * \operatorname{Rand}() * (pbest_d - x_{i_d}^{(t)})), \end{aligned}$$
 (V.28)

$$x_{i_d}^{(t+1)} = x_{i_d}^{(t)} + v_{i_d}^{(t+1)}, i = 1, 2, \dots, N, d = 1, 2, \dots, M.$$
(V.29)

where N is the number of particles in a swarm, M is the number of members in a particle, t is the counter of generations, $\chi \in [0, 1]$ is the constriction factor which controls the velocity magnitude, w is the inertia weight factor, c_1 and c_2 are acceleration constants, rand() and Rand() are uniform random values in a range [0, 1], $v_i^{(t)}$ is the velocity of particle i in generation t, and $x_i^{(t)}$ is the current position of particle i in generation t.

VI. THE PROPOSED APPROACH

In this study, a Constrained Mixed-Integer Multi-Objective PSO (CMIMOPSO) is developed to derive a set of nondominated solutions by appropriately combining different sources of energy subject to certain constraints.

A. CMIMOPSO

• Mixed-integer PSO: Since the target problem involves the optimization of system configuration, integer numbers are used to indicate the unit sizing. The standard PSO is in fact a real-coded algorithm, thus some revisions are needed to enable it to deal with the binary-coded optimization problem. In the discrete binary PSO [17], the relevant variables are interpreted in terms of changes of probabilities. A particle flies in a search space restricted to zero and one in each direction and each v_{i_d} represents the probability of member x_{i_d} taking value 1. The update rule governing the particle flight speed can be modified accordingly by introducing a logistic sigmoid transformation function:

$$S(v_{i_d}) = \frac{1}{1 - e^{-v_{i_d}}}$$
(VI.30)

The velocity can be updated according to this rule: If $rand() < S(v_{id})$, then $x_{id} = 1$; or else $x_{id} = 0$. The maximum allowable velocity V_{max} is desired to limit the probability that member x_{id} will take a one or zero value. The smaller the V_{max} is, the higher the chance of mutation is for the new individual.

- · Multi-objective PSO: In this study, since a multiobjective optimization problem is concerned, the standard PSO algorithm is also modified accordingly to facilitate a multi-objective optimization approach, i.e., multi-objective particle swarm optimization (MOPSO). The Pareto-dominance concept is used to appraise the fitness of each particle and thus determine which particles should be chosen as the non-dominated solutions [7, 11, 20]. For this purpose, the archiving mechanism is used to store the non-dominated solutions throughout the optimization process. The best historical solutions found by the optimizer are absorbed continuously into the archive as the non-dominated solutions generated in the past. Furthermore, to enhance the solution diversity, some diversity preserving measures such as fuzzified global best selection, niching and fitness sharing, and turbulence are taken [26]. For instance, a fuzzification mechanism is adopted for the selection of global best position *gbest*. Here initially *abest* is not interpreted as a point but as an area, and each point in the area has different possibilities of being chosen as the gbest. The fuzzification formula used for this purpose is $N(gbest, std^2)$, which represents a set of normally distributed particles with *qbest* as their mean value and std as standard deviation.
- Constrained PSO: In the proposed method, a natural constraint checking procedure called rejecting strategy is adopted to deal with the imposed constraints. When an individual is evaluated, the constraints are first checked to determine if it is a feasible candidate solution. If it satisfies all of the constraints, it is then compared with the non-dominated solutions in the archive. The concept of Pareto dominance is applied to determine if it is eligible to be chosen to store in the archive of non-dominated solutions. As long as any constraint is violated, the candidate solution is deemed infeasible. This procedure is simple to implement but it turned out to be quite effective in ensuring solution feasibility while not significantly slowing down the search.

B. Representation of candidate solutions

The design variables including WTG swept area, PV area, portion of power purchased from the grid, and total SB capacity are encoded as the position value in each dimension of a particle. Several member positions indicate the coordinate of the particle in a multi-dimensional search space. Each particle is considered as a potential solution to the optimal design problem, since each of them represents a specific configuration of the hybrid generation system. Excluding $P_{b_{cap}}$, all the remaining positions are real-coded. The *i*-th particle (i.e., candidate design) D_i can be represented as follows:

$$D_i = [P_{w,i}, P_{s,i}, \kappa_i, P_{b_{cap},i}], \quad i = 1, 2, \dots, N$$
(VI.31)

where the total SB capacity $P_{b_{cap}}$ is encoded using three binary bits.

C. Data flow of the optimization procedure

The computational procedure of the proposed method is as follows:

- Step 1: Specify the lower and upper bounds of WTG swept area, area of PV panels, number of batteries, and other pre-determined parameters.
- Step 2: Randomly generate a population of particles.
- Step 3: Evaluate each particle D_i in the population based on the concept of Pareto-dominance.
- Step 4: Store the non-dominated solutions found so far in the archive.
- Step 5: Initialize the memory of each particle where a single personal best *pbest* is stored. The memory is contained in another archive.
- Step 6: Increase the iteration number by one.
- Step 7: Choose the personal best position *pbest* for each particle based on the memory record; Choose the global best *gbest* from the fuzzified region using binary tournament selection [26]. The niching and fitness sharing mechanism is also applied in order to enhance solution diversity.
- Step 8: Update the member velocity v of each individual D_i . For the real-encoded design variables,

$$\begin{split} v_{i_d}^{(t+1)} &= \chi * (w * v_i^{(t)} + c_1 * \mathrm{rand}() * (pbest_{i_d} - P_{Gi_d}^{(t)}) \\ &+ c_2 * \mathrm{Rand}() * (gbest_d - P_{Gi_d}^{(t)})), \\ &i = 1, \dots, N; d = 1, 2. \end{split}$$
 (VI.32)

• Step 9: Update the member position of each particle D_i based on (V.29). For real-coded variables,

$$D_{i_d}^{(t+1)} = D_{i_d}^{(t)} + v_{i_d}^{(t+1)}$$
(VI.33)

For the binary-encoded design variable, update the member position based on the updating rule for discrete variables discussed in Subsection A.

Following this, add the turbulence factor into the current position. For the real-coded positions,

$$D_{i_d}^{(t+1)} = D_{i_d}^{(t+1)} + R_T D_{i_d}^{(t+1)}$$
(VI.34)

where R_T is the turbulence factor, which is used to enhance the solution diversity by refraining the search from undesired premature convergence.

- Step 10: Update the archive which stores non-dominated solutions. A candidate solution can be chosen to store in the archive only if it satisfies one of the following four selection criteria [26]:
 - The archive is empty;
 - The archive is not full and the candidate solution is not dominated by or equal to any solution currently stored in the archive;
 - The candidate solution dominates any existing solution in the archive;
 - The archive is full but the candidate solution is nondominated and is in a less crowded region than at least one solution. Euclidean distance is defined to measure the similarity between any two potential solutions.
- Step 11: If the current individual is dominated by the *pbest* in the memory, then keep the *pbest* in the memory; Otherwise, replace the *pbest* in the memory with the current individual.

TABLE I The data used in the simulation program.

System parameters	Values
Efficiency of WTG (η_w)	50%
Efficiency of PV (η_s)	16%
Efficiency of SB (η_b)	82%
Inflation rate (β)	9%
Interest rate (γ)	12%
Escalation rate (ν)	12%
Life span of project (N_p)	20 years
Life span of WTG (N_w)	20 years
Life span of PV (N_s)	22 years
Life span of SB (N_b)	10 years
PV panel price (α_s)	$450\$/m^2$
WTG price (α_w)	$100\%/m^2$
SB price (α_b)	100\$/KWh
PV panel salvage value (S_s)	$45\$/m^2$
WTG salvage value (S_w)	$10\$/m^2$
OM costs of WTG (α_{OM_w})	2.5 $m^2/year$
OM costs of PV panel (α_{OM_s})	4.3 /m ² /year
OM costs of SB (α_{OM_k})	10\$/KWh
Cut-in wind speed (V_{ci})	2.5 m/s
Rated wind speed (V_r)	12.5 m/s
Cut-out wind speed (V_{co})	20.0 m/s
Rated WTG power (P_r)	4.0 kW
Period under observation (T)	8760 hours
Maximum swept area of WTGs $(A_{w_{max}})$	$10,000m^2$
Minimum swept area of WTGs $(A_{w_{min}})$	$400m^{2}$
Maximum area of PV panels (A_{smax})	$200m^{2}$
Minimum area of PV panels $(A_{s_{min}})$	$8,000m^2$
Maximum conversion capacity $(P_{b_{max}})$	3 kWh
Minimum storage level $(P_{b_{min}})$	3 kWh
Rated battery capacity (P_{b_r})	8 kWh
Maximum total SB capacity $(P_{b_{max}})$	40 kWh
Price of utility grid power (φ)	0.12\$/kWh

- Step 12: If the maximum number of iterations is reached, then go to Step 13; Otherwise, go to Step 6.
- Step 13: Print out a set of Pareto-optimal solutions from the archive as the final possible system configurations.

VII. SIMULATION AND EVALUATION OF THE PROPOSED APPROACH

In this section, the tradeoff solutions are derived by the developed optimization procedure.

A. System parameters

The data used in the simulation program are listed in Table I [5]. The hourly wind speed patterns, the hourly insolation conditions, and the hourly load profile are shown in Figure 2. These time-series data will be used to calculate the available wind power, solar power, and the insufficient or surplus power at each time instant.

B. PSO parameters

In the simulations, both the population size and archive size are set to 100, and the maximum number of iterations is set to 500. The acceleration constants c_1 and c_2 are chosen as 1. Both turbulence factor and niche radius are set to 0.02. The inertia weight factor w decreases with the increasing iterations:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter$$
(VII.35)

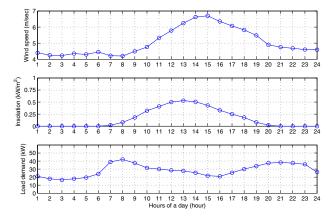


Fig. 2. Hourly average wind speed, insolation, and load profiles.

where $iter_{max}$ is the maximum number of iterations and *iter* is the current number of iterations. The simulation program is coded using C++ and executed in a 2.20 GHz Pentium-4 processor.

C. Simulation results

The Pareto-optimal fronts for different optimization scenarios evolved using the proposed approach are shown in Figure 3 and Figure 4.

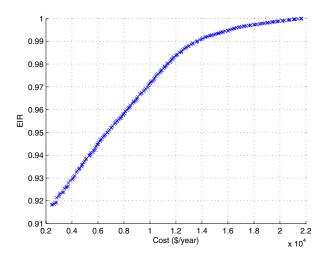


Fig. 3. Pareto front reflecting the tradeoff between cost and reliability.

From the tradeoff surfaces obtained, we can find that the non-dominated solutions are smoothly and evenly distributed on the surface, and the Pareto fronts are sufficiently wide for providing a set of representative decision-making options. The decision-maker may choose a specific solution based on system design requirements and his/her preference or experiences. Two illustrative non-dominated solutions for triobjective optimization are listed in Table II.

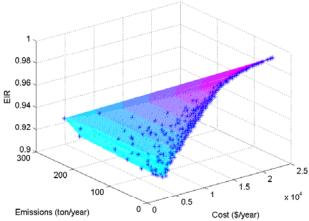


Fig. 4. Pareto front reflecting the tradeoff between reliability, cost, and emissions.

TABLE II Two illustrative non-dominated solutions for tri-objective optimization.

Variables/objectives	Design 1	Design 2
$A_w(m^2)$	420	640
$A_s(m^2)$	50	40
$P_{b_{cap}}(kWh)$	16	16
κ	0.20	0.58
Cost (\$/year)	5323	6802
EIR	0.9394	0.9505
Emissions (ton/year)	12.4609	65.3812

VIII. CONCLUDING REMARKS

The utilization of renewable sources of energy such as wind and solar power has experienced remarkably rapid growth in the last decade and most of them are pollution-free sources of abundant power. They may also eliminate the need of running new high-voltage transmission lines which may cost a significant investment [24]. In this paper, a grid-linked hybrid power generation system is designed using a modified particle swarm optimization algorithm. Three design objectives are considered, which include cost, reliability, and emissions. These design objectives are conflicted with one another and thus a set of tradeoff solutions is derived to support decision-making for different system requirements. Although distributed generation using renewable resources accounts for a small portion of the world's existing power supply, it is anticipated that renewables will contribute more significantly in the coming years. In the future work of this study, uncertainty factors such as generator failures and renewable power availability will also be taken into account in calculating system reliability indices with penetration of time-dependent sources.

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