Renewable Energy 34 (2009) 2765–2773

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Promotion strategy of clean technologies in distributed generation expansion planning

Ali Zangeneh [a], Shahram Jadid [a,b,*], Ashkan Rahimi-Kian [c]

[a] Center of Excellence for Power System Operation and Automation, Iran University of Science and Technology, Tehran, Iran
[b] Green Research Center, Iran University of Science and Technology, Tehran, Iran
[c] CIPCE, School of ECE, College of Eng., University of Tehran, Tehran, Iran

ARTICLE INFO

Article history:
Received 25 August 2008
Accepted 14 June 2009
Available online 21 July 2009

Keywords:
Distributed generation
Renewable technologies
Expansion planning
Multi-objective optimization
Monte Carlo simulation
Uncertainty

ABSTRACT

Distributed generation expansion planning (DGEP) has been frequently reported in the literature around the world. In this scope, renewable technologies which are considered as a kind of distributed generations are developing due to their environmental benefits. However, only a few renewable energies have proven to be competitive so far, while their economic viability is also limited to certain regions of the world. In this paper, an encouraging mechanism is proposed in favor of clean technologies in the planning process. This mechanism is defined based on a grant function of emission not polluted which is paid to DG owners to promote renewable and clean technologies. In the planning process, a multi-objective optimization algorithm is applied to produce a Pareto set of optimal planning schemes by taking into account different objective functions (cost and grant functions). The best planning scheme among the Pareto set is chosen based on a composite utility which are obtained through a Monte Carlo simulation of uncertain situations. Distributed generation technologies which are considered in this paper are conventional and renewable technologies, namely photovoltaic (PV), wind turbine (WT), fuel cell (FC), micro turbine (MT), gas turbine (GT), and reciprocal engine (RE). To assess the ability of the proposed method, a typical distribution system is used for expansion planning under two environmental scenarios.

© 2009 Elsevier Ltd. All rights reserved.

1. Introduction

Distributed generation (DG) is an emerging approach to provide electric energy close to load center [1,2]. Changing economic and regulatory environment and also technological innovations have resulted in a renewed interest for distributed generation in the last decade [3].

Because of the wide definition of DG units, there are different types of DGs from the technological point of view. These technologies generally can be divided into two groups namely: combustion and non-combustion or renewable and nonrenewable. Nowadays, most of the DG capacities which are installed in the world are: Diesel/gas reciprocating engines and gas turbines. However, in one hand, renewable technologies such as photovoltaic and wind turbine are growing extremely quickly due to strong policy support. PV has the fastest growing renewable technology in the world by 60% per year from 2000 to 2004 and during the same 5-year period WT grew by 28% per year [4]. On the other hand, new DG technologies such as micro-turbines and fuel cells are being developed and are seen as a potential for the future too [5].

Nevertheless, there is not a unique DG technology until now that captures different aspects such as: economical, operational, environmental, etc. Therefore various types of DG technologies must be included in the planning strategy to choose the best ones according to the objectives and constraints of the planner. Many methods and techniques have been employed for DG expansion planning problem so far. Kim et al. [6] presented an approach based on Hereford ranch algorithm to minimize energy losses in a subtransmission system. El-Khaltam et al. [7,8] presented a heuristic approach to determine the optimal DG size and site from an investment point of view and the optimal planning was obtained through a cost-benefit analysis. They considered several cost functions in their planning model. Keane and O'Malley [9] presented an optimal allocation of DG based on maximizing generation penetration subject to technical constraints. In recent years,

* Corresponding author at: Center of Excellence for Power System Operation and Automation, Iran University of Science and Technology, Tehran, Iran. Tel.: +98 21 77491223; fax: +98 21 77491242.
E-mail addresses: zangeneh@iust.ac.ir (A. Zangeneh), jadid@iust.ac.ir (S. Jadid).

0960-1481/$ – see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.renene.2009.06.018

Nomenclature

Sets, parameters and scalars:

a_j	availability factor of unit type j at the end of planning horizon
D_j	expected peak power demand in *j*th load bus at the end of planning horizon
ER_j	emission rate of DG technology type *j*
ERP	average of emission rate of integrated fueled power plants
GR	Grant rate of emission not polluted ($/Kg)
IC_j	yearly investment of DG technology type *j*
L_i	length of *i*th line
LF	load factor of the consumption at the end of planning horizon
OC_j	hourly operating cost of DG technology type *j*
nb	total number of buses in the distribution system
nlb	number of load buses in the distribution system
ns	number of substations which feed the distribution system
pf	system power factor
PL_i	emission limitation at *i*th bus
TIB	total investment budget
Z_{ij}	impedance of branch between *i*th and *j*th bus

Greek letters

α	average plant factor of integrated power plants in the grid
π	hourly price of electricity market
λ	probability rate of outage line

Variables

V_i	voltage of *i*th bus
$P_{DG,ij}$	capacity of technology type *j* in the *i*th bus

another kind of planning methods based on the multi-objective optimization techniques have been proposed by the researchers [10–12] due to the ability of considering several conflicting objectives at the same time.

Globally, burning carbon has significant negative effects on the well-being of humans and eco-systems [13]. The main concentration of many of published literatures is focused on economical and technical issues; however, recently a part of them consider the environmental problem which is an important factor of sustainable development. Dicorato et al. [14,15] presented a comprehensive and interesting energy planning methodology including environmental constraints to allocate required electricity generation in whole power system. However, it is not compatible with unbundling of the electricity network after deregulation and also siting of power plant (centralized and decentralized) in the electricity network are not determined in their proposed method. In [16] some supporting schemes such as feed-in tarrifs, net metering and green pricing were presented to reduce production costs of renewable technologies. Van Alphen et al. [17] demonstrated that current subsidies for conventional energy can be removed or shifted to towards renewable energy technologies (RET) to promote these kinds of technology. They also illustrated that rebates on investments and low-interest loans should be provided to RET project developers to overcome the high initial project costs. Sarafidis et al. [18] expressed to promote renewable energies it is necessary to shift from a centralized view of the energy sector to a regional perspective. They used a bottom-up approach intended to match the supply of available renewable resources to the particular energy demand profile of the regional level. A detailed overview of the policies and measures implemented in Denmark aiming to meet 35% of energy demand based on renewable energies are presented in [19]. do Valle Costa et al. [20] presented an analysis about the developments in renewable energy policies and the prospects for Brazil based on the European experience in promoting renewable energy sources.

In the medium term, dependency on the traditional fossil fuel resources must be reduced gradually, in favor of clean energy sources and this will be occurred by considering some encouraging instructions, subsidy, or limiting constraints. This paper presents a theoretical and practical approach based on multi-objective expansion planning of DG technologies subject to technical, economical, and environmental constraints. Addition to the conventional cost functions, a grant function as a pollution not emanated is proposed that must be maximized. Afterwards, Monte Carlo Simulation (MCS) is applied to the options of the Pareto set, output of multi-objective optimization, to consider probabilistic behavior of uncertain parameters in the long term planning and choose the best planning scheme. Six technologies of DG that are taken into account in this paper are: photovoltaic (PV), wind turbine (WT), fuel cell (FC), micro turbine (MT), gas turbine (GT) and diesel reciprocating engine.

2. Mathematical model

2.1. Objective functions of DGEP problem

The future environmental rules like Kyoto protocol put a new vision in front of the planner's and legislator's eyes. Therefore a new objective related to the emitted pollution function will be added to the conventional cost functions in generation expansion planning problems. In the proposed planning model, a grant function is introduced in addition to the conventional cost functions such as: the cost of investment and operation, cost of energy losses and purchased energy. The grant function is based on the pollution not generated due to employing new DG technologies.

2.1.1. Cost function of investment and operation

This function (1) takes into account the investment and operation cost of DG technologies. According to (1), all load buses are possible candidate for DG installation.

$$f_1 = \sum_{i=1}^{nlb} \sum_{j \in Tech} CPV_1 \cdot IC_j \cdot P_{DG,ij} + \sum_{i=1}^{nlb} \sum_{j \in Tech} CPV_2 \cdot OC_j \cdot P_{DG,ij} \cdot a_j \times 8760 \quad (1)$$

where *j* denotes to the DG technologies that is studied in this paper, i.e., PV, WT, FC, MT, GT, and RE. *IC* and *OC* are yearly DG investment and hourly operating costs respectively, *nlb* is the number of load buses in the distribution system, $P_{DG,ij}$ is the capacity of technology type *j* in the *i*th bus, CPV_1 and CPV_2 are cumulative present values related to fixed and variable costs respectively which are illustrated in appendix and a_j is the plant factor of *j*th technology at the end of planning horizon [21].

2.1.2. Cost function of energy losses and purchased power

This objective function comprises two consistent objective functions: the total cost of the energy losses in the distribution system and the purchased energy from the grid [22]. The aim of the objective (f_2) is to minimize both cost functions according to the penetration level, capacity and location of DG units. Power flow in feeder connecting bus i to j which is used to formulate energy loss function is approximately defined in (3).

$$f_2 = \left(\sum_{i=1}^{nb} \sum_{j=i+1}^{nb} \frac{\left(|V_i| - |V_j|\right)^2}{|Z_{ij}|} \cdot pf \cdot \pi + \sum_{i=1}^{ns} \sum_{j=1}^{nlb} |V_i| \frac{\left(|V_i| - |V_j|\right)}{|Z_{ij}|} \cdot \pi \cdot pf \right) \cdot LF \cdot CPV_2 \times 8760 \quad (2)$$

$$P_{ij} \approx |V_i| \cdot \frac{\left(|V_i| - |V_j|\right)}{|Z_{ij}|} \cdot pf \quad (3)$$

where nb is the total number of buses in the distribution system, ns is the number of substations which feed the distribution system, V is the bus voltage, Z_{ij} and P_{ij} are impedance and power flow of branch between ith and jth bus respectively, pf is the system power factor, π is the hourly price of electricity market and LF is the prediction of load factor in the last year of planning horizon.

2.1.3. Grant or subsidy function as a pollution not emanated

One of the advantages of the new DG technologies is the reduction of the greenhouse gas (GHG) emission using less fossil fueled power plants. Pollution not emanated can be considered as an appropriate objective function defined by authorized entities to encourage distribution companies (DisCo) or independent power producers (IPP) towards new technologies. This objective function (4) must be maximized which is defined as the cost saving of pollution not generated due to utilization of clean DG units. For this purpose a pollution rate is used for each technology of DG units.

$$f_3 = \left(DG^{cap} \cdot \alpha_p \cdot ERP - \sum_{i=1}^{nlb} \{EDG_i\} \right) \cdot GR \cdot CPV_2 \times 8760 \quad (4)$$

$$DG^{cap} = \sum_{i=1}^{nlb} \sum_{j \in Tech} P_{DG,ij} \quad (5)$$

$$EDG_i = \sum_{j \in Tech} \left(P_{DG,ij} \cdot a_j \sum_{k=1}^{3} \omega_k \cdot ER_{jk} \right), \quad i \ \forall \ nlb \quad (6)$$

where DG^{cap} is the total capacity of DG units which is planned to be installed in the distribution system, ERP is the emission average rate of integrated fueled power plants, α is the average plant factor of integrated power plants in the grid, EDG_i is the total emission of DG units in the ith bus related to the technology type of DG, GR is the grant rate of emission not polluted, ER_{jk} is the emission rate of kth pollutant related to jth DG technology and w_k is the weighting factor of kth pollutant.

2.2. Constraints of DGEP problem

The predefined objective functions are optimized subject to various constraints to satisfy the technical, economical and environmental aspects of the distribution networks.

2.2.1. Balance of supply and demand

One of the most important constraints in the planning process is to meet future demand of the distribution system in peak load conditions (7). This is an equality constraint that sum of all incoming and outgoing active power from each load bus must be balanced.

$$\sum_{i=1}^{nb} \left\{ P_{ij} - \frac{\left(|V_i| - |V_j|\right)}{|Z_{ij}|} \cdot pf \right\} + P_{DG,j}^{CAP} = D_j \quad j \ \forall \ nlb \quad (7)$$

$$P_{DG,i}^{cap} = \sum_{j \in Tech} P_{DG,ij} \quad i \ \forall \ nlb \quad (8)$$

where D_j is the peak power demand in jth bus and P_{DG}^{CAP} is capacity of DG units at each bus.

2.2.2. Voltage limits

Voltage magnitude of all the load buses must be limited within allowed upper and lower limits (9). In this paper, upper and lower limits of voltage are assumed to be 1.05 p.u. and 0.95 p.u. respectively.

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \forall \ i \in nlb \quad (9)$$

2.2.3. Feeder capacity constraint

Power flow of the distribution feeders must be limited under maximum capacity of the feeders (10).

$$P_{ij} \le P_{ij}^{Max}, \quad i \ \forall \ ns \ \& \ j \ \forall \ nlb \quad (10)$$

2.2.4. Maximum installed capacity

Maximum installed capacity at each bus is determined for DG units according to technical characteristics of distribution system. The calculated capacity of DG units through optimization algorithm must be less than maximum installed capacity of DG units at each bus (11).

$$P_{DGi}^{cap} \le P_{DG}^{\max} \quad \forall \ i \in nlb \quad (11)$$

where $P_{DG}^{\max}$ is the maximum permitted capacity of the total installed DG units at each bus of the distribution system. This value is considered to be 4 MVA according to the voltage limits and short circuit level of distribution system [7].

2.2.5. Total investment budget

Either DisCo or IPPs have to carry out investment planning according to their maximum financial budget. It is taken as a significant factor in calculating the capacity of DG units.

$$\sum_{i=1}^{nlb} \sum_{j \in Tech} IC_j \cdot P_{DG,ij} \le TIB \quad (12)$$

where TIB is the total yearly investment equal to US$ 438000 which is available for investment in distributed generation. This yearly parameter is obtained according to a planning horizon of 10 years and discount rate of 9.15%.

2.2.6. Pollution emission

An important constraint in the future generation expansion planning is the emission limitation. This constraint can be defined either as the maximum rate in entire distribution system (13) or as the maximum emission rate at each bus (14).

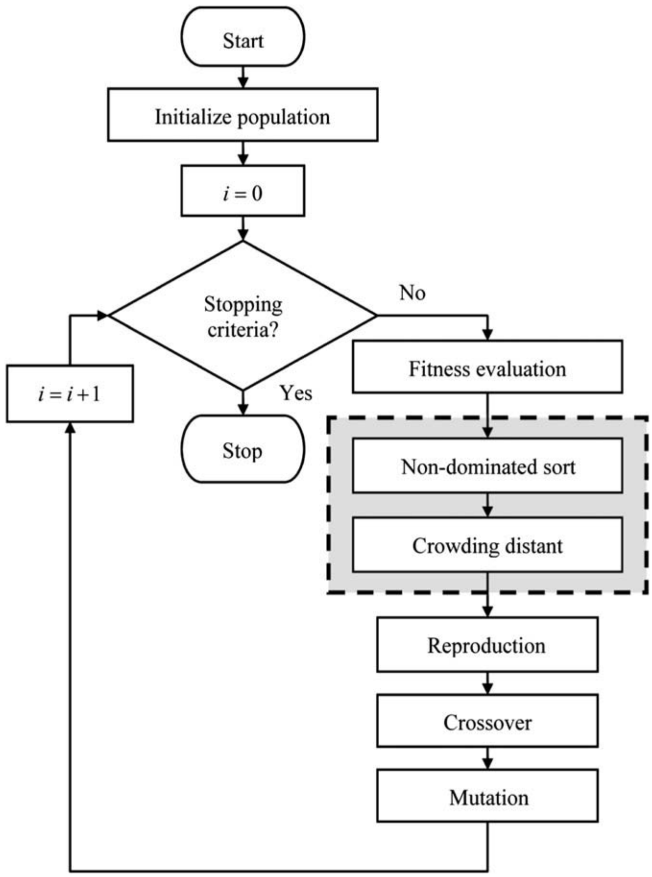

Fig. 1. Non-dominated sort in genetic algorithm.

$$\sum_{i=1}^{nlb} EDG_i \leq TPL \tag{13}$$

$$EDG_i \leq PL_i \tag{14}$$

where EDG_i is the total emission of DG units in the ith bus and PL_i is the emission limitation at ith bus and TPL is the total emission limitation in whole distribution system.

3. Multi-objective optimization algorithm

A multi-objective optimization problem has a number of conflicting objective functions which are to be minimized or maximized [23]. This optimization problem can be stated as (15).

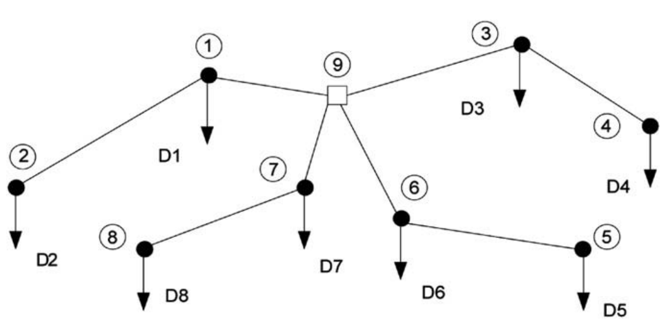

Fig. 2. Typical distribution system.

Table 1
Peak load demand of buses at the end of planning horizon.

Bus Number	1	2	3	4	5	6	7	8
Demand (MVA)	7.6	8.7	4.6	4.0	5.1	6.1	7.6	7.4

Table 2
Technical and economical data of DG technologies.

Technology	*IC* ($/MW-year)	*OC* ($/MWh)	Commercial size (KW)	Plant factor (%)	Pollution (kg/MWh)		
					CO_2	NO_x	Others
PV	618,000	0	100	25	0	0	0
WT	206,000	10.9	200, 300	20	0	0	0
FC	278,100	36.4	100, 200	75	460	0.001	0.027
MT	180,250	47.3	100, 200, 300	55	720	0.1	0.478
GT	103,300	54.5	300, 500, 1000	60	630	0.5	1.135
RE	36,050	64.4	300, 500, 1000	15	685	10	2.724

$$\begin{aligned} &\min F(\boldsymbol{x}) = \{f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_n(\boldsymbol{x})\} \\ &s.t. \quad g(\boldsymbol{x}) \leq 0\,, \quad h(\boldsymbol{x}) = 0 \end{aligned} \tag{15}$$

where n is the number of objective functions, $\boldsymbol{x}$ is the vector of variables for the optimization problem, $f_i(\boldsymbol{x})$ is the ith objective function, $g(\boldsymbol{x})$ and $h(\boldsymbol{x})$ are equality and inequality constraints of the problem. In contrary to single objective optimization, the solution of (15) involves a set of solutions called Pareto or trade-off surface. After a set of such trade-off solutions are found, a decision maker can then use higher level qualitative considerations to choose an option. Numbers of the Pareto set are set to 200 in the simulations.

Non-Dominated Sorting in Genetic Algorithms is a popular non-domination based genetic algorithm for multi-objective optimization [24]. In this paper a modified version, NSGA-II which has a better sorting algorithm is applied to find trade-off optimal solutions of DG technologies, location and size. In this method, two blocks are added to the conventional genetic algorithm to solve

Table 3
Maximum emission rate throughout distribution system in scenario A.

	Maximum permitted emission (kg/h)
Case study I	8000
Case study II	7000
Case study III	6000

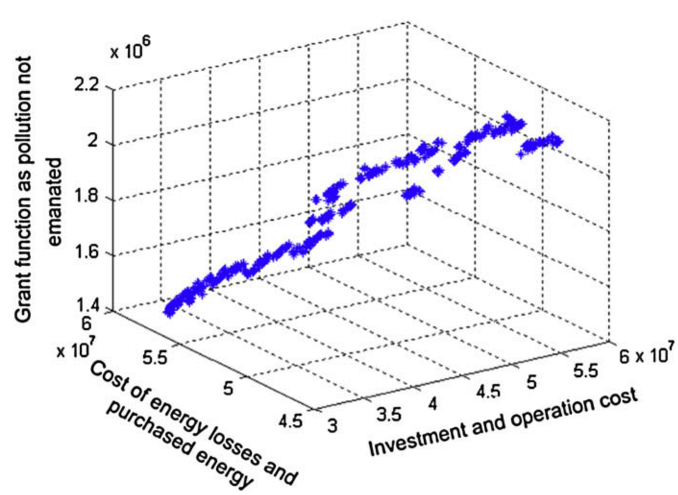

Fig. 3. Pareto set of three objective functions during the planning period.

Table 4
Five samples of the planning schemes among Pareto set of case study I.

Scheme	DG technologies	Bus number							
		1	2	3	4	5	6	7	8
1	PV	0.5	0	0	0	0.3	0	0	1.2
	WT	0	0	0	0	1.5	0	0	1.5
	FC	0	0	0	0	1.2	0	0	0.4
	MT	1.3	1.4	0	0	0	0	0	0
	GT	0.8	0	0	0	0	0	0	0
	RE	1.7	1.5	0	0	0	3.3	0	1
2	PV	0	0	0	0	0	0	0	0.3
	WT	0	0	0	0	1.1	0	0	1
	FC	0	0	0	0	0	0	0	0
	MT	0	1.4	0	0.9	0	0	0.9	0.9
	GT	0	1.4	0	0	1.7	0	2	0
	RE	0	0	0	2.1	0	0	0	1
3	PV	0	0	0.5	0	0.7	0	0	0.5
	WT	0	0	1.5	0	1.3	0	0	1.3
	FC	0.8	0	0	0	0	0	0	0
	MT	0	0	0	0	0.7	0	0	0.9
	GT	0.9	0	0.8	0	0	0	0	0.3
	RE	2.2	0	1.1	0	1	0	0	0.9
4	PV	0	0	0	0	0.2	0	0	0
	WT	0	0	0	0	1	0	0	0
	FC	0	0	0	0	1	0	0	1.5
	MT	0	0	0	0	0	0	0	0
	GT	0	0.9	0	0	0	0	0	1.2
	RE	2	2.1	0	3	0.8	0	0	0
5	PV	0	0.4	0	0	0	0	0	0
	WT	0	0	1.1	0	0.3	0	0	0
	FC	0	1.6	0	0	0	0.2	0.8	0
	MT	0	0.5	0.9	0	0	0.6	0	0
	GT	1.7	0	0	0	0	1.7	0	0
	RE	1.4	0.3	1.1	0	0	0.3	2.2	0

multi-objective problems. These parts, shown in Fig. 1 are described as follow.

3.1. Non-dominated sort

The population, P in each generation is classified and sorted to several fronts according to non-domination hypothesis [25]. Each individual in main population, P is compared with the other individuals to determine whether it is dominated or not. Those individuals that are not dominated with the others form the first front. After removing the individuals belong to the first front from the main population, this process which is described in detail in [23] is carried out to find out the next fronts (16).

$$P = \cup_{j=1}^{\rho} P_j \tag{16}$$

where P_j is the jth front of the sorted population.

3.2. Crowding distance

After completing non-dominated sort, the crowding distance is assigned. Since the individuals are selected based on rank and crowding distance, all the individuals in the population are assigned a crowding distance value. The crowding distance is a measure of how close an individual is to its neighbors. Large average crowding distance will result in better diversity in the population. The basic idea behind the crowing distance is finding the Euclidian distance between each individual in a front. This parameter is calculated between two individuals in the same front.

$$d_j(k) = \sum_{i=1}^{n} \frac{f_i(k-1) - f_i(k+1)}{f_i^{\max} - f_i^{\min}}, \quad j = 1, \ldots, \rho \tag{17}$$

where $d(k)$ is the distant of kth individual in the jth front. An infinite distance is assigned to boundary individuals in each front.

Table 5
Penetration level (%) of DG technologies among Pareto set for scenario A.

	PV	WT	FC	MT	GT	RE
Case study I	6.9	12.8	12.6	10.2	15.4	42.1
Case study II	10.1	16.9	13.5	5.4	17.6	36.6
Case study III	12.4	19.8	22.5	2.9	27.1	15.3

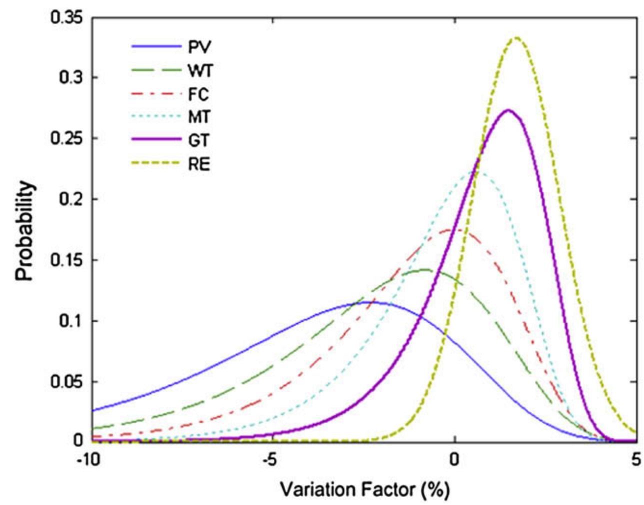

Fig. 4. Probability distribution function of yearly investment cost associated with DG technologies.

4. Monte carlo simulation

Monte Carlo Simulation is one of the methods for simulating real systems by analyzing uncertainty propagation, where the goal is to determine how random variation, lack of knowledge, or error affects the sensitivity, performance, or reliability of the system that is being modeled [26]. Since the uncertain

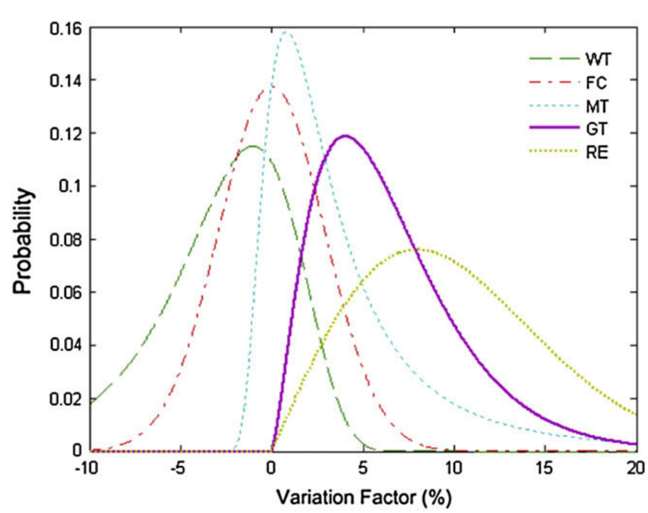

Fig. 5. Probability distribution function of hourly operating cost associated with DG technologies.

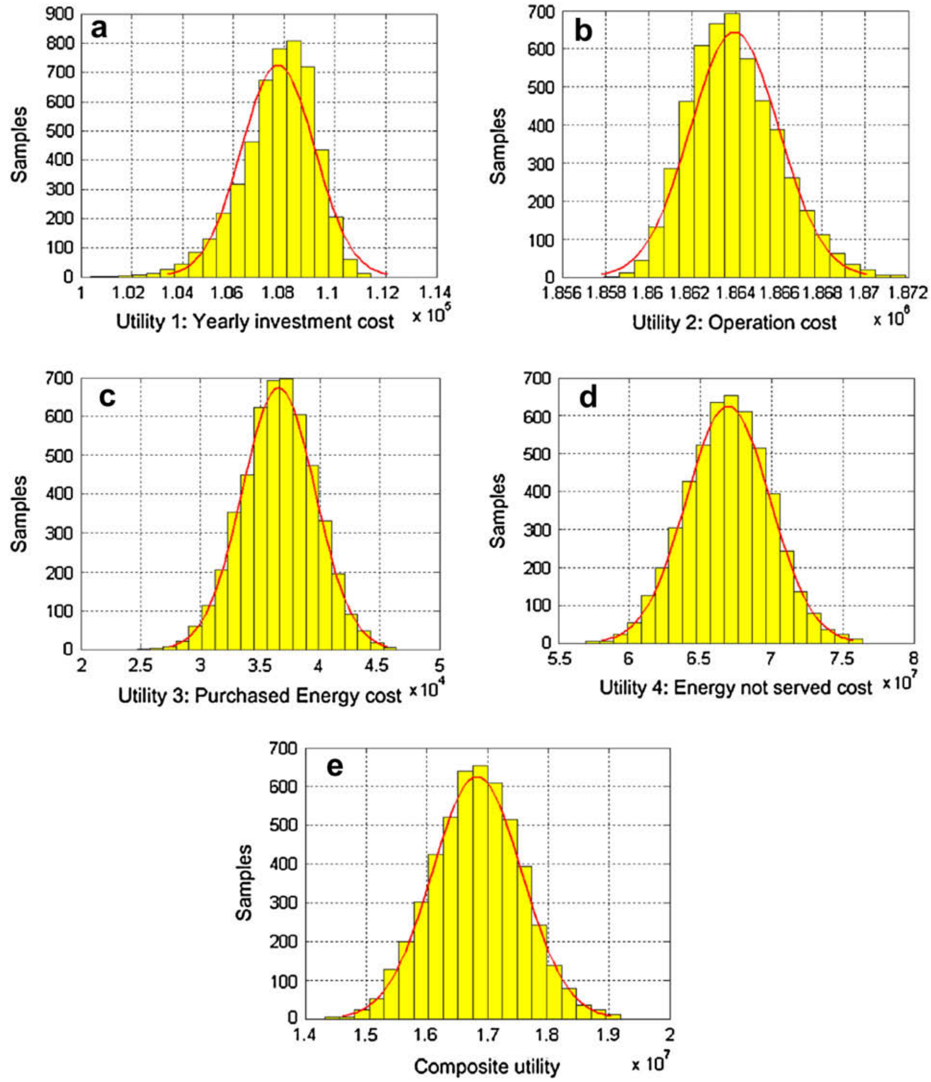

Fig. 6. Histogram samples of MCS for scheme no. 154 by composite utility function.

parameters as inputs of MCS are randomly generated from a probability distribution function, MCS is known as a sampling technique. This characteristic can be defined as the ability of the technique that takes into account randomness by investing hundreds of thousands of different situations [27]. The results are then gathered and used to make decisions. This process will help decision maker to come closer to the reality.

MCS method is performed in the following steps [28,29]:

Step 1: Determine an appropriate distribution function for each uncertainty regarding the available records and experts' opinion.

Step 2: Determine number of runs that the simulation should be performed. It is determined according to the problem size and importance of risks.

Table 6
Ten first schemes of DG expansion planning of case study I according to different utility functions.

Schemes ranking based on different utility functions				
Investment cost ($)	Operating cost ($)	Cost of energy losses & purchased	Cost of energy not served ($)	Composite utility function
127	160	4	15	146
2	109	5	76	144
22	13	83	145	174
180	67	33	70	142
171	168	120	49	192
200	182	195	157	103
3	97	8	29	29
117	45	166	36	23
65	106	37	78	41
84	154	7	38	149

Table 7
Candidate DG schemes: capacity, location and technology type of best schemes in scenario A.

Bus no.	Case I: Scheme no. 154						Case II: Scheme no. 46						Case III: Scheme no. 97					
	PV	WT	FC	MT	GT	RE	PV	WT	FC	MT	GT	RE	PV	WT	FC	MT	GT	RE
1	0	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0
2	0.5	0	1.0	0	1.3	1.2	0.4	0	1.2	0	1.4	0.8	0.3	0	1.3	0	1.6	0.8
3	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	1	0	1.2	0	0	0.9	0	0	0.9	0	0	0.9	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.5	0	0.4	0	0	2.2	0.4	0	0	0	1.8	0.9	0.3	0	0	0	1.7	0.8
8	0.3	0.7	0.3	0	0	1.8	0.8	1.1	0.2	0	0	0.8	0.8	1	0.3	0	0	0.9

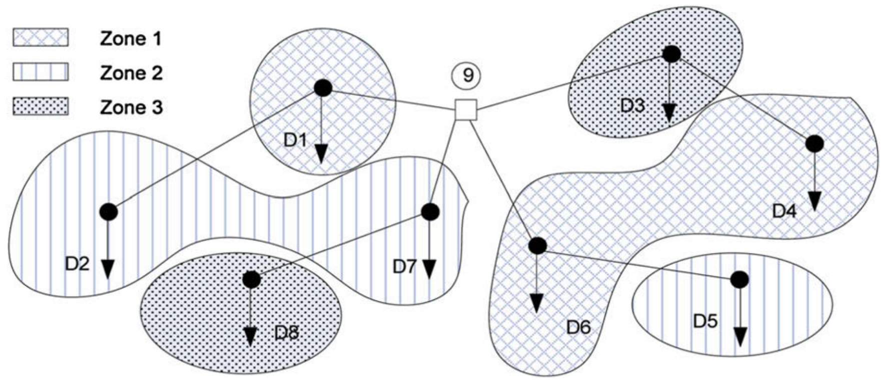

Fig. 7. Zoning of distribution system according to ecological criterion.

Step 3: In each run, allocate a random number for each uncertainty according to the predefined distribution function.

Step 4: Utility function measure is determined based on the value of uncertainties obtained in current run.

Step 5: Do steps 3 and 4 for all simulation runs and then draw the histogram diagram of utility function results.

According to the uncertain parameters, a composite utility function (18) is defined to assess the sensitivity of the uncertain parameters on planning schemes of the Pareto set. The composite function is weighted sum of the yearly investment cost (U_1), average of yearly operation cost (U_2), cost function of energy losses and energy purchased (U_3) and penalty cost of energy not served (U_4). The utility function of energy not served (19) is the probability cost of energy not served according to the uncertainty of electricity demand.

$$U_c = \sum_{i=1}^{4} w_i U_i \tag{18}$$

$$U_4 = \sum_{i=1}^{nl} \left(D_i^t - P_{DG,i}^t\right) \cdot L_i \cdot \lambda \cdot Cu \tag{19}$$

where w is the weighting factor of the utility functions assumed to be equal to 0.25, D_i^t and $P_{DG,i}^t$ are total demand and local generation in the deliberate island respectively that is downward of the fault location, nl is the number of lines in the distribution system, L_i is the length of ith line, λ is the yearly probability rate of line outage and Cu is the average cost of energy not served through the distribution system. It is assumed to be 350 \$/MWh.

As MCS is a stochastic technique, if the simulation is repeated, a different set of summary statistics will have been calculated. Therefore, if the sample size becomes larger, the difference between the repeated simulations will be smaller. Number of samples is assumed to be 5000 in this paper.

5. Simulation results

As it was described, a strategy based on encouragement (grant function) and convincement (emission constraints) is proposed to promote clean technologies in the DGEP problem. To assess the ability of the proposed approach, a typical distribution system shown in Fig. 2 is used [7]. The distribution system consists of 8 load buses and one junction substation connecting remainder of the system to the main grid. The capacity of the substation is 40 MVA. It is assumed that planning horizon consists of 10 years and DisCo has to supply peak demand at the end of planning horizon by investing in DG capacities. Peak demand of load buses at the end of planning horizon is presented in Table 1. Power factor is assumed unity in the distribution system.

The technical and economical data of DG technologies are presented in Table 2 [5]. The emission rate of some greenhouse gases are presented for each technology in this table. The total amount of emission for each technology is determined based on the weighted sum of the pollutants. The weighting factors are equal to 0.3, 0.5, and 0.2 for CO_2, NO_x and the other gases like SO_2 and CO. The grant rate of emission not polluted is considered equal to 0.25 \$/kg [30]. Electricity market price at the end of planning horizon, tenth year, is assumed to be 60 \$/MWh. Since siting of WT is strongly related to geographical factors, it is assumed that appropriate places to install WT units are just buses 3, 5 and 8.

In this section two scenarios based on maximum emission rate are considered to assess the capability of the proposed methodology under future uncertainties.

5.1. Scenario A: emission constraint throughout distribution system

In this scenario, total emission by overall installed DG is limited by a constraint. It can be an appropriate constraint if system under study has small geography extent, especially for small distribution system. Maximum permitted emission rate throughout the typical distribution system under three case studies is presented in Table 3. The Pareto set of multi-objective optimization as a set of optimal planning schemes is depicted in Fig. 3 for case I and Table 4 gives five sample schemes among Pareto set for this case study. Average penetration level of each DG technology among the Pareto set are presented in Table 5. It is shown that penetration level percentage of such DG technologies with high emission rate (RE, MT and GT) is decreased in favor of clean technologies (PV, WT and FC) from case I to case III by reducing maximum emission rate. Next step is to achieve a final decision among the obtained planning schemes. In this paper, a MCS method is applied to choose the best planning scheme by considering future uncertainties. MCS method is performed according to section 3 and uncertain parameters are defined as yearly investment cost, hourly operating cost, electricity market price and maximum electricity demand at each bus. A special distribution function is defined for each uncertain parameter to simulate the future variations. These distribution functions are chosen according to the probability of the future technology development and expert's opinions. Figs. 4 and 5 show the distribution function of investment and operation costs related to DG technologies. For example, in Fig. 4, investment cost of DG technologies varies in different trend according to the future

Table 8
Maximum emission rate at each bus of distribution system in scenario B.

	Zone 1 (kg/h)	Zone 2 (kg/h)	Zone 3 (kg/h)
Case study IV	2600	2200	1800
Case study V	1800	2600	2200
Case study VI	2200	1800	2600

Table 9
Penetration level (%) of DG technologies for scenario B.

	PV	WT	FC	MT	GT	RE
Case study IV	4.3	10.7	8.7	8.4	19.8	48.1
Case study V	8	12.1	12.5	6.9	20.5	40
Case study VI	10.8	16	17.4	8.6	12.6	34.6

development. Similarly, operation cost variations of conventional technologies like GT and RE show the probability of increasing prices due to future increasing prices of oil and gas. MCS method with 5000 samples is applied on different utility functions by using predefined uncertain parameters. Standard deviation value of MCS samples is calculated for each scheme and the scheme with lowest standard deviation is chosen as the best planning scheme in viewpoint of a specified utility function. Table 6 shows ranking of 10 first planning schemes according to different utility functions. Final decision is made based on a composite utility function which is weighted sum of defined utility functions. It is assumed that all the weighting factors are equal to 0.25. Histogram curves of MCS samples for scheme no. 154 is shown in Fig. 6 as the best scheme of the case study I. Candidate schemes for three case studies are presented in Table 7. It presents capacity, location and technology type of DG units.

5.2. Scenario B: emission constraint at each bus

In this scenario, a hard emission constraint is considered at each bus. This constraint could be applied in the expansion planning of large urban distribution systems which have a great concern about emitted pollution. For this purpose, as shown in Fig. 7, the distribution system under study is divided into three zones according to the ecological and pollutant criterion. Maximum emission rate at each bus is presented under three case studies in Table 8. The results of the penetration level percentage of DG technologies are presented in Table 9. It is seen that RE has the largest penetration level in three case studies; however its amount is reduced from 48.1% in case IV to 34.6% in case VI. Since zone 2 of the distribution system consists of important buses in viewpoint of DG siting such as 2 and 5, case VI has the strictest conditions among the case studies due to emission constraint in zone 2. Table 9 shows that clean and renewable technologies have the highest penetration level in case study VI. The Penetration level of these technologies is increased from cases IV to VI. However, the penetration of conventional technologies is decreased from cases IV to VI. It is observed from Table 8 that zone 2 and after that zone 1 have severe emission constraints in case VI. These zones include important candidate buses (2, 4, 5 and 1, 7) due to either their locations at the end of distribution system or their high power demand.

Candidate schemes of DG expansion planning are presented in Table 10 for three case studies. It is observed that none of the schemes have DG at buses 3 and 6. It is also seen that installation of PV units is just economical in the case VI.

It was observed by comparison of simulation results in two scenarios that emission constraint in scenario A is a limiting constraint in whole distribution system and location of DG units is not affected by this constraint. On the contrary, the assumed emission constraints in scenario B affect the location of DG units according to the case study as well as limit the emission in each zone.

Table 10
Candidate DG schemes: capacity, location and technology type of best schemes in scenario B.

Bus no.	Case IV: Scheme no. 43						Case V: Scheme no. 141						Case VI: Scheme no. 45					
	PV	WT	FC	MT	GT	RE	PV	WT	FC	MT	GT	RE	PV	WT	FC	MT	GT	RE
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.9	0	0	1.1
2	0	0	0	0.9	0.9	1	0	0	0	0.8	0.9	1	1.4	0	1	0	0.9	0.6
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	3	0	0	1.5	0	1	0.3	0	0	0	0	0	0
5	0	0.9	0	0	0	2.1	0	1	0	0	0	2	0.4	1.8	0	0	1	0.8
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0.9	2.1	0	0	0	0	0.9	2.1	0.6	0	0	0	1.5	1.1
8	0	1	0	0	0	2.1	0	1	0	0	0	2	0	1.8	0.4	0	1	0.9

6. Conclusion

By approving and executing Kyoto protocol approximately in most of the countries, it is obvious that environmental issues will be a significant concern besides economical and technical criteria in policy and decision makings. This paper proposed a promotion strategy based on a grant of pollution not emanated to encourage DisCo or IPP for applying clean technologies. This encouraging mechanism is used along with emission constraint to control emitted pollution in the distribution system. A multi-objective optimization method (NSGA-II) and Monte Carlo Simulation were applied to choose the best planning scheme consists of information about DG technologies, capacity and location in the distribution system. Simulation results of this paper appropriately shows that renewable energy sources will be the most favoured technologies of the future, if new technologies have a eye-catching development in the next decade or emission constraints are established more severe than today.

Acknowledgements

The authors wish to thank anonymous referees and the Renewable Energy's editor for their helpful advice.

Appendix. Cumulative present value (CPV)

Cumulative present value is a factor to actualize total costs during a certain period of time. CPV of fixed costs (CPV_1) is calculated as follow:

$$S_0 = \sum_{n=1}^{t} S_c \left(\frac{1}{1+d} \right)^n = S_c \sum_{n=1}^{t} (P_1)^n = S_c \cdot CPV_1 \quad \text{(A1)}$$

$$CPV_1 = \sum_{n=1}^{t} (P_1)^n = \frac{(P_1) - (P_1)^{t+1}}{1 - (P_1)} \quad \text{(A2)}$$

where S_0 is the cumulative present value of expenditures during years, S_c is the yearly fixed payment and d is the discount rate.

If the variable costs increase according to inflation and load growth rate in each year (A3), cumulative present value of variable costs (CPV_2) is calculated as follows:

$$S_n = S_1 [(1+f)(1+g)]^n \quad \text{(A3)}$$

$$S_0 = \sum_{n=1}^{t} S_n \left(\frac{1}{1+d} \right)^n = \sum_{n=1}^{t} S_1 \left[\frac{(1+f)(1+g)}{1+d} \right]^n = S_1 \sum_{n=1}^{t} (P_2)^n = S_1 \cdot \overline{CPV_2} \quad \text{(A4)}$$

$$\overline{CPV}_2 = \sum_{n=1}^{t} (P_2)^n = \frac{(P_2) - (P_2)^{t+1}}{1 - (P_2)} \tag{A5}$$

where S_1 and S_n are variable costs at first and nth year respectively and $\overline{CPV_2}$ is the cumulatively present value based on the variable cost at the first year (S_1). Since in this paper, variable cost is calculated at the end of the planning horizon according to the predicted load duration curve, the equation (A5) is changed as follows by putting (A3) into (A4).

$$CPV_2 = \frac{\overline{CPV}_2}{[(1+f)(1+g)]^t} \tag{A6}$$

Discount, inflation and load growth rate are considered equal to 0.06, 0.05 and 0.02 in this paper.

References

[1] Ackermann T, Andersson G, Söder L. Distributed generation: a definition. Electric Power Systems Research 2001;57:195–204.

[2] El-Khatam W, Salama MMA. Distributed generation technologies, definitions and benefits. Electric Power Systems Research 2004;71:119–28.

[3] Pepermans G, Driesen J, Haeseldonckx D, Belmans R, D'haeseleer W. Distributed generation: definition, benefits and issues. Energy Policy 2005;33:787–98.

[4] Bilena K, Ozyurta O, Bakırcıa K, Karslıb S, Erdoganc S, Yılmaza M, et al. Energy production, consumption, and environmental pollution for sustainable development: a case study in Turkey. Renew Sustain Energy Reviews 2008;12:1529–61.

[5] Distributed generation in liberalised electricity markets. Paris, France: International Energy Agency; 2002.

[6] Kim JO, Nam SW, Park SK, Singh C. Dispersed generation planning using improved Hereford ranch algorithm. Electric Power Systems Research 1998;47:47–55.

[7] El-Khaltam W, Bhattacharya K, Hegazy Y, Salama MMA. Optimal investment planning for distributed generation in a competitive electricity market. IEEE Transaction on Power Systems 2004;19(3):1674–84.

[8] El-Khaltam W, Hegazy Y, Salama MMA. An integrated distributed generation optimization model for distribution system planning. IEEE Transaction on Power Systems 2005;20(2):1158–65.

[9] Keane A, O'Malley M. Optimal allocation of embedded generation on distribution networks. IEEE Transaction on Power Systems 2005;20(3):1640–6.

[10] Celli G, Ghiani E, Mocci S, Pilo F. A multiobjective evolutionary algorithm for the sizing and siting of distributed generation. IEEE Transaction on Power Systems 2005;20(2):750–7.

[11] Zangeneh A, Jadid S, Rahimi-Kian A. Normal boundary intersection and benefit -cost ratio for distributed generation planning. European Transactions on Electrical Power. 2008, doi: 10.1002/etep.291.

[12] Heinrich G, Basson L, Cohen B, Howells M, Petrie J. Ranking and selection of power expansion alternatives for multiple objectives under uncertainty. Energy 2007;32:2350–2369.

[13] Kadiana R, Dahiyaa RP, Garg HP. Energy-related emissions and mitigation opportunities from the household sector in Delhi. Energy Policy 2007;35:6195–211.

[14] Cormio C, Dicorato M, Minoia A, Travato M. A regional energy planning methodology including renewable energy sources and environmental constraints. Renew Sustain Energy Reviews 2003;7:99–130.

[15] Dicorato M, Forte G, Travato M. Environmental-constrained energy planning using energy efficiency and distributed generation facilities. Renew Energy 2008;33:1297–313.

[16] Ackermann T, Andersson G, Söder L. Overview of government and market driven programs for the promotion of renewable power generation. Renew Energy 2001;22:197–204.

[17] Van Alphen KS, Kunz HP, Hekkert M. Policy measures to promote the widespread utilization of renewable energy technologies for electricity generation in the Maldives. Renew Sustain Energy Reviews 2008;12: 1959–73.

[18] Sarafidis Y, Diakoulaki D, Papayannakis L, Zervos A. A regional planning approach for the promotion of renewable energies. Renew Energy 1999;18:317–30.

[19] Meyer NI. Promotion of renewable energy in a liberalised energy market. Renew Energy 1998;15:218–23.

[20] do Valle Costa C, La Rovere E, Assmann D. Technological innovation policies to promote renewable energies: lessons from the European experience for the Brazilian case. Renew Sustain Energy Reviews, 2008;12(1):65–90.

[21] Yildirim M, Erkan K, Ozturk S. Power generation expansion planning with adaptive simulated annealing genetic algorithm. International Journal of Energy Research 2006;30:1188–99.

[22] Zangeneh A, Jadid S. Normal boundary intersection for generating Pareto set in distributed generation planning. In: Proceedings of international power engineering conference; 2007. p. 1077–082.

[23] Deb K. Multi-objective optimization using evolutionary algorithms. New York: John Wiley.

[24] Srinivas N, Deb K. Multiobjective optimization using nondominated sorting in genetic algorithms. Evolutionary Computation 1994;2(3):221–48.

[25] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 2002;6(2):182–97.

[26] Papaefthymiou G, Schavemaker PH, Sluis LVD, Kling WL, Kurowicka D, Cooke RM. Integration of stochastic generation in power systems. Electrical Power and Energy Systems 2006;28:655–67.

[27] Kräupl S, Wieckert C. Economic evaluation of the solar carbothermic reduction of ZnO by using a single sensitivity analysis and a Monte-Carlo risk analysis. Energy 2007;32:1134–47.

[28] Rezaie K, Amalnik MS, Gereie A, Ostadi B, Shakhseniaee M. Using extended Monte Carlo simulation method for the improvement of risk management: consideration of relationships between uncertainties. Applied Mathematics and Computation 2007;190:1492–501.

[29] Kalos MH, Whitlock PA. Monte Carlo methods. New York: John Wiley; 1988.

[30] Banzhaf S, Burtraw Dallas, Palmer K. Efficient emission fees in the U.S. electricity sector. Resources for the future. Discussion Paper 02–45. Available at: www.rff.org/Documents/RFF-DP-02-45.pdf; 2002.