Multi-Objective Design under Uncertainties of Hybrid Renewable Energy System Using NSGA-II and Chance Constrained Programming

Azadeh Kamjoo, Alireza Maheri, Arash M. Dizqah and Ghanim A. Putrus

Faculty of Engineering and Environment

Northumbria University

Newcastle upon Tyne, United Kingdom

azadeh.kamjoo@northumbria.ac.uk

Abstract

The optimum design of Hybrid Renewable Energy Systems (HRES) depends on different economical, environmental and performance related criteria which are often conflicting objectives. The Non-dominated Sorting Genetic Algorithm (NSGA-II) provides a decision support mechanism in solving multi-objective problems and providing a set of non-dominated solutions where finding an absolute optimum solution is not possible. The present study uses NSGA-II algorithm in the design of a standalone HRES comprising wind turbine, PV panel and battery bank with the (economic) objective of minimum system total cost and (performance) objective of maximum reliability. To address the uncertainties in renewable resources (wind speed and solar irradiance), an innovative method is proposed which is based on Chance Constrained Programming (CCP). A case study is used to validate the proposed method, where the results obtained are compared with the conventional method of incorporating uncertainties using Monte Carlo simulation.

Keywords: multi-objective optimisation; NSGA-II; standalone hybrid wind-PV-battery; reliability; chance constrained programming; design under uncertainties

I.   INTRODUCTION

Decision making problems can be categorized in two classes based on the number of objective functions that are involved in the problem; single objective and multi-objective. In a single objective problem, the aim is to identify the best solution corresponding to minimising or maximising a single objective function. However, in real life, the decision making process usually involves more than one objective function. Multi-objective problems do not have a single optimal solution but they have a set of compromised solutions between different objective functions known as Pareto set.

In optimal sizing of HRESs, there are normally more than one objective function to be considered. Two important objective functions in the design of a HRES are cost and reliability. Since these objectives are contradicting, a single optimal solution cannot be found (with minimum cost and maximum reliability) and a multi-objective optimisation is needed to find a trade-off; Pareto set solutions. Several studies have been reported in multi-objective optimisation of HRES considering different objection functions and using various optimisation techniques.

Kaviani et al. [1] used a PSO to optimize a hybrid wind-photovoltaic-fuel cell generation system with the objective of minimizing the annual cost of the hybrid system subject to reliable supply to meet the demand. Diaf et al. [2] analysed the optimum configuration of a stand-alone hybrid photovoltaic-wind system that guarantees the energy autonomy of a typical remote consumer with the lowest levelized cost of energy. The search method was used to analyze different combinations. Kaabeche et al. [3] recommended an optimisation model based on iterative technique to optimise the size of a hybrid wind/photovoltaic system combined with a battery bank with the objective being to minimise the deficiency of power supply and levelized unit of electricity cost.

Bernal-Agustín et al. [4] applied the Multi-Objective Evolutionary Algorithm (MOEA) to the multi-objective design of isolated hybrid systems (photovoltaic–wind–diesel) where the objectives were minimizing the total cost and pollutant emissions during useful life of the installation.

Giannakoudis et al. [5] proposed an optimisation method based on stochastic optimization algorithms (such as simulated annealing) for the design and operation of a hybrid power generation system that consists of PV panels, wind generators, accumulators, an electrolysis apparatus, hydrogen storage tanks, a compressor, a fuel cell and a diesel generator.

Genetic Algorithms (GA) proved to be popular in solving optimisation problems. Ould [6] proposed a Pareto-based multi-objective GA for sizing a hybrid solar–wind-battery system with the aim of minimizing the annualized cost and minimizing the probability of loss of power supply.

Montoya et al. [7] presented a hybrid Pareto- based multi-objective meta-heuristic approach to minimize voltage deviations and power losses in power networks, which can be extended to hybrid systems. Yang et al. [8] proposed a GA based optimal sizing technique using typical meteorological yearly data. The proposed optimisation model determines the system optimum configuration which is able to provide the desired Loss of Power Supply Probability (LPSP) with minimum Annualized Cost.

The Non-dominated Sorting Genetic Algorithm (NSGA-II) was proposed [9] to perform multi-objective evolutionary algorithms (MOEA) in which an elite-preserving operator gives the best individuals the opportunity to be directly transferred to the next generation. By doing so, a 'good' solution which is found in early generations is never removed from the population unless a better solution is discovered. Katsigiannis [10] used the NSGA-II to design a small autonomous hybrid power system that contained both renewable and conventional power sources with the objectives of minimizing the energy cost of the system and total greenhouse gas emission during the system life time. However, the effects of uncertainties in renewable energy generation were not considered in this study.

Different methods to include the uncertainties in renewable resources in the design of HRES have been reported. Giannakoudis et al [11] considered adding a known disturbance to the design inputs to maintain optimum mix of renewable resources. Nandi et al.[12] assumed that wind speed variation follows the Weibull distribution. Lujano-Rojas el al [13] used time series theory to simulate the uncertainties in wind speed in the design of small wind/battery systems. Usually, the Monte Carlo simulation approach is used in solving probabilistic problems. Given a significantly large sample size, this method can provide highly accurate results. However, the main drawback is the computational burden associated with the large number of repeated calculations [14]. The Chance Constrained Programming (CCP) approach, first introduced by Charnes and Cooper [15] in 1959, is now popular method in solving problems that include random parameters. Its main feature is that it ensures the probability of the resulting decision to comply with the specified constraints [16]. The CCP method has been widely applied in different disciplines for optimisation under uncertainty[17], but very few studies are reported on using this
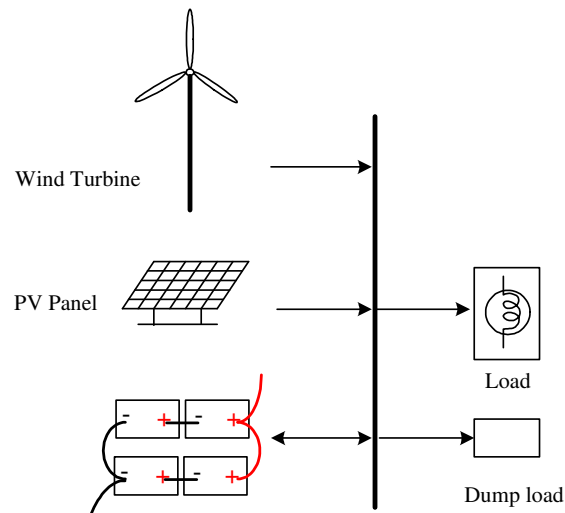
Figure 1. Concept diagram of HRES

method for the design of HRES. Arun et al. [18] used the CCP approach in the design of a PV-battery system to deal with the uncertainties in the solar radiation. Seeraj et al. [19] used this method to find the battery bank size when renewable energy resource availability, ratings and load demand were assumed to be known.

This paper presents the results of a multi-optimisation NSGA-II based approach for the design of a standalone HRES, shown in Figure 1, considering uncertainties in the resources available. The approach employs the chance constrained programming to deal with the effects of uncertainties in renewable resources instead of common approach of using Monte Carlo simulation. Authors in [20] have shown that chance constrained programming can result in optimum solution for a predefined reliability in a single-objective optimisation problem in design of HRES, however in a multi-objective optimisation problem where there is no predefined reliability, conventionally Monte Carlo simulation is employed. This study proposes a novel method in employing chance constrained programming in multi-objective problems as a substitute of Monte Carlo simulation. The study proposes a method in which chance constrained programing is used as a tool in estimating the expected value of the objective function which is affected by the uncertainties, in other words instead of finding the optimum solution for a predefined value of reliability, chance constrained programing is used to estimate the expected value of the reliability of the design candidates in a multi-objective optimisation problem. To evaluate the performance of the proposed method, the results obtained are compared with those obtained by employing the Monte Carlo simulation.

The outline of this paper is as follows:

The components modelling and cost modelling are presented in sections 2.

Problem formulation and design methodology are presented in section 3.

A case study is described in section 4. Results and discussion are described in section 5 and finally conclusions are presented in section 6.

II. COMPONENTS AND COST MODELLING

The HRES design is crucially dependent on the performance of its individual components. Different mathematical models have been proposed to estimate the output power of wind turbine, photovoltaic panel and batteries (considered in this work). The models implemented in this study are chosen with consideration of giving a realistic estimation of the output of each

component without being too complicated with details. The mathematical models of components used in this study are briefly presented in Appendices A. More details on components modelling is discussed in [20] .

In this study the total cost of the system TC (of the design candidates) is calculated as the economical measure taking into account the initial capital cost (C_{IC}), replacement cost ($C_{replacement}$) and present value of maintenance cost ($C_{O\&M}$). That is:

$$TC = C_{IC} + C_{replacement} + C_{O\&M} \tag{1}$$

A. Initial Capital Cost

The initial capital cost consists of the components cost and their installation cost.

$$C_{IC} = \left(A_{PV} P_{PV,Nom} C_{Unit,PV}\right) + \left(A_{WT} C_{Unit,WT}\right) + \left(N_{Bat} c_{Bat} C_{Unit,Bat}\right) + C_0 \tag{2}$$

C_0 ; the total installation constant cost including the cost of installation of the wind turbine and PV panels and is considered to be 20% of the component cost of the wind turbine and 40% of the component cost of the PV system [3].

B. The Present Value of Replacement Cost

In this study the only component which needs to be replaced during life time of the HRES is assumed to be the battery bank so this cost is only calculated when the battery bank exists in the configuration.

The replacement cost of the battery bank can be calculated as [3]:

$$C_{replacement} = N_{Bat} c_{Bat} C_{Unit,Bat} \sum_{i=1}^{N_{rep}} \left[\frac{1+f}{1+k_d}\right]^{N_i/N_{rep}+1} \tag{3}$$

C. The Present Value of Operation and maintenance Cost

The present value of operation and maintenance cost of the hybrid system is expressed as[3]:

$$C_{O\&M,HRES} = \begin{cases} C_{(O\&M)_0}\left(\dfrac{1+f}{k_d-f}\right)\left[1-\left(\dfrac{1+f}{1+k_d}\right)^Y\right], & k_d \neq f \\ C_{(O\&M)_0}Y, & k_d = f \end{cases} \tag{4}$$

$C_{(O\&M)_0}$; the operation and maintenance cost in the first year and can be given as a fraction (k) of the initial capital cost C_{IC} as:

$$C_{(O\&M)0} = kC_{IC} \tag{5}$$

The value of k is assumed to be 1% for the PV system, 3% for wind turbine and 1% for battery bank [3].

III. PROBLEM FORMULATION AND DESIGN METHODOLOGY

The proposed technique adopts the non-dominated sorting genetic algorithm (NSGA-II) [9] in combination with the chance constrained programming (CCP) [15] to effectively solve the multi-objective optimisation problem of design of a HRES under uncertainties.

The aim is to find the Pareto set solutions based on the desired objective functions using NSGA-II. The NSGA-II provides a very efficient procedure in keeping the elitism optimisation process as well as preserving the diversity which assures a good convergence towards the Pareto-optimal front without losing the solution diversity [21].

The following steps are implemented in the NSGA-II algorithm.

1: Initial population is generated based on defined decision variables and number of populations.

2: Evaluation of each chromosome in terms of defined objective functions. The adopted methods in evaluation the objective functions affected by uncertainties are explained in sub-section (III-A) and (III-B).

3: Set the generation count

4: Prepare the mating pool

5: Perform crossover and mutation operators

6: Evaluation of new offspring in terms of defined objective functions.

7: Perform non-dominated sorting

8: Calculate the crowding distance

9: Perform the selection based on rank. If individuals with the same rank are encountered, crowding distance is compared. A lower rank and higher crowding distance is the selection criteria.

10: Increment the generation count and repeat steps 4 to 9 until the counter reaches the maximum number of generation

11.Generate Pareto set.

The decision variables are the wind turbine rotor swept area (A_{WT}), the PV panel area (A_{PV}) and the number of batteries (N_{Bat}).

The optimisation problem can be defined as:

$$\min_{A_{WT},A_{PV},N_{Bat}} \{TC, DPSP\} \tag{6}$$

$$\text{Subject to}$$

$$SOC \geq SOC_{min} \tag{7}$$

$$\text{where}$$

$$TC = C_{IC} + C_{O\&M} + C_{replacement} \tag{8}$$

$$DPSP = \frac{\sum_{i=1}^{h} DPS_i}{\sum_{i=1}^{h} Demand_i} \, 100 \tag{9}$$

As Equation 6 shows, two objective functions have been considered associated with both minimisation of the system total cost (TC) and the deficiency of power supply probability ($DPSP$); where DPS is the amount of power shortage at each hour and h is the total hours under study. Since different applications of HRES need different reliability requirements the trade-off between reliability and cost of the designed system expectedly would result in obtaining different HRES with

reliability values between 0 and 100% and that would be the decision makers choice to choose the design option that suits the application.

The energy balance of the system can be modelled as:

$$P_{HRES} = \begin{cases} P_{WT} + P_{PV}, & (a) \\ P_{WT} + P_{PV} + P_{Bat} & (b) \end{cases} \tag{10}$$

(a) if total power generated by the wind turbine and PV is sufficient to cover the load demand, otherwise

(b) $P_{WT} + P_{PV}$ is not sufficient to meet the demand and the battery has to supply the difference.

In order to compare the performance of the proposed method, the NSGA-II algorithm objectives affected by uncertainties are evaluated with CCP (explained in section III-A) as well as a conventional method based on Monte Carlo simulation (explained in section III-B).

A. Optimal Estimation of the Objective Functions Affected by Uncertainties Using CCP

Each design candidate in the main optimisation process needs to be evaluated in terms of the desired objective functions; here these are the total cost (TC) and deficiency of power supply probability $(DPSP)$. As uncertainties with renewable resources have direct effects on the second objective function (DPSP); finding an exact value for $DPSP$ is not realistically possible. Therefore, this objective function needs to be estimated using stochastic methods, in this study using chance constrained programming.

As $DPSP_{estimated}$ is completely dependent on the correct estimation of uncertain variables, here the aim would be to estimate the hourly values of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$. The estimation problem of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$ can be written as a chance constrained problem. The aim of this problem would be to estimate the hourly values of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$ in such way that their sum would have a value with a desired confidence level α. The estimation problem can be described as a chance constrained problem, as:

$$Pr(P_{WT_t} + P_{PV_t} \geq P_{WT_{t,estimated}} + P_{PV_{t,estimated}}) \geq \alpha \tag{11}$$

Following the method proposed by the authors [20], the hourly values of $P_{WT_{t,estimated}}$ and $P_{PV_{t,estimated}}$ are extracted and then used to calculate the $DPSP_{estimated}$. As shown in the case study (section IV), this method requires considerably shorter process time as compared with the conventional Monte Carlo simulation.

B. Monte Carlo Simulation

Monte Carlo simulation is conventionally used to estimate the expected value of the parameters with uncertainties. The performance of the Monte Carlo simulation is dependent on the accurate modelling of uncertainties in the wind speed and solar irradiance. Different approaches are used to model the renewable sources. One of the common approaches is by fitting the uncertainties to known distributions such as Weibull or Beta distributions [22]. However, research show that for some locations (e.g. in the UK), using predefined distributions may not simulate the weather data properly[23]. Erken [24] used different distributions to find the best fitted distribution for each hourly meteorological data. Another method in considering uncertainties is adding a random disturbance to the average values of wind speed and solar irradiance [11]. Lujano-Rojas [13] and Ji [25] used a time series analysis to model wind speed and solar irradiance variations. To obtain accurate modelling of

Table 1. The components design parameters

Component	Efficiency (%)	Lifetime (year)	Initial Cost	O&M Cost	Interest Rate (%)	Inflation rate (%)	Nomial Capacity (Ah)	Nominal Voltage (V)	Depth of Discharge (%)
PV panel	12.3	25	600 ($/m2)	1% of price	8	4	-	-	-
WT		20	700 ($/m2)	3% of price	8	4	-	-	-
Battery Bank	90	8	1.5 ($/Ah)	1% of price	8	4	40	24	90

wind speed and solar irradiance variations, two methods are used to correlate historical data to known distributions and time series analysis using autoregressive moving average models (ARMA)[26]. Based on the location of the desired site, the performance of different modelling methods should be investigated and the most suitable model selected as the random data generator to model the uncertainties in Monte Carlo simulation. Using these random data generators, the Monte Carlo simulation is repeated enough for each configuration until the expected values of the objective function; here $E[DPSP]$, is calculated with the confidence level of %90 and variation value of less than %3.

The flowchart of the implemented NSGA-II using adopted methods in evaluation the objective functions affected by uncertainties are explained in sub-section (III-A) and (III-B) is presented in Figure 2.

IV. CASE STUDY

The proposed method is used to design a standalone HRES for a household in Kent, UK. The input data for the design are historical hourly data (2000-2008) of wind speed and solar irradiance for 12 months of the year together with typical summer and winter load profiles shown in Figure 3. The load profile is a typical load profile in the UK which is adopted from [27]. Details of technical and economical characteristics of the system components are given in Table I.

The system under study consists of a wind turbine, a PV panel and a battery bank. The wind turbine rotor area is varied in the range from 0 to 154 m^2 (in 10 steps), PV panels area is from 0 to 260 m^2 and minimum number of batteries required to meet the probabilistic constraint is determined for each case. The number of batteries is assumed to vary from 0 to 478. The maximum permitted number of batteries in this study is calculated, using Equation 12, considering required storage for one day of autonomy with highest daily load demand; here typical winter load demand is used.

$$N_{Bat} = \frac{Load S_D}{c_{Bat} V_{Bat} DOD_{max} \eta_{Bat}}$$

(12)

where $Load$ is maximum daily load (W); S_D is the number of autonomy or storage days (in this study considered as 1day); V_{Bat} is the battery bank voltage in (V); DOD_{max} is the maximum depth of discharge and η_{Bat} is the battery efficiency.

The NSGA-II algorithm is performed for 250 iterations with a population number of 100, the mating pool size is considered as 0.5 of the population, crossover probability pc = 0.9 and mutation probability of $1/n$; where n is the number of variables; here 3.

To select the best model for wind speed and solar irradiance in Monte Carlo simulation, the results of ARMA simulation are compared with those obtained from fitting the historical data of wind speed to Weibull distribution and solar irradiance to

Input Data:
- Historical Meteorological Data (Wind Speed (WS), Solar Irradiance (SI))
- Summer and Winter Load Profiles
- Design Variables

Generate initial population

Generate initial population

Evaluating the objective functions of each chromosome using CCP (Section III-A)

Calculating Joint CDF of WT power and PV panel power for A_{PV} and A_{WT}

Find the values of WT and PV output powers for each hour according to desired α=0.9

Calculate DPSP & TC

Evaluating the objective functions of each chromosome using Monte Carlo Simulation (Section III-B)

Simulate hourly WS, SI variation using the identified ARMA model

Simulate hourly WS,SI variation using identified distributions

Compare the results with observed data Choose the best method to simulate hourly WS,

Perform Monte Carlo simulation for required times

Calculate mean value of DPSP and TC

Prepare the mating pool

Perform Cross-over & Mutation

Evaluating the offspring using CCP

Perform non-dominated sorting

Calculate the crowding distance

Perform the selection based on rank

Max No. of Generations?   No

Yes

Generate the Pareto set

Prepare the mating pool

Perform Cross-over & Mutation

Evaluating the offspring using Monte Carlo Sim.

Perform non-dominated sorting

Calculate the crowding distance

Perform the selection based on rank

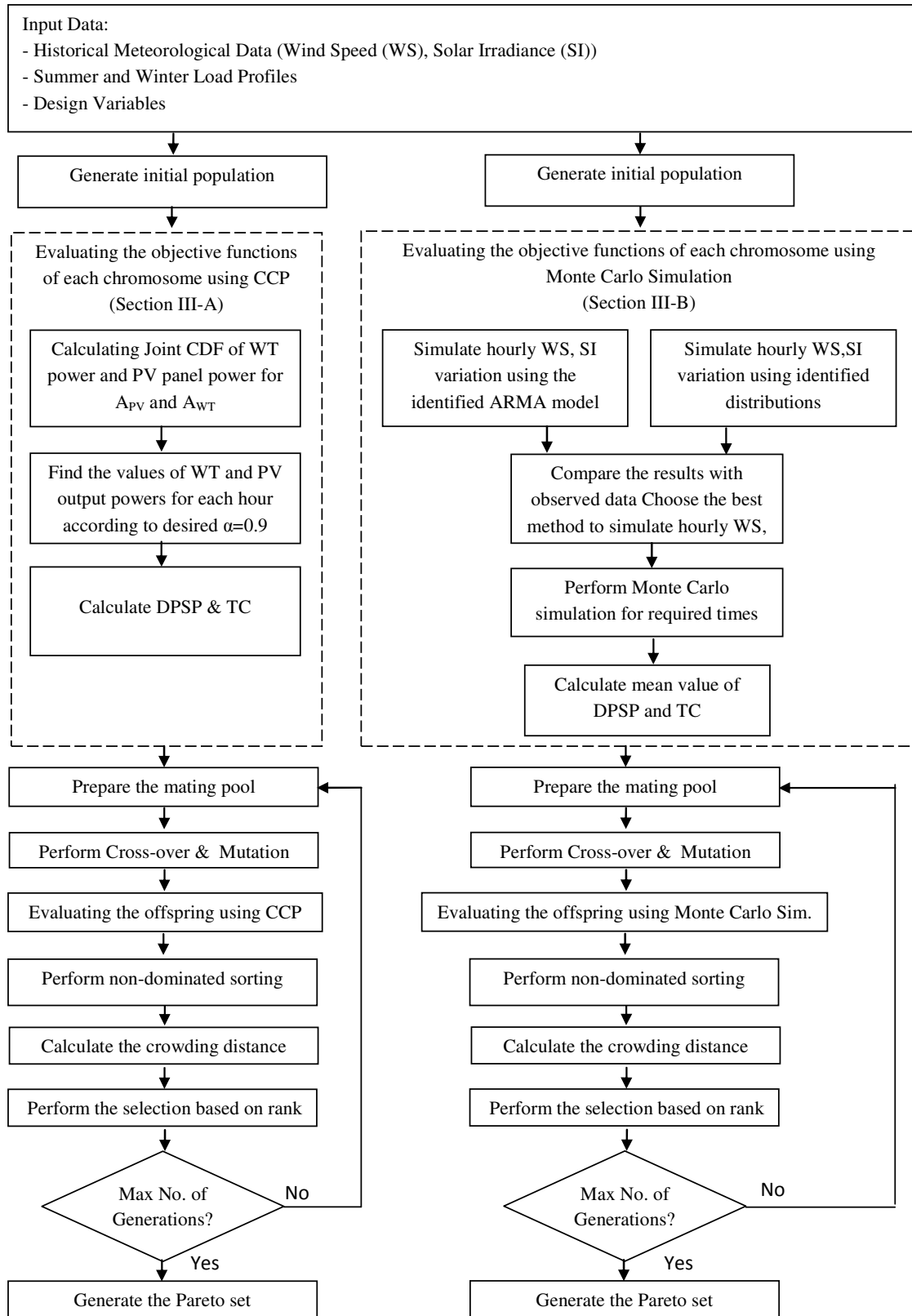Max No. of Generations?   No

Yes

Generate the Pareto set

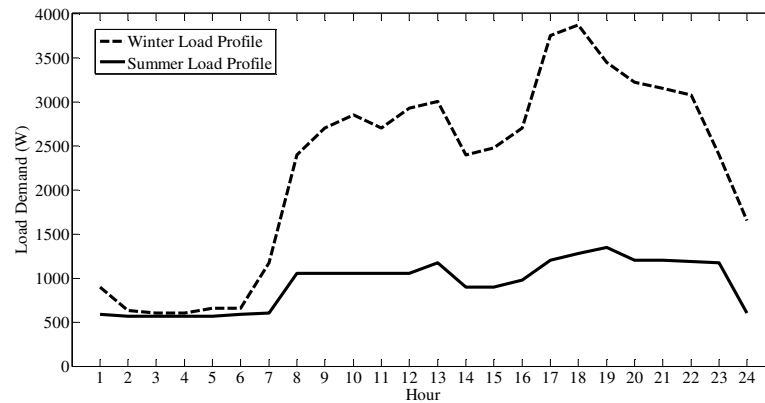Figure 2. Flowchart of NSGA-II using CCP/ Monte Carlo Simulation

Figure 3. Summer and Winter load profiles

Beta distribution. Based on the results presented in [20] Weibull distribution showed better performance in modelling wind speed variation and ARMA simulation is used to model solar irradiance in the desired site.

V. RESULTS AND DISCUSSION

The system under study was designed based on the methodologies explained in section III and results are presented in this section.

Figures 4-a and 5-a present a comparison between the initial populations and the final Pareto sets of performing NSGA-II in combination with CCP and Monte Carlo simulation. It can be observed that the NSGA-II with CCP produces more conservative results as compared to the other method, as it results in solutions with higher total cost. However, it obtains better results in high reliabilities close to 100%; with lower total cost of the system.

Figures 4-b and 5-b show how the output of each technique converges to its final Pareto set. As can be seen, in both cases (using the CCP and Monte Carlo simulation), the outputs of the NSGA-II converges to the final Pareto set at generation 150. The final Pareto sets of performing optimisation process using proposed NSGA-II algorithm on the site under study; in combination with CCP as well as Monte Carlo simulation are compared ; Figure 6. The Pareto sets obtained in both cases of employing NSGA-II are well defined and solutions are spread over the reliability axis. It should be noted that a solution with zero total cost is not feasible.

Although using CCP instead of Monte Carlo simulation results in more conservative set of solutions (as shown in Figure 6); the execution time is significantly lower. The calculation time for evaluating the objective function of each chromosome is 11.44 seconds using CCP which is significantly lower than performing the Monte Carlo simulation, which takes 56.81 seconds for each design candidate.
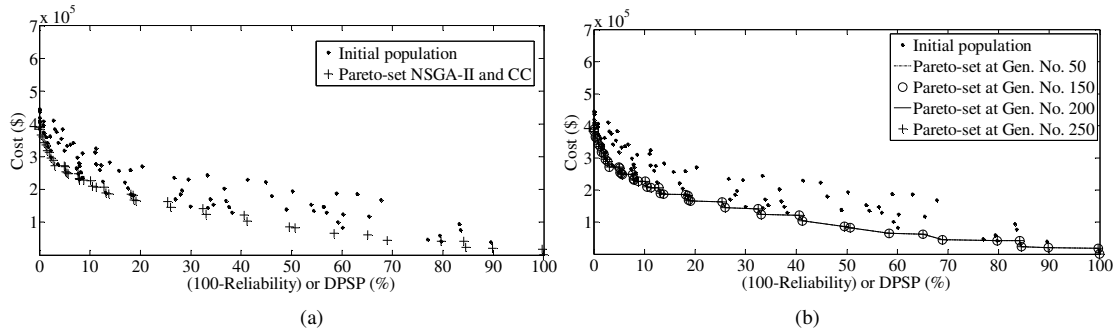
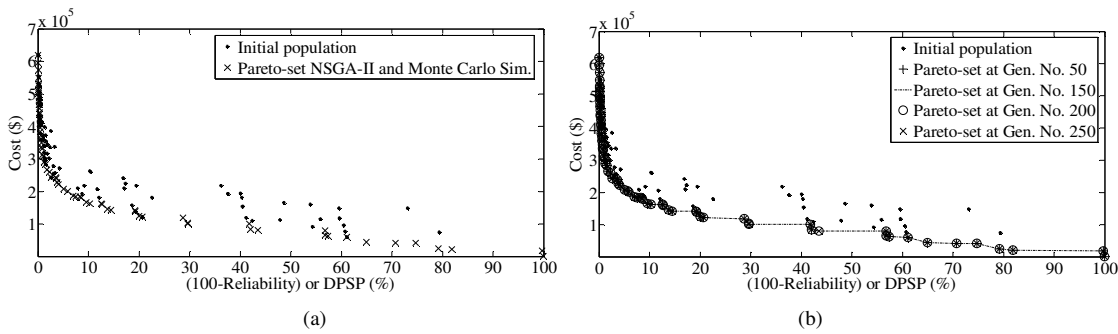Figure 4. NSGA-II with chance constrained programming
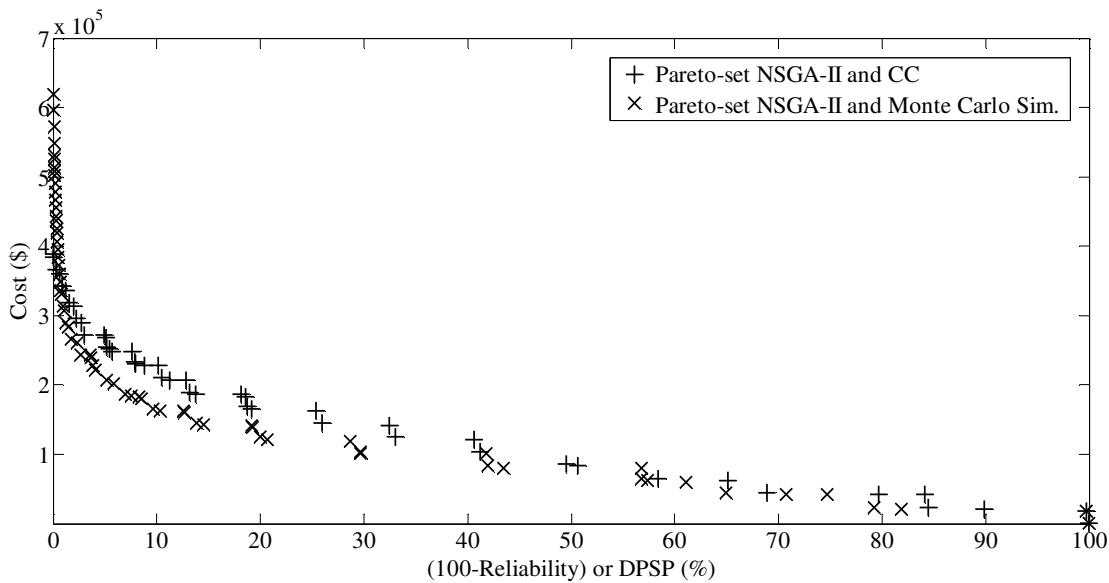

Figure 5. NSGA-II with Monte Carlo simulation

Figure 6. Comparison between Pareto sets obtained with different optimisation methods

The Figure 6 also shows that maximum deviation between two Pareto sets happens when the DPSP is between 15% to 35%. To help the decision maker to choose the solution which fits the requirements, the output solution of two design methods for reliability of 80% or DPSP of 20% is studied in detail. Design parameters of CCP and the optimum solutions of two design methods are presented in Table 2. To evaluate the performance of each of the selected solutions; Monte Carlo simulation is performed for the simulation number of 2500 runs. A selection of results is presented in Figures 7-8. Figures 7-a and 8-a present the distribution of different blackout occurrence probabilities along the hours of a year. By comparing these two

graphs one can see that there are more hours in the year with very little chance of having power shortages in solution -1 than in solution-2. It is also observed that the maximum hourly blackout occurrence probability is less in solution-1 than solution-2; 0.6 for solution-1 and around 0.8 for solution-2.

Figures 7-b and 8-b present the average daily probability of blackout occurrence throughout the year. Comparing these to figures shows that in solution-1 the last three months of the year have the highest probability of blackout occurrence which is due higher load demand in winter (see Figure 3) as well as less renewable resources available in these months. However, in solution-2 the second half of the year has higher probability of power loss.

The day that has the largest probability of blackout occurrence in Figures 7-b and 8-b is selected and details of having blackout at each hour of that day is presented in Figures 7-c and 8-c.

Figures 7-d and 8-d show the results of performing Monte Carlo simulation for 2500 times on the hour with most probability of blackout and presents the frequency and load satisfaction percentage for that hour.

Table 2. Optimum solutions of two design methods for reliability=0.8

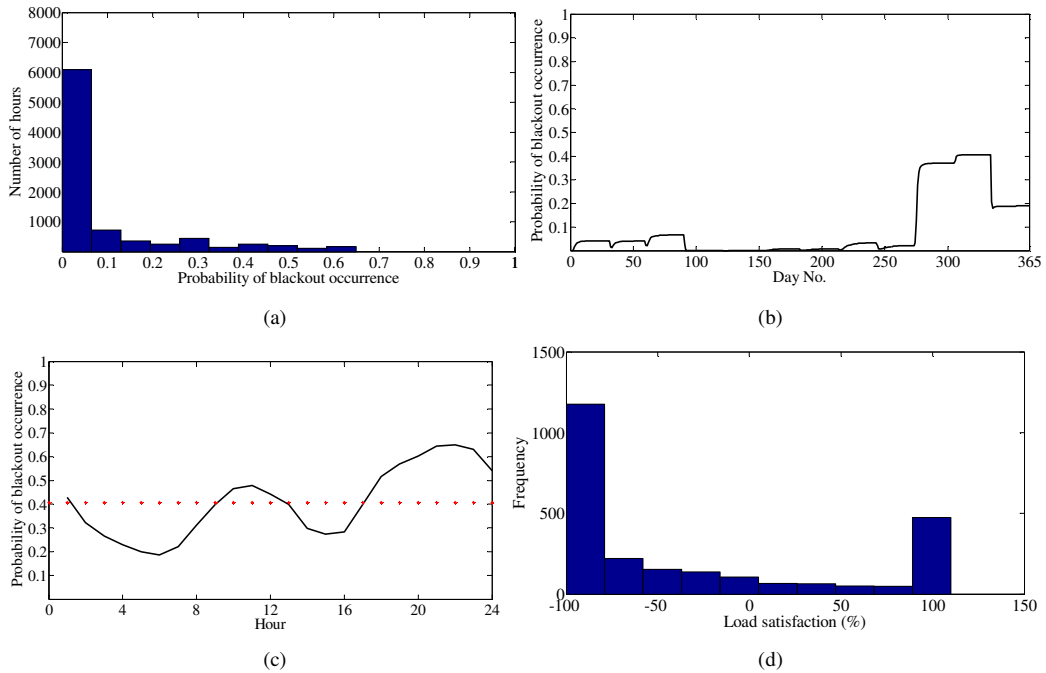| α	NSGA-II and chance constrained programming (Solution-1)			NSGA-II and MonteCarlo simulation (Solution-2)		
	WT Rotor Area (m2)	PV Panel Area (m2)	Number of Batteries	WT Rotor Area (m2)	PV Panel Area (m2)	Number of Batteries
0.9	92	26	49	77	0	96

(a)

(b)

(c)

(d)

Figure 7. Monte Carlo simulation results on optimum solution of NSGA-II with chance constrained prog. for reliability=0.8
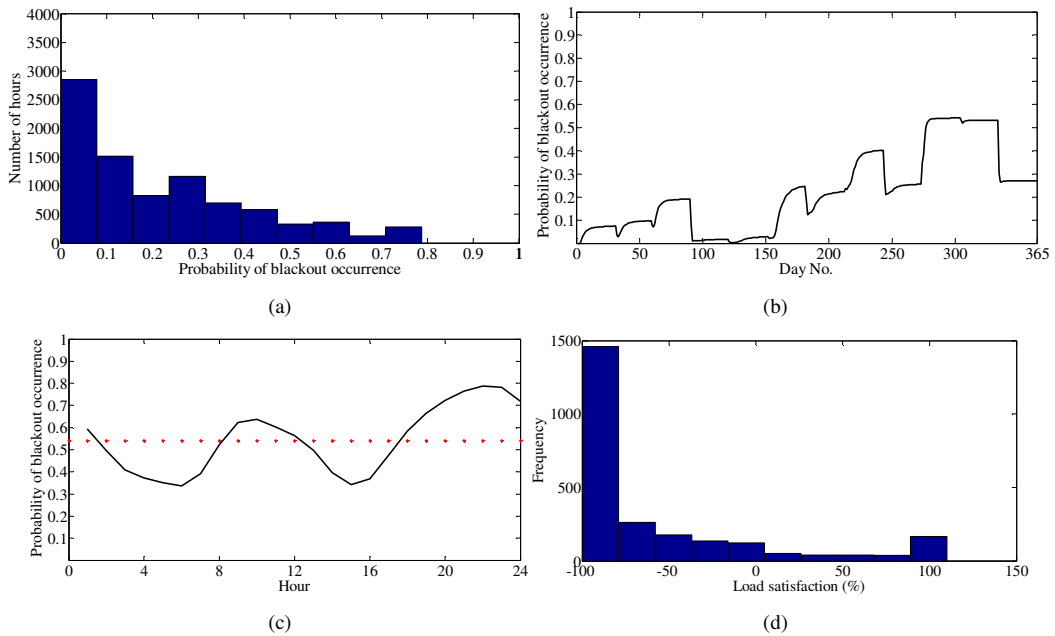

(a)

(b)

(c)

(d)

Figure 8. Monte Carlo simulation results on optimum solution of NSGA-II with Monte Carlo sim. for reliability=0.8

VI. CONCLUSIONS

This paper proposes a multi-objective optimisation algorithm for optimum economic and reliability oriented design of hybrid renewable energy system. The algorithm takes into account the uncertainties in renewable resources. The decision variables are the wind turbine rotor swept area, the PV panel area and the number of batteries. Two conflicting objectives which are total cost and system reliability are considered. A novel method in using chance constrained programming is proposed in this study to estimate the expected value of the objective function; the reliability of design candidate; affected by uncertain values of wind speed and solar irradiance at each jour under study. This reduces the evaluation time of the design candidate and consequently the run time of the NSGA-II program.

The results obtained by using the proposed method are compared with those obtained using a conventional Monte Carlo simulation. The comparison shows that the proposed method yields conservative results in lower reliability values and better results in high reliability values.

APPENDIX A- COMPONENTS MODELLING

Table A-1 Wind Turbine Model	
The wind power generated by a wind turbine	$P_{WT} = \dfrac{1}{2}\rho C_p V_w^3 A_{WT}$
The wind speed V_w at the hub height	$V_w = V_{ref}\dfrac{ln\left(z_{hub}/z_0\right)}{ln\left(z_{ref}/z_0\right)}$
The wind turbine power coefficient, C_p	$C_p = 3.646e^{-7}v_w^{\,6} - 2.95e^{-5}v_w^{\,5} + 0.9088e^{-3}v_w^{\,4}$ $- 0.01295v_w^{\,3} + 0.07874v_w^{\,2} - 0.11\,v_w - 0.001027$
Table A-2 Photovoltaic Panel Model	
The power generated by PV	$P_{PV} = IA_{PV}\eta_{PV}$
Table A-3 Battery Bank Model	
The state of the charge (SOC), during the charging process	$SOC_{t+1} = SOC_t(1-\delta_t) + \dfrac{I_{Bat_t}\Delta t\eta_C}{c_{Bat}}$
The battery current I_{Bat} during the charging process	$I_{Bat_t} = \dfrac{P_{PV_t} + P_{WT_t} - P_{load_t}}{V_{Bat}}$
The state of the charge (SOC), during the discharging process	$SOC_{t+1} = SOC_t(1-\delta_t) - \dfrac{I_{Bat_t}\Delta t}{c_{Bat}}$
The battery current I_{Bat} during the discharging process	$I_{Bat_t} = \dfrac{P_{load_t} - P_{PV_t} - P_{WT_t}}{V}$

Nomenclature

A_{PV}	PV panel area (m2)	I	horizontal solar irradiance in (W/m^2)
A_{WT}	wind turbine rotor disk area (m2)	I_{Bat}	battery current
C_0	total constant cost including the cost of installation of the wind turbine and PV panels	k_d	annual real interest rate
C_{Bat}	nominal battery bank capacity (Ah)	L_p	system life period in years
C_{IC}	the total cost of the system	N_{Bat}	Total number of batteries
$C_{O\&M}$	present value of maintenance cost	N_{rep}	number of replacements of the battery over the system life period
C_{rep}	the present value of replacement cost	P_{Bat}	battery bank available power (W)
$C_{Unit,Bat}$	unit Cost of battery bank ($/Ah)	P_{PV}	the PV array output power (W)
$C_{Unit,PV}$	unit Cost of PV panel ($/m2)	P_{WT}	wind turbine power (W)
$C_{Unit,WT}$	unit cost of the wind turbine($/m2)	$P_{PV,Nom}$	PV panel nominal power (W)
C_p	wind turbine power coefficient,	ρ	air density (1.225 Kg/m^3)
Δ_t	the time step (one hour in this study)	SOC	state of the charge of the battery
η_{PV}	efficiency of the PV array and corresponding converters	TC	the total cost of the system
η_{Bat}	battery efficiency	V_{Bat}	battery voltage
η_C	battery bank charge efficiency factor	V_{ref}	the wind speed at the reference height
f	inflation rate	V_w	hourly average wind velocity (m/s)
η_{PV}	efficiency of the PV array and corresponding converters	Y	system life span in (years)
η_{Bat}	battery efficiency	z_{hub}	wind turbine hub height
η_C	battery bank charge efficiency factor	z_0	surface roughness length (m)
f	inflation rate	z_{ref}	reference height (m)

REFERENCES

[1] Kashefi Kaviani A, Riahy GH, Kouhsari SM. Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages. Renewable Energy. 2009;34(11):2380-90.
[2] Diaf S, Belhamel M, Haddadi M, Louche A. Technical and economic assessment of hybrid photovoltaic/wind system with battery storage in Corsica island. Energy Policy. 2008;36(2):743-54.
[3] Kaabeche A, Belhamel M, Ibtiouen R. Sizing optimization of grid-independent hybrid photovoltaic/wind power generation system. Energy. 2011;36(2):1214-22.
[4] Bernal-Agustin JL, Dufo-Lopez R, Rivas-Ascaso DM. Design of isolated hybrid systems minimizing costs and pollutant emissions. Renewable Energy. 2006;31(14):2227-44.
[5] Giannakoudis G, Papadopoulos AI, Seferlis P, Voutetakis S, Ferraris SPaGB. On the Systematic Design and Optimization under Uncertainty of a Hybrid Power Generation System Using Renewable Energy Sources and Hydrogen Storage. Computer Aided Chemical Engineering: Elsevier; 2010. p. 907-12.
[6] Ould Bilal B, Sambou V, Ndiaye PA, Kebe CMF, Ndongo M. Optimal design of a hybrid solar-wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP). Renewable Energy. 2010;35(10):2388-90.
[7] Montoya FG, Banos R, Gil C, Espin A, Alcayde A, Gomez J. Minimization of voltage deviation and power losses in power networks using Pareto optimization methods. Engineering Applications of Artificial Intelligence. 2010;23(5):695-703.
[8] Yang H, Zhou W, Lu L, Fang Z. Optimal sizing method for stand-alone hybrid solar/wind system with LPSP technology by using genetic algorithm. Solar Energy. 2008;82(4):354-67.
[9] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. Evolutionary Computation, IEEE Transactions on. 2002;6(2):182-97.
[10] Katsigiannis YA, Georgilakis PS, Karapidakis ES. Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables. Renewable Power Generation, IET. 2010;4(5):404-19.
[11] Giannakoudis G, Papadopoulos AI, Seferlis P, Voutetakis S. Optimum design and operation under uncertainty of power systems using renewable energy sources and hydrogen storage. International Journal of Hydrogen Energy. 2010;35(3):872-91.
[12] Nandi SK, Ghosh HR. Prospect of wind-PV-battery hybrid power system as an alternative to grid extension in Bangladesh. Energy. 2010;35(7):3040-7.
[13] Lujano-Rojas JM, Dufo-LÃ³pez R, Bernal-AgustÃn JL. Optimal sizing of small wind/battery systems considering the DC bus voltage stability effect on energy capture, wind speed variability, and load uncertainty. Applied Energy. 2012;93(0):404-12.
[14] Hajian M, Glavic M, Rosehart WD, Zareipour H. A Chance-Constrained Optimization Approach for Control of Transmission Voltages. Power Systems, IEEE Transactions on. 2012;27(3):1568-76.
[15] Charnes A, Cooper WW. Chance-constrained programming. Management Science. 1959;6:73-9.
[16] Li P, Arellano-Garcia H, Wozny Gn. Chance constrained programming approach to process optimization under uncertainty. Computers & Chemical Engineering. 2008;32(1â€“2):25-45.
[17] Uryasev S. Probabilistic Constrained Optimization: Methodology and Applications. Dordrecht: Kluwer Academic Publishers. 2000.
[18] Arun P, Banerjee R, Bandyopadhyay S. Optimum sizing of photovoltaic battery systems incorporating uncertainty through design space approach. Solar Energy. 2009;83(7):1013-25.
[19] Sreeraj ES, Chatterjee K, Bandyopadhyay S. Design of isolated renewable hybrid power systems. Solar Energy. 2010;84(7):1124-36.
[20] Kamjoo A, Maheri A, Putrus GA. Chance constrained programming using non-Gaussian joint distribution function in design of standalone hybrid renewable energy systems. Energy. 2014;66(0):677-88.
[21] Pires DFo, Antunes CH, Martins AnG. NSGA-II with local search for a multi-objective reactive power compensation problem. International Journal of Electrical Power & Energy Systems. 2012;43(1):313-24.
[22] Karaki SH, Chedid RB, Ramadan R. Probabilistic Performance Assessment of Autonomous Solar-Wind Energy Conversion Systems. IEEE Transactions on Energy Conversion. 1999;14(3).
[23] Dizqah AM, Maheri A, Busawon K. An assessment of solar irradiance stochastic model for the UK. Environment Friendly Energies and Applications (EFEA) Symposium. 2012:670-5.
[24] Ekren BY, Ekren O. Simulation based size optimization of a PV/wind hybrid energy conversion system with battery storage under various load and auxiliary energy conditions. Applied Energy. 2009;86(9):1387-94.
[25] Ji W, Chee KC. Prediction of hourly solar radiation using a novel hybrid model of ARMA and TDNN. Solar Energy. 2011;85(5):808-17.

[26] Kamjoo A, Maheri A, Putrus G. Wind Speed and Solar Irradiance Variation Simulation Using ARMA Models in Design of HybridWind-PVBattery System. Journal of Clean Energy Technologies. 2013;1:14-7.

[27] Putrus GA, Suwanapingkarl P, Johnston D, Bentley EC, Narayana M. Impact of electric vehicles on power distribution networks. Conference Impact of electric vehicles on power distribution networks. p. 827-31.