Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 50 (2014) 368 – 375

Energy Procedia

The International Conference on Technologies and Materials for Renewable Energy, Environment and Sustainability, TMREES14

Multiobjective Optimization of Renewable Energy Penetration Rate in Power Systems

Hasnae Bilil[a,*], Ghassane Aniba[a], Mohamed Maaroufi[a]

[a]*Ecole Mohammadia d'Ingénieurs (EMI), Mohammed V Agdal University, Rabat, Morocco*

Abstract

Nowadays, multi-source systems based on renewable energy technologies become the key to a sustainable energy supply infrastructure against the rising cost and the pollutant nature of fossil primary energy used in conventional power plant. However, the cost of renewable energy technologies and the reliability of a multi-sources generation system are generally conflicting with each other. This paper presents a multiobjective formulation to allow optimizing simultaneously both the annualized renewable energy cost the system reliability defined as the renewable energy - load disparity (RELD). This later takes into account the lack of energy as well as the exceed weighted by a penalty factor. The optimization is reach by acting on the penetration rate of each type of renewable generation technologies in order to satisfy a certain load curve. In order to solve this problem, this work suggests to use the fast and elitist multiobjective genetic algorithm: NSGA-II. A case study shows that the use of diversified resources allows to handle the RELD and to decrease the exceed renewable energy (RERE) and load energy notsupplied (LENS).

Selection and peer-review under responsibility of the Euro-Mediterranean Institute for Sustainable Development (EUMISD)

Keywords: Renewable Energy Cost, Power System Reliability, multiobjective Optimization, Evolutionary Algorithms, NSGA-II.

1. Introduction

The target behind the emergence of renewable energy policies is to reduce greenhouse gas emissions produced by conventional fossil fuel power plants and to limit the electricity dependence to fuel rising price. However, the major drawback of the use of renewable energy resources is their variability with weather and climatic changes especially wind speed variability. Besides, the cost of solar generation is higher compared with wind generation. In order to overcome these disadvantages, the use of diversified sources is considered as the best solution deal with these issues [1–3].

During the past decades, many studies have been investigated to design hybrid renewable energy systems and to propose the operating procedure of its components. In [4], a frequency regulator is proposed to

*Corresponding author. Tel.: +212 - 537-77-2647; fax: +212 - 537-77-8853.
E-mail address: bilil@emi.ac.ma

Selection and peer-review under responsibility of the Euro-Mediterranean Institute for Sustainable Development (EUMISD)
doi:10.1016/j.egypro.2014.06.044

reduce the frequency deviation of an isolated hybrid system and a critical study is carried out for a system with or without energy storage while in [5] control and supervision systems are proposed to optimize the used energy provided by an hybrid energy system. Other studies have been carried out and some develop efficient power management in microgrids such as the approach in [6] which proposes a dynamic assignment of renewable energy tokens algorithm for collaborative microgrids based on the load management side and allowing to keep the power balance. Besides, the paper [7] proposes non-uniform hierarchical 16-QAM to provide a reliable data transmission over wireless links to achieve an efficient information exchange between the participants in such collaborative system. More studies were interested on the optimal design of hybrid energy systems in terms of the installed power rate of each source technology in order to minimize the cost installation and specially the cost of the produced kilowatt hour (kWh) of electricity such as the work presented in [8,9].

Recently, the use of evolutionary algorithms is increasing due to their abilities to resolve complex problems especially in the electrical field such as active and reactive power dispatch problems [10,11]. This paper considers fast and elitist multiobjective genetic algorithm NSGA-II to optimize the use of renewable energy technologies taking into account the annualized cost and power system reliability in terms of load supplying and contribution of renewable sources in power generation.

The paper is structured as follows: Section 2 presents a renewable power generation model in terms of climatic parameters and in normalized form then the problem formulation is developed while Section 3 details the used optimization approach.The results discussion are conducted in Section 4 and finally, Section 6 provides conclusions and some perspectives.

2. Problem formulation

2.1. Renewable power generation model

In literature, there are various models that express mathematically the electrical power produced by renewable technologies using deterministic or probabilistic approaches [12,13]. Most of them in terms of climatic parameters. In this section, the formulation of both photovoltaic and wind turbine productions is presented and then the per unit presentation is suggested in order to give the characteristic shape which depends only on the expected location of the installation.

The power produced by a photovoltaic (PV) generator is estimated based on manufacturer data as well as climate data (radiation and temperature). The output power of the PV generator [14] can be calculated by

$$P_p = \eta S E \tag{1}$$

with

$$\eta = \eta_{ref}(1 - \gamma(T - T_{ref})) \tag{2}$$

where η is the solar radiation efficiency of photovoltaic module, S is the total area of the photovoltaic generator [m^2] and E is the peak power per surface unit [Wp/m^2]. On the other hand, η varies with the cell temperature T, η_{ref} is the reference efficiency of the PV generator, γ is the temperature coefficient of short-current [K] and T_{ref} is the reference cell temperature [K].

The output power of a wind turbine varies at different wind speeds and accordingly to the power curve given by the manufacturer. Indeed, the power output of wind turbine can be approximated by [14,15],

$$P_w(v) = \begin{cases} 0 & v < v_c, v > v_f \\ p_r \frac{v - v_c}{v_r - v_c} & v_c \leq v \leq v_r \\ p_r & v_r \leq v \leq v_f \end{cases} \tag{3}$$

where p_r is the rated electrical power, v_c is the cut-in wind speed at which the turbine first starts to rotate and generate power, v_f the Cut-off wind speed which is the breaking system employed to avoid damage to the rotor and v_r the rated wind speed [m/s] at which the power output reaches the best operating at p_r.

In order to give general results and make the study related only to the concerned geographical area, we suggest elaborating an approximate unit production curve of a unit PV or wind capacity. Expected generation curves can be developed using climatic data over a year or on the generation curve per unit installed capacity in the same area of the expected installation under study.

2.2. Optimization problem formulation

The proposed approach aims to give a global vision of power contribution of each renewable energy technology in order to satisfy the demand curve. Since the climatic parameters on which is based solar production are different from those of wind production and then the characteristic shapes are different and sometimes complementary, then this paper suggests a multiobjective formulation of wind solar system design. Indeed, two main objective functions are considered in order to allow a great use of diversified renewable technologies in terms of best compromise of cost and reliability. The global formulation of the system cost is given by

$$f_1 = C_p^a \sum_{k=1}^{N_p} P_{p_k} + C_w^a \sum_{k=1}^{N_w} P_{w_k}, \tag{4}$$

where C_p^a is the total annualized cost of unit installed photovoltaic power, C_w^a is the total annualized cost of unit installed wind power, P_{p_k} and P_{w_k} are the installed power of the k^{th} photovoltaic and wind generators respectively, N_p and N_w are the photovoltaic and wind generators number respectively.

In the other hand, the annualized system cost C^a consists of the annualized capital cost C_{cap}^a, maintenance cost C_{main}^a and replacement cost C_{rep}^a. It is expressed by

$$C^a = C_{cap}^a + C_{main}^a + C_{rep}^a, \tag{5}$$

The annualized capital cost of each component (PV cells and wind turbine generator) is given by [15]

$$C_{cap}^a = C_{cap} \frac{i(1+i)^{L_t}}{(1+i)^{L_t}+1}, \tag{6}$$

where C_{cap} is the initial capital cost, L_t is the project life time and is the annual real interest rate i which is linked to the intensity j of nominal interest rate and to the annual inflation rate f by the following expression:

$$i = \frac{j-f}{1+f}, \tag{7}$$

The annualized replacement cost is the annualized value of all the replacement costs occurring throughout the lifetime of the project, taking into account the inflation rate can be expressed by:

$$C_{rep}^a = C_{rep} \frac{i}{(1+i)^{L_t}-1}, \tag{8}$$

The cost of the system maintenance is considered constant by year.

The second objective function is the minimization of the renewable energy - load disparity (RELD). In fact, several reliability indices are used to evaluate system and load satisfaction such as the loss of load expectation (LOLE), expected energy not supplied (EENS) and loss of power supply probability (LPSP) [**?**]. In this work, it is proposed to evaluate the disparity between renewable energy and load energy curves which is noted RELD. This disparity can be both a lack of energy (negative disparity) or an excess quantity (positive disparity). In general, the lack is recompensed by a basic fossil production, stored energy or interconnection with other areas or countries. In contrast, the excess of energy can be stored or exported into other areas or, in some cases, transformed to heat. Since these two quantities depend on the energy strategy, we suggest using a penalty factor in terms of the energy disparity sign. RELD index, for a given period, can be calculated by,

$$f_2 = RELD = \frac{1}{L_t T} \sum_{y=1}^{L_t} \sum_{t=1}^{T} \frac{\mathbf{D}\left[E_g(y,t) - E_l(y,t)\right]}{E_l(y,t)} \tag{9}$$

with

$$\mathbf{D}[x] = \begin{cases} (1+\omega)x & \text{if } x > 0, \\ -(1-\omega)x & \text{if } x \leq 0, \end{cases} \tag{10}$$

and

$$E_g(y,t) = \left(\sum_{k=1}^{N_p} P_{p_k} S_{p_k}(y,t) + \sum_{k=1}^{N_w} P_{w_k} S_{w_k}(y,t) \right) \Delta T \tag{11}$$

where ω is the penalty factor, $E_g(y,t)$ is the expected average energy, $S_{p_k}(y,t)$ and $S_{w_k}(y,t)$ are the expected average characteristic shapes in the year y over the sample time t of solar and wind power, respectively, and ΔT is the sample time duration.

Theoretically, the penalty factor can be in the range from 0 to 1. However, this factor is used to penalize the energy excess in a minimization problem, then using high values close to 1 means that we minimize as disparity only the excess without caring about the energy lack. Then, we will take the penalty factor in the range from 0 to 0.5.

3. Optimization method

The problem defined above needs a multiobjective optimization approach to be solved. Thus, this section defines a multiobjective problem and Preto dominance then describes the proposed algorithm by developing the operating process then by the flow chart of NSGA-II. A general multiobjective optimization problem can be mathematically expressed as follows:

$$\begin{array}{ll} \text{Minimize} & \mathbf{F}(\mathbf{x}) = \left[f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_{N_{\mathrm{obj}}}(\mathbf{x})\right] \\ \text{Subject to} & g_k(\mathbf{x}) \leq 0, k = 1, \ldots, N_{\mathrm{c}}, \end{array} \tag{12}$$

where $\mathbf{x} = [x_1, x_2, \ldots, x_D]^{\mathrm{T}}$ with x_j can be either real, integer or boolean values, and D is the research space dimension. $f_r(\cdot)$ are the N_{obj} objective functions and $g_k(\cdot)$ are the N_{c} constraint functions of the problem.

The family of optimal solutions of this MOP is composed of all those potential solutions such that the components of the corresponding objective vectors whose elements cannot be simultaneously improved. This is known as the concept of Pareto optimality. In a minimization problem, Pareto dominance and Pareto optimality are defined as follows:

Definition 1 (Pareto dominance)**.** *A given vector* $\mathbf{x} = [x_1, x_2, \ldots, x_D]$ *is said to dominate* $\mathbf{y} = [y_1, y_2, \ldots, y_D]$ *if and only if* $\forall j \in \{1, 2, \ldots, D\}, x_j \leq y_j$ *and* $\exists j_0 \in \{1, 2, \ldots, D\}, x_{j_0} < y_{j_0}$*.*

Definition 2 (Pareto optimality)**.** *For a general MOP, a given solution* $\mathbf{x}^\star \in \mathcal{F}$*, where* $\mathcal{F}$ *is the feasible solution space, is Pareto optimal if and only if there is no* $\mathbf{x} \in \mathcal{F}$ *that dominates* $\mathbf{x}^\star$*.*

Fast and elitist multiobjective genetic algorithm (NSGA-II) is the second version of NSGA which improves this later to overcome the computation complexity and the non-elitist characteristic of solutions [16]. The basic operations of NSGA-II are as follows:

- Fast Non-dominated Sorting: which is based on two entities. The first one is the calculation of the number of solutions dominating each solution in the current population. This number determine the rank of each solution. The second entity is the set of solutions that a solution dominates.
- Density estimation (crowding distance): presents the density of solutions surrounding a particular point in Pareto front. It is the average distance of two points on either side of this point along each of the objectives.

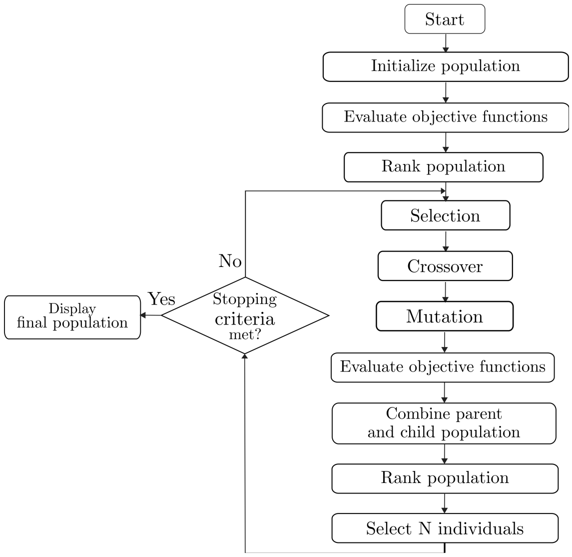


Fig. 1: Flow chart of NSGA-II

- Crowded-Comparison Operator: which compares two solutions on the basis of both the rank and crowded distance. The better solution is this with smaller rank. In the case of rank equality, the saved solution is this with smaller crowded distance.

Fig. 1 presents the main loop of NSGA-II which starts by initializing the population and assigning to each point the appropriate rank. Thereafter, reproduction operators such as tournament selection, recombination and mutation are used to create the offspring population. Then, the two populations parent and offspring are combined and sorted following the comparison operators mentioned above. More details and complexity evaluation of NSGA-II are given in [16].

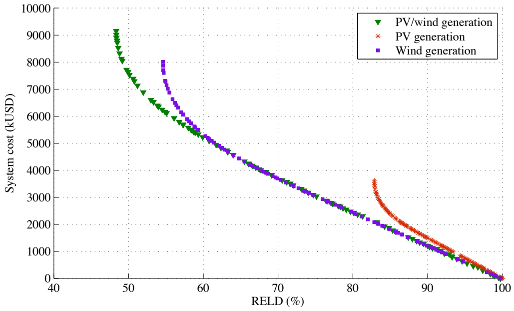
4. Simulation and results

In order to show performance of the proposed approach, PV and wind production curves of Belgium's electricity transmission system operator [17] as well as the load curve during the period Sep 2012 - Aug 2013 are used. Then, the generation data are normalized by the installed power capacity of each one presenting the characteristic production shape per installed unit. Concerning the load curve, it is normalized by the load peak. For all simulations, we take the duration of sample time $\Delta T = 15$min. The initial capital cost per MW of installed power capacity and maintenance cost of both PV and wind technologies are given in Table 1. Interest rate is $j = 3.5$ and inflation rate $f = 1.5$.

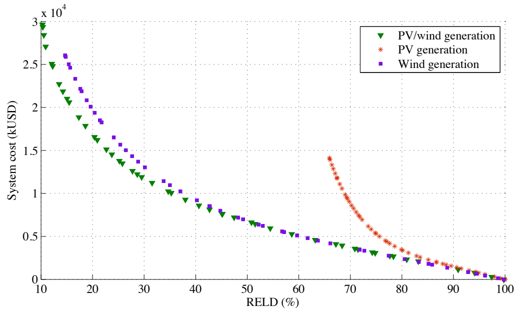
Table 1: Initial capital cost and maintenance cost of wind and PV technologies

	Capital cost (kUSD/MW)	M&O cost (kUSD/MW/year)
Wind turbine	1500	16
PV	6500	10

The optimization method is utilized for three installation scenarios: system production generated by PV technology alone, wind turbine alone and finally a scenario with both PV and wind generators. The



(a)



(b)

Fig. 2: Pareto fronts of optimal renewable energy penetration rate in the case of $\omega = 0.5$ and $\omega = 0.1$, respectively.

obtained curves illustrated in Fig. 2 show the Pareto fronts of considered scenarios. Each solution presents an optimized renewable energy integration possibility depending on a fixed target. This later can be the total annualized cost over the life time of system components or the disparity between renewable energy production and load curves presented by RELD. A domination relation is observed between the three figured scenarios. Indeed, following the Pareto dominance, using both solar and wind technologies (green curve ▼) is obviously better than using wind generators alone (purple curve ■) and this later is better than generating energy by PV alone 1 (red curve ⋆). Table 2 presents solutions corresponding to best RELD in the case of penalty factors $\omega = 0.5$ and $\omega = 0.1$. The RELD, in the studied case with the proposed data shapes, cannot be less than 48.3% for $\omega = 0.5$. However, 10.43% of load energy disparity in the case of $\omega = 0.1$ can be released. That shows clearly the utility of our approach. Indeed, it gives previously the expected value of covered load limits depending on the characteristic shapes specified to each region.

Table 2: Best renewable energy - load disparity

	$\omega = 0.5$			$\omega = 0.1$		
	PV	Wind	Wind/PV	PV	Wind	Wind/PV
Wind capacity (pu)	0	2.54	1.35	0	8	3.72
PV capacity (pu)	0.88	0	0.75	3	0	1.40
Systeme cost (kUSD)	3609.9	8004.4	9152.0	14080.1	26050.1	29945.5
RELD (%)	82.8	54.6	48.3	65.96	14.68	10.43

In order to show the performance of the proposed approach in terms of lack and excess of energy, Fig. 3 presents different monthly average energy curves for different generation system scenarios and for three different penalty factors. Then, for $\omega = 0.1$ (Figs. 3a and 3b), the produced energy in the case of PV generation exceed twice the required load energy for six months while around 90% of load energy is not supplied. In contrast, for $\omega = 0.5$ (Figs. 3c and 3d), it is almost the same curve of average load energy not supplied but it is gained a lot in the average exceed renewable energy which is less than 50% for most months. However, for the system generation with only wind generators or both wind and PV generators, the use of small values of ω allows to reduce the load energy not supplied to 30% against more than 40% in the case of high value of ω. Finally, in order to compare systems with different ω values, we set the PV/wind generation cost ($9000k/MW) and different average energy curves are shown in Figs. 3e and 3f. Thus, for the same cost, the power system designer can decide in terms of the penalty factor ω to gain in lack or excess of produced energy.

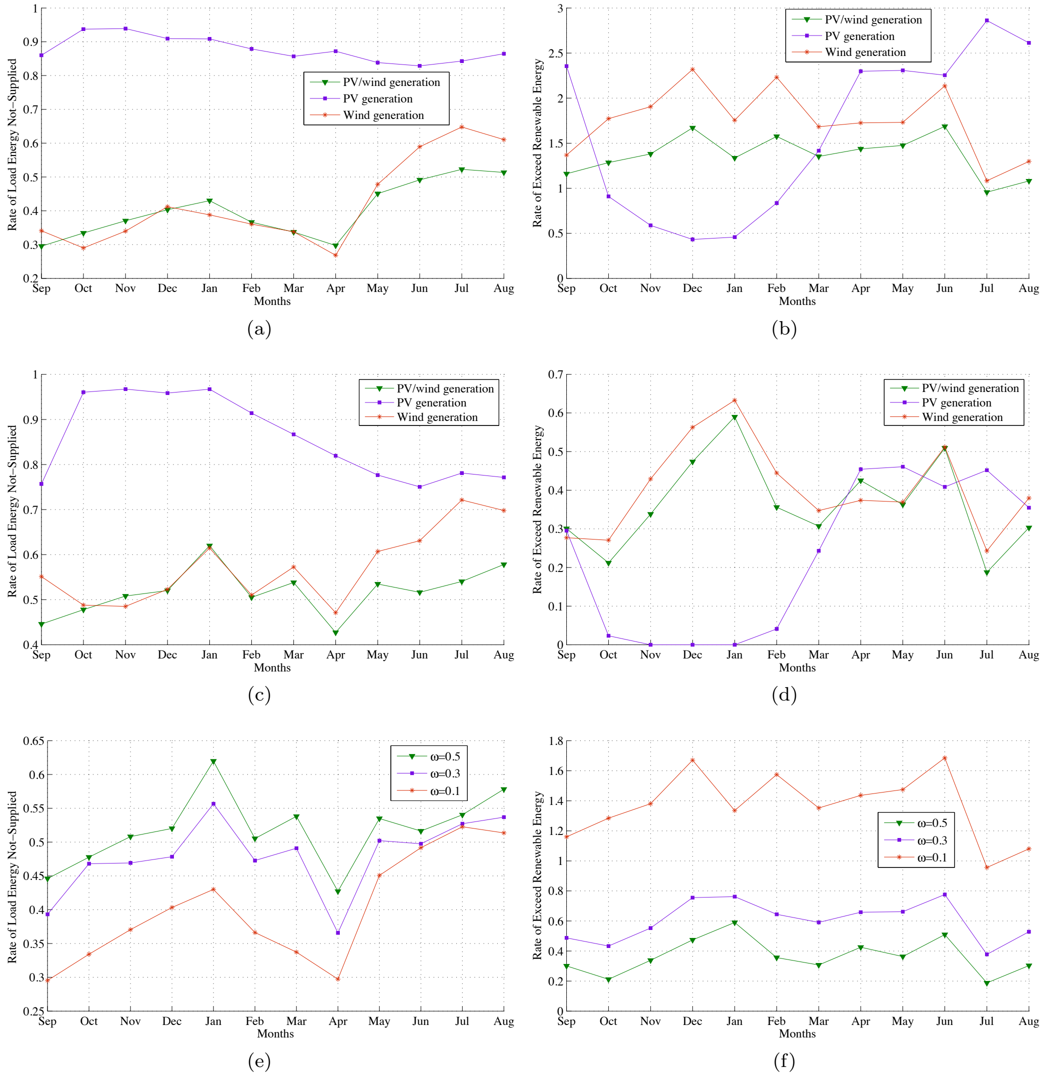


Fig. 3: Rate of (a, c, e) average load energy not supplied and of (b, d, f) exceed renewable energy for different generation scenarios for $\omega = 0.1$ and $\omega = 0.5$ in the case of best RELD and for different ω in the case of system generation cost equals to \$9000k/MW, respectively, during during the period Sep 2012 - Aug 2013

5. Conclusion and perspectives

The target of this work is to optimize simultaneously the annualized cost and renewable energy - load disparity (RELD) by acting on the penetration rate of each source type. This work has proposed a new formulation of the system reliability in terms of the produced energy based on the penalty factor of renewable energy excess. Then, the metaheuristic multiobjective optimization approach called fast and elitist multi-objective genetic algorithm (NSGA-II) has been used to solve the problem. An analytic and comparative simulation study has done. Results show diversity of solutions in terms of the used generation technologies and of the penalty factor. This study can be extended to analyze and find the optimal penetration of power system with more renewable energy sources diversity such as biomass, concentrated solar power with and without storage, geothermal, solar thermal and heliostat and/or in the case of combined heat and power. On the other hand, conducting the renewable energy penetration optimization in parallel with a load management side (LMS) allows to better reduce the disparity of generation and load curves with the minimum storage power. Besides, we have presented a global study in terms of the installation cost and expected produced energy. However, in terms of produced power, the study of unpredictable power variability is as important as the study already done.

References

[1] G. Xydis, Comparison study between a renewable energy supply system and a supergrid for achieving 100% from renewable energy sources in islands, International Journal of Electrical Power & Energy Systems 46 (2013) 198–210.

[2] M.Belhamel, M.Haddadi, S.Diaf, D.Diaf, A.Louche, A methodology for optimal sizing of autonomous hybrid pv/wind system, Energy Policy 81 (2007) 76–84.

[3] R. Ionescu, L. R. E. I. Ragazzi, M.and Battisti, Potential of electricity generation from renewable energy sources in standard domestic houses, WIT Transactions on Ecology and the Environment (2013) 245–253.

[4] P.K.Ray, S. Mohanty, N. Kishor, Frequency regulation of hybrid renewable energy system for large band wind speed variation, in: The 3th IEEE International Conference on Power Systems, 2009, pp. 1–6.

[5] D. Delimustafic, J. Islambegovic, A. Aksamovic, S. Masic, Model of a hybrid renewable energy system: Control, supervision and energy distribution, IEEE International Symposium on Industrial Electronics (ISIE) (2011) 1081–1086.

[6] S. Belmoubarik, H. Bilil, G. Aniba, M. Maaroufi, B. Elgraini, Dynamic assignment of renewable energy tokens in a collaborative microgrids, in: The 4th IEEE International Conference on Next Generation Networks & Services, 2012, pp. 189–192.

[7] H. Bilil, S. Belmoubarik, G. Aniba, B. Elgraini, M. Maaroufi, Non-uniform hierarchical modulation for wireless communication in smart grid, in: The 10th IEEE International Conference on Networking, Sensing and Control, 2012, pp. 690–695.

[8] D. Delimustafic, J. Islambegovic, A. Aksamovic, S. Masic, Optimal design of hybrid renewable energy system for electrification of isolated grids, in: IEEE Region 10 Conference TENCON, 2012, pp. 1–6.

[9] Y. Hongxing, Z. Wei, L. Chengzhi, Optimal design and techno-economic analysis of a hybrid solarwind power generation system, Applied Energy 86 (2009) 163–169.

[10] H. Bilil, R. Ellaia, M. Maaroufi, A new multi-objective particle swarm optimization for reactive power dispatch, in: IEEE International Conference on Multimedia Computing and Systems (ICMCS), 2012, pp. 1119–1124.

[11] H. Bilil, R. Ellaia, M. Maaroufi, A new multi-objective particle swarm optimization for economic environmental dispatch, in: IEEE International Conference on Complex Systems (ICCS), 2012, pp. 1– 6.

[12] M. Deshmukh, S. Deshmukh, Modeling of hybrid renewable energy systems, Renewable and Sustainable Energy Reviews 12 (1) (2008) 235–249.

[13] M. Fadaee, M. Radzi, Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review, Renewable and Sustainable Energy Reviews 16 (5) (2012) 3364–3369.

[14] S. X. Chen, H. B. Gooi, M. Q. Wang, Sizing of energy storage for microgrids, IEEE Transactions on Smart Grid 3 (1) (2012) 142–151.

[15] H. Yang, Z. Wei, L. Chengzhi, Optimal design and techno-economic analysis of a hybrid solarwind power generation system, Applied Energy 86 (2) (2009) 163–169.

[16] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm, IEEE Transactions on Evolutionary Computation 6 (2) (2002) 182–197.

[17] Official website of elia (Nov. 2013).
URL `http://www.elia.be`