Journal of Zhejiang University SCIENCE A
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Robust design and optimization for autonomous PV-wind hybrid power systems

Jun-hai SHI[†], Zhi-dan ZHONG, Xin-jian ZHU, Guang-yi CAO

(*Institute of Fuel Cells, Shanghai Jiao Tong University, Shanghai 200240, China*)

[†]E-mail: shjh@sjtu.edu.cn

Received June 19, 2007; revision accepted Aug. 1, 2007; published online Dec. 8, 2007

Abstract: This study presents a robust design method for autonomous photovoltaic (PV)-wind hybrid power systems to obtain an optimum system configuration insensitive to design variable variations. This issue has been formulated as a constraint multi-objective optimization problem, which is solved by a multi-objective genetic algorithm, NSGA-II. Monte Carlo Simulation (MCS) method, combined with Latin Hypercube Sampling (LHS), is applied to evaluate the stochastic system performance. The potential of the proposed method has been demonstrated by a conceptual system design. A comparative study between the proposed robust method and the deterministic method presented in literature has been conducted. The results indicate that the proposed method can find a large mount of Pareto optimal system configurations with better compromising performance than the deterministic method. The trade-off information may be derived by a systematical comparison of these configurations. The proposed robust design method should be useful for hybrid power systems that require both optimality and robustness.

Key words: PV-wind power system，Robust design, Constraint multi-objective optimizations, Multi-objective genetic algorithms, Monte Carlo Simulation (MCS), Latin Hypercube Sampling (LHS)

doi:10.1631/jzus.A071317 **Document code:** A **CLC number:** TB21; TK01

INTRODUCTION

The application of an autonomous hybrid energy system, typically a photovoltaic (PV)-wind hybrid power system, is a promising solution to electrifying the isolated locations far from the electrical distribution network. It can improve the economical and technical performance of the stand-alone power supplies in many situations (Wichert, 1997). However, this performance improvement comes from the well-configured hybrid power system considering techno-economical performance and robustness, and thus the optimization of the system design gains importance to run the hybrid power system effectively.

There are several methods proposed for the optimal design of the hybrid energy system in literature. The most common one is an iterative technique that varies and simulates the system configuration iteratively (Notton *et al*., 2001; Kellogg *et al*., 1996). The most economical system configuration can be derived from the candidate ones that meet the technical requirements. The electricity cost (life-cycle cost) usually stands for economical performance while the loss of load probability stands for technical performance. These methods have been extended to seeking the techno-economical optimal PV-wind hybrid system configuration with considering the total system cost (the sum of component costs) and the system autonomy level as the design objectives (Celik, 2003; Protogeropoulos *et al*., 1997). The analysis of the distributions of renewable energy and load decides the iterative step size of the system configuration which helps to reduce the iterative time. However, these iterative methods cannot find the global optimal solution because the design process is divided into the sizing sub-process and the optimizing sub-process. Nevertheless, these iterative methods cannot efficiently deal with these designs which have a large number of decision variables because the relationship between the iterative time and the number of decision variables is exponential. Shi *et al*.(2007) considered this design as a multi-objective optimization problem by adopting a multi-objective genetic algorithm as a solver. The multi-objective genetic algorithm, NSGA-II, is used to configure the optimal PV-wind hybrid system with total system cost, system autonomy level and wasted energy as design objectives. Although this problem is difficult to solve because of its nonlinearity and complexity, the better results have been obtained comparing with the iterative methods. Bernal-Agustín *et al*.(2006) adopted another multi-objective genetic algorithm, SPEA, to successfully optimize the system configuration and control strategies of PV-wind-diesel systems simultaneously with electricity cost (life-cycle cost) and pollutant emission as design criteria. These two studies show that a multi-objective genetic algorithm can find the global optimal hybrid energy system configurations even if more decision variables and design criteria are considered.

Although many approaches are available for design and optimization of the hybrid energy system in literature, most of them are deterministic methods without optimizing stochastic performance measures. Stochastic performance measures reflect the effect of randomness and uncertainty on the candidate system configuration. Randomness and uncertainty are inherent for the actual hybrid power system and come from the system design process, the manufacture process, the power generating process, the aging process, and so on. These factors may worsen the performance of an optimal hybrid power system. However, the structural optimization methods of mechanical engineering take stochastic performance measures as objectives to achieve optimum design with respect to either variation of some structural parameters or extreme uncertain events during the last three decades. Recently, Lagaros *et al*.(2005) elevated structural stochastic performance measures using the Monte Carlo Simulation (MCS) method, combined with Latin Hypercube Sampling (LHS). They developed a cascade evolutionary algorithm to solve the structural robust design problem. So the stochastic performance measures of hybrid energy systems should be considered. The robust design methods are required to gain the system configuration insensitive to randomness and uncertainty.

This study presents a robust design method for autonomous PV-wind hybrid power systems to obtain an optimum system configuration insensitive to randomness and uncertainty. The proposed method formulates the robust optimal design of the PV-wind hybrid power system as a constraint multi-objective optimization problem. The NSGA-II combined with the constraint handling method solves the optimization problem because of the encouraging results of applying a multi-objective genetic algorithm to the design of the hybrid power system in (Shi *et al*., 2007; Bernal-Agustín *et al*., 2006). Electricity cost and system autonomy level are two issues in the design for obtaining a reasonable system configuration because they represent two different system performances and conflict each other. The mean values of electricity cost and autonomy level, as well as their standard square deviations, are adopted as stochastic performance measures to reflect and explore the effect of randomness and uncertainty on the candidate system configuration. MCS method, combined with LHS, evaluates these stochastic performance measures of the PV-wind hybrid power system. The effectiveness of the proposed design method has been demonstrated with a conceptual PV-wind power system design considering decision variable variations.

This paper has been divided into six sections. In Section 2, the robust design of PV-wind hybrid power system has been developed into a constraint multi-objective optimization problem. The next section presents MCS method, combined with LHS method, for evaluating the stochastic performance measures of the PV-wind hybrid power system. In Section 4, the adopted multi-objective genetic algorithm, NSGA-II, is described briefly. The effectiveness of the proposed method has been demonstrated with a stand-alone PV-wind power system design for a particular application and a comparative study between a robust and a deterministic design method is presented in Section 5. Section 6 puts forth the conclusions drawn from this work.

PROBLEM FORMULATION

The robust design of the PV-wind hybrid power system is formulated as a constraint multi-objective optimization problem to achieve the optimal system configurations insensitive to randomness and uncertainty. The peak power of photovoltaic array (P_{PV}), the rated power of wind turbine (P_{wt}) and the capacity of battery (C_{bat}) are decision variables. This study expands the deterministic measures to the stochastic performance measures. For the deterministic design methods, electricity cost and autonomy level are two critical objectives for the comparison of the candidate configurations in (Celik, 2003; Notton *et al*., 2001; Kellogg *et al*., 1996; Protogeropoulos *et al*., 1997). But these deterministic objectives cannot reflect the effect of randomness and uncertainty on the candidate system configuration. On the other hand, the stochastic measures of system performance, usually its mean value and standard deviation, are adopted to represent and explore the effect of randomness on the robust optimization framework where its random characteristics are unknown (Lagaros *et al*., 2005). For the PV-wind hybrid power system, the mean values of electricity cost and autonomy level are adopted as stochastic performance objectives, as well as their standard square deviations. The maximum electricity cost and the minimum system autonomy level are used as constraints to limit the solutions to the preferring scope. Table 1 shows the multi-objective optimization problem formulation of the robust design of the PV-wind hybrid power system. For calculating the stochastic objective values, the adopted method will be introduced in the next section.

Table 1 The objectives, constraints and decision variables for the PV-wind hybrid power system

Item	Description
Objectives	Maximizing system autonomy level mean value (ALM)
	Minimizing system autonomy level standard square deviation (ALSTD)
	Minimizing electricity cost mean value (ECM)
	Minimizing electricity cost standard square deviation (ECSTD)
Constraints	Simulation model
	Max allowable electricity cost mean value (MaxEC)
	Minimum allowable autonomy level mean value (MinAL)
Decision variables	The peak power of photovoltaic array (P_{PV})
	The rated power of wind turbine (P_{wt})
	The rated capacity of battery (C_{bat})

MONTE CARLO SIMULATION

MCS method, combined with LHS method, is used to evaluate the stochastic performance measures of the PV-wind hybrid power system. The PV-wind hybrid power system is a complex nonlinear system, and an analytical solution to its performance is not attainable. MCS method, as a stochastic analysis method, has the capability of handling practically this case regardless of its complexity and variation of the uncertain variable. MCS method has been proven to be efficient for the calculation of the statistical quantities in the framework of a robust optimal design problem (Lagaros *et al*., 2005). In order to reduce the computation effort, LHS method is used to construct the samples for every candidate system configuration (Avramidis and Wilson, 1996). LHS method generates the random samples from all ranges of possible values, and thus allows extracting a large amount of uncertainty and sensitivity information with a relatively small sample size.

In the stochastic analysis process, an MCS is performed for every candidate system configuration where each evaluation consists of a specified number (sample size) of runs. The samples of a candidate system configuration are constructed using LHS method from variable parameter statistical distributions. For each run, all non-variable parameters are fixed at their specified values. The variable parameter values for each run are ordered from the samples of the given candidate system configuration consequently. After setting these parameter values, an hourly time-step simulation procedure of the PV-wind hybrid power system is performed to evaluate system performance (Protogeropoulos *et al*., 1997; Shi *et al*., 2007). The results from the MCS of a candidate system configuration are its stochastic measure values.

MULTI-OBJECTIVE OPTIMIZATION

A multi-objective genetic algorithm, NSGA-II, is adopted to optimize the robust design of PV-wind hybrid power system which has been formulated as a constraint multi-objective optimization problem with four objectives and three constraints in the previous section. The resolution of this multi-objective problem is a complete, non-dominated or Pareto set, which includes the alternatives representing potential system configurations among the design criteria. A multi-objective genetic algorithm is well suited to solve these kinds of problems because it can find a large amount of Pareto-optimal solutions in a single run with no concerns of the shape or continuity of the Pareto set (Kicinger *et al*., 2005; Deb *et al*., 2002). The encouraging results have been achieved by NSGA-II for a deterministic optimal design of a PV-wind hybrid power system, although it is difficult to solve the multi-objective optimal design problem of a PV-wind hybrid power system due to its complexity, nonlinearity, incommensurable objectives, and implicit constraints (Shi *et al*., 2007). In presence of constraints, the constraint handling method proposed by Deb (2000) is adapted to guide the search towards the feasible region. Combined with the constraint handling method, NSGA-II is used to solve the robust design problem of the PV-wind hybrid power system.

The proposed robust design process of the PV-wind hybrid power system is summarized as follows:

Step 1. Set the ranges of design variables, the parameters of NSGA-II, and the stochastic distributions of variable parameters for MCS.

Step 2. Generate candidate system configurations randomly to construct a parent population *P*. Perform the MCS for every individual of population *P* to calculate stochastic objective and constraint values. According to these objective and constraint values, assign the fitness value to every individual of population *P*.

Step 3. Use selection, crossover and mutation and create a child population *Q* from the parent population *P*. Perform the MCS for every individual of population *Q* to calculate stochastic objective and constraint values.

Step 4. Assign the fitness value to every individual of the multi-set union of populations *P* and *Q* based on its objective and constraint values.

Step 5. Replace all the individuals of the population *P* with the individuals from the multi-set union of populations *P* and *Q* based on the fitness values.

Step 6. If the stopping criterion is satisfied, output the set of decision variables represented by the dominated individuals in the population *P*. Otherwise, go to Step 3.

The detailed description of NSGA-II is presented in (Deb *et al*., 2002).

RESULTS AND DISCUSSION

The proposed design method has been validated by the design of a conceptual PV-wind hybrid power system (Shi *et al*., 2007). Decision variable variations are assumed following a uniform distribution and are considered uncertain for the test because of little information about their stochastic characteristics. In the stochastic analysis process for a given system configuration, every decision variable is assumed to be an equally probable value in the range from 90% to 110% of its given value. The sample size is an important parameter of MCS method (Lagaros *et al*., 2005). A large sample size may help to reduce the distribution estimating error but this effect gets less and less as the size increases. On the other hand, the large sample size implies longer system simulation time. The MCS requires large computation efforts. The sample size takes 100 after comparing the results of MCS with different sample sizes for a given system configuration. This sample size allows a reasonable estimate for the performance distribution with less computation effort. The electricity cost of auxiliary power sources is assumed to be 1.00 ECU. The electricity cost of PV-wind hybrid power system should not be more than that of auxiliary power sources (Celik, 2003), and thus the mean value of the maximum allowable electricity cost takes 1.00 ECU. The economical analysis method and cost data have been used as well as the PV-wind system simulation model and the technical analysis method in (Notton *et al*., 1998; 2001; Shi *et al*., 2007). The parameters for NSGA-II refer to the previous work (Shi *et al*., 2007). The researched Pareto solutions are presented in Fig.1.

The proposed algorithm, NSGA-II, can handle the robust design problem of PV-wind power system effectively. The numerical results reported in Fig.1 show that a large mount of candidate system configurations with different objective values have been found by the proposed algorithm in a single run. The found solutions are located at the feasible region in Fig.1a and satisfy the constraints. The distribution of the researched Pareto solutions in Fig.1 is irregular

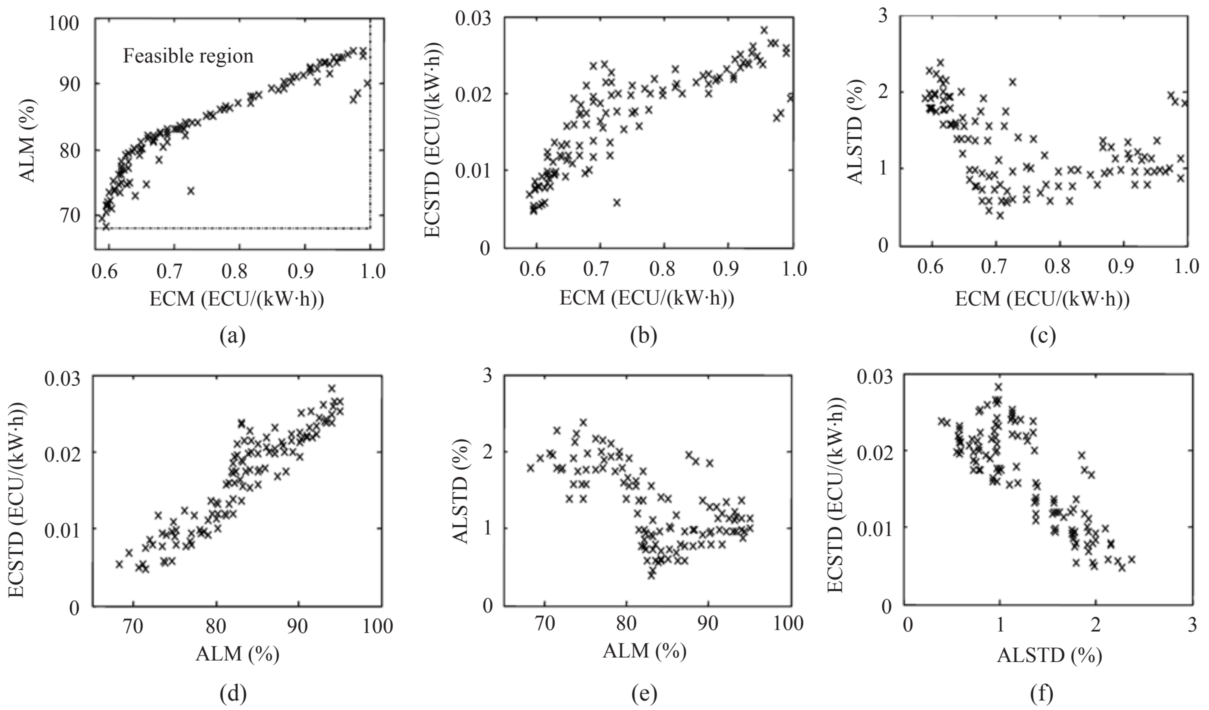

Fig.1 The searched Pareto solutions in the objective space
(a) ECM vs ALM; (b) ECM vs ECSTD; (c) ECM vs ALSTD; (d) ALM vs ECSTD; (e) ALM vs ALSTD; (f) ALSTD vs ECSTD

and located in some disconnected sub regions due to the nonlinear and complex nature of the robust design problem of PV-wind power system. In other words, the robust design problem is hard to solve because of the difficulties in finding and uniformly sampling solutions from the irregular and disconnected Pareto solution space. However, the adapted algorithm is so robust that it can uniformly sample Pareto solutions without concerning the shape or continuity of Pareto solution space.

The trade-off information among those decisive criteria can be derived from these candidate system configurations. Six plots in Fig.1 represent the pare-wise intersections among the four objectives. The trade-off information for any pair-wise objectives may be derived on the basis of the corresponding plot in Fig.1. The high ALM leads to the high ECM. As shown in Fig.1a, ALM and ECM increase at the same time. The ALM value increases fast in the about ECM range from 0.60 to 0.70 ECU/(kW·h) but slowly in the about ECM range from 0.70 to 1.00 ECU/(kW·h). The ECM value varies with the ECSTD value. Fig.1b shows that the ECSTD value changes greatly in the about ECM range from 0.60 to 0.70 ECU/(kW·h), but little in the about ECM range from 0.70 to 1.00 ECU/(kW·h). The engineer may acknowledge the trade-off information among those decisive criteria after analyzing all the six plots in Fig.1. It should be mentioned that the candidate systems with about ECM 0.70 ECU/(kW·h) divide the searched results into two parts and the trade-off relationship for these two parts show different.

With the help of the above criterion trade-off information, three outstanding candidate designs are selected as shown in Table 2. Design No. 1 stands for the most economic candidate system configurations. Its ECM and ECSTD are the lowest, but it has the lowest ALM and the highest ALSTD. On the contrast, Design No. 3 is one of the most technical optimum configurations. Its ALM is the highest, while its ALSTD is lower. But it has the highest ECM and ECSTD. Design No. 2 with ECM 0.70 ECU/(kW·h) stands for the compromising candidate configurations. The criteria relationship of the candidate configurations with ECM less than 0.70 ECU/(kW·h) is different from the criteria relationship of those with ECM more than 0.70 ECU/(kW·h) as mentioned above. The ALM for Design No. 2 is larger and its

ECM, ECSTD and ALSTD are smaller.

The relationship between the design objective value and the component size can be obtained further with the researched candidate solutions. The increasing size of the renewable components gives rise to the high system performance as shown in Fig.2. The larger size of the PV array leads to a high value of the design objective for the candidate systems with the same size of the wind turbine. So does the wind turbine. The battery size influences the system performance. ECM, ALM and ECSTD become larger when the battery size is increased as shown in Fig.3. At the same time, the selectable range of ALSTD becomes small.

The proposed robust design method has been compared with the deterministic method in (Bernal-Agustín *et al*., 2006). Using this deterministic method, the hybrid energy system has been designed with autonomy level (AL) value and electricity cost (EC) value as criteria. The deterministic design results (circle) are shown in Fig.4a. The corresponding stochastic performance measures (square) have been plotted in Fig.4. The robust designs (cross) with the proposed method have also been plotted in Fig.4.

Design variable variation can give rise to performance variability. For the candidate systems obtained by the deterministic method in Fig.4a, their AL values are larger than their ALM values. Their EC values are smaller than their ECM values. Design variable variation worsens the performance of the candidate systems obtained by the deterministic method. Engineers prefer a design insensitive to the variation.

The optimal candidate solutions obtained with the proposed design method are less sensitive to design variable variation than those with deterministic

Table 2 Some candidate designs for the hybrid PV-wind power system

Design No.	P_{PV} (kW)	P_{wt} (kW)	C_{bat} (kW)	ECM (ECU/(kW·h))	ALM (%)	ECSTD (ECU/(kW·h))	ALSTD (%)
1	1.8	2.8	3.7	0.589	69.51	0.007	1.92
2	2.2	3.8	11.3	0.700	83.17	0.019	0.73
3	2.6	6.6	28.2	0.990	94.15	0.026	0.87

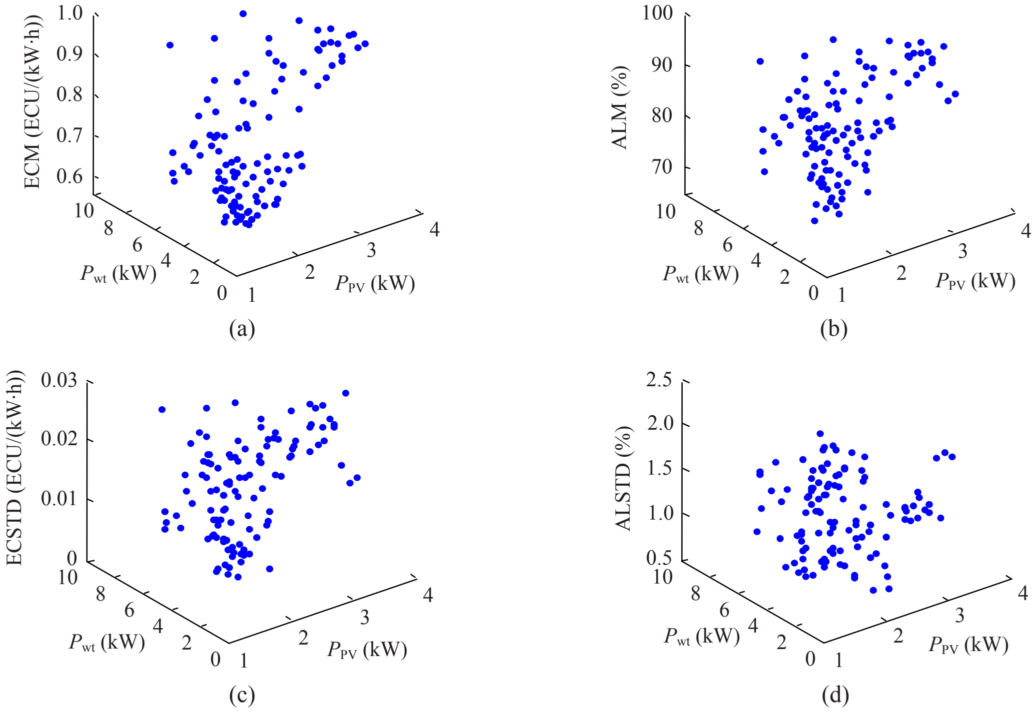

Fig.2 The relationship between the performance measures and the renewable component sizes
(a) P_{wt} and P_{PV} vs ECM; (b) P_{wt} and P_{PV} vs ALM; (c) P_{wt} and P_{PV} vs ECSTD; (c) P_{wt} and P_{PV} vs ALSTD

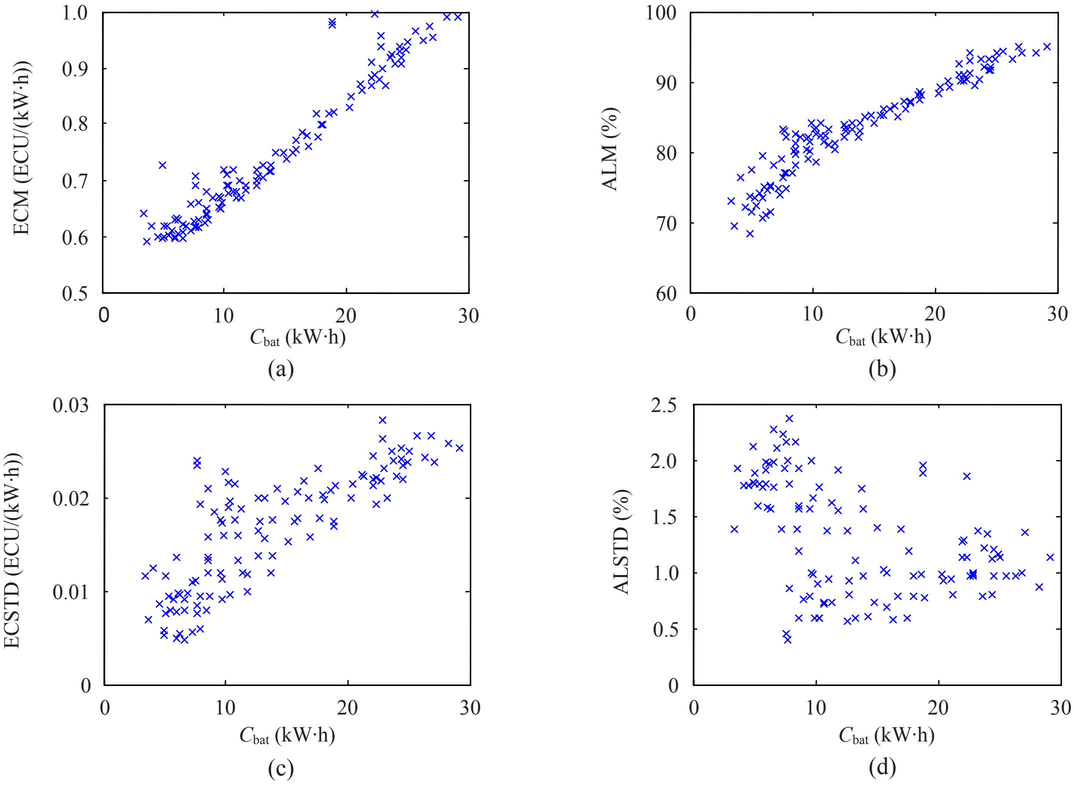

Fig.3 The relationship between the performance measures and the battery capacity
(a) C_{bat} vs ECM; (b) C_{bat} vs ALM; (c) C_{bat} vs ECSTD; (d) C_{bat} vs ALSTD

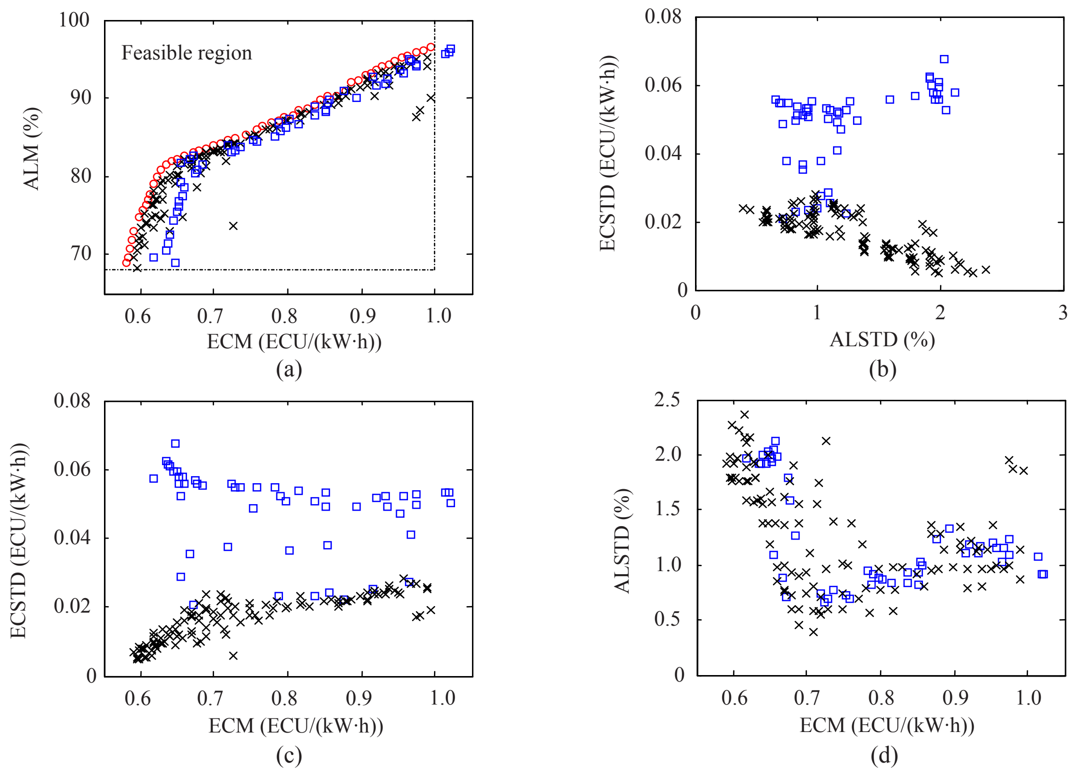

Fig.4 The comparison between the deterministic design method and the proposed robust design method
(a) ECM vs ALM; (b) ALSTD vs ECSTD; (c) ECM vs ECSTD; (d) ECM vs ALSTD

methods. Considering stochastic performance measures, the deterministic results distribute below the right region of the robust results in Fig.4a. In other words, there always exists a robust design whose ALM is larger than a given deterministic design but ECM is smaller. The deterministic results locate at the right-up region of the robust results in Fig.4b. This means that there always exists a robust design whose ECSTD and ALSTD are smaller than a given deterministic design. Therefore, the proposed robust design method can find a large mount of Pareto optimal system configurations insensitive to design variable variation.

The robust candidate configurations have better compromising performance (techno-economical performance and robustness) than those deterministic ones. The deterministic trade-off line (circle) in Fig.4a is the design limit line whose points indicate the best performance that the designer may achieve. For any given ECM, there exists a robust design close to the design limit line. Nevertheless, the proposed robust design method can find a candidate configuration superior to the given one by the deterministic method considering the design variable variation. For a setting ECM value, we may find at least one robust candidate configuration whose ALM value is larger than that for the corresponding deterministic configuration in Fig.4a. Meanwhile, we may find at least one robust design whose ECSTD and ALSTD are smaller than that for the corresponding deterministic design in Figs.4c and 4d.

CONCLUSION

The robust optimal design of PV-wind hybrid power system has been formulated as a constraint multi-objective optimization problem to achieve candidate system configurations insensitive to randomness and uncertainty. Combined with the constraint handling method, NSGA-II is used to solve the complex nonlinear problem. Three issues (the total system cost, electricity cost, and the system autonomy level) are considered as the objective or constraint form for the robust design problem. MCS method, combined with LHS method, is used to evaluate the stochastic measures of the PV-wind hybrid power system. The proposed method has been tested in a conceptual PV-wind hybrid power system where the design variable variation, as an uncertainty, is considered.

The adopted optimization algorithm handles the robust design problem of PV-wind hybrid power system effectively, which means that a large mount of Pareto optimal system configurations insensitive to design variable variation have been found by the proposed robust design method. The trade-off information may be derived by comparing the performance of these configurations systematically. The satisfying design may be identified by these candidate system configurations.

These candidate system configurations have been compared with those obtained by deterministic methods in literature. Design variable variation can give rise to performance variability. The optimal candidate solutions obtained with the proposed design method are less sensitive to design variable variation than those obtained with deterministic methods. Meanwhile they have enough techno-economical performance. The proposed robust design method should be useful for hybrid power system designs that require techno-economical optimality and robustness simultaneously.

References

Avramidis, A.N., Wilson, J.R., 1996. Integrated variance reduction strategies for simulation. *Operations Research*, **44**(2):327-346.

Bernal-Agustín, J.L., Dufo-López, R., Rivas-Ascaso, D.M., 2006. Design of isolated hybrid systems minimizing costs and pollutant emissions. *Renewable Energy*, **31**(14): 2227-2244. [doi:10.1016/j.renene.2005.11.002]

Celik, A.N., 2003. Techno-economic analysis of autonomous PV-wind hybrid energy systems using different sizing methods. *Energy Conversion and Management*, **44**(12): 1951-1968. [doi:10.1016/S0196-8904(02)00223-6]

Deb, K., 2000. An efficient constraint handling method for genetic algorithms. *Computer Methods in Applied Mechanics and Engineering*, **186**(2-4):311-338. [doi:10.1016/S0045-7825(99)00389-8]

Deb, K., Pratap, A., Agarwal, S., Meyariva, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, **6**(2): 182-197. [doi:10.1109/4235.996017]

Kellogg, W., Nehrir, M.H., Venkataramannan, G., Gerez, V., 1996. Optimal unit sizing for a hybrid wind/photovoltaic generating system. *Electric Power Systems Research*, **39**(1):35-38. [doi:10.1016/S0378-7796(96)01096-6]

Kicinger, R., Arciszewski, T., de Jong, K., 2005. Evolutionary computation and structural design: A survey of the state-of-the-art. *Computers and Structures*, **83**(23-24): 1943-1978. [doi:10.1016/j.compstruc.2005.03.002]

Lagaros, N.D., Plevris, V., Papadrakakis, M., 2005. Multi-objective design optimization using cascade evolutionary computations. *Computer Methods in Applied Mechanics and Engineering*, **194**(30-33):3496-3515. [doi:10.1016/j.cma.2004.12.029]

Notton, G., Muselli, M., Poggi, P., 1998. Costing of a stand-alone photovoltaic system. *Energy*, **23**(4):289-308. [doi:10.1016/S0360-5442(97)00092-3]

Notton, G., Muselli, M., Poggi, P., Louche, A., 2001. Decentralized wind energy systems providing small electrical loads in remote areas. *International Journal of Energy Research*, **25**(2):141-164. [doi:10.1002/er.670]

Protogeropoulos, C., Brinkworth, B.J., Marshall, R.H., 1997. Sizing and techno-economical optimization for hybrid solar photovoltaic/wind power systems with battery storage. *International Journal of Energy Research*, **21**(6): 465-479. [doi:10.1002/(SICI)1099-114X(199705)21:6<465::AID-ER273>3.0.CO;2-L]

Shi, J.H., Zhu, X.J., Cao, G.Y., 2007. Design and techno-economical optimization for stand-alone hybrid power systems with multi-objective evolutionary algorithms. *International Journal of Energy Research*, **31**(3): 315-328. [doi:10.1002/er.1247]

Wichert, B., 1997. PV-diesel hybrid energy systems for remote area power generation—A review of current practice and future developments. *Renewable and Sustainable Energy Reviews*, **1**(3):209-228. [doi:10.1016/S1364-0321(97)00006-3]