JOURNAL OF OPTOELECTRONICS AND ADVANCED MATERIALS Vol. 10, No. 5, May 2008, p. 1233 - 1240

A multiobjective evolutionary algorithm approach for the optimum economic and environmental performance of an off-grid power system containing renewable energy sources

Y. A. KATSIGIANNIS*, P. S. GEORGILAKIS
Department of Production Engineering and Management, Technical University of Crete, GR 73100, Chania, Greece

The optimum performance of an off-grid power system depends on economic and environmental criteria, and it belongs to the field of non-linear combinatorial multiobjective optimization. In this paper, the economic objective refers to the minimization of the total net present cost, while the environmental objective refers to the minimization of the total CO_2 equivalent emissions during the life cycle of system's components, which can be wind turbines, photovoltaics, diesel generator and batteries. A binary evolutionary algorithm is proposed for the solution of the problem. The results show that in order to satisfy constraints related with system's initial cost and reliability performance, the energy supply has to be provided mainly by the diesel generator and secondarily by the wind turbines. The contribution of photovoltaics is negligible, but it can be improved significantly in the future through the evolution of their manufacturing procedure, which is expected to cause reduction in their cost and their total CO_2 emissions.

(Received March 13, 2008; accepted May 5, 2008)

Keywords: Off-grid systems, Life cycle assessment, Multiobjective optimization, Evolutionary algorithms, Renewable energy sources

1. Introduction

The majority of real-world problems involve simultaneous optimization of several objective functions. Generally, these functions contain often conflicting objectives that cannot be easily expressed in quantitative terms in order to compare them directly. Therefore, a compromise solution has to be sought in accordance with the preferences of the decision maker. The mathematical process of seeking such a solution is known as multiobjective programming.

In the design of off-grid power systems, mainly two conflicting objectives are important: cost and pollutant emissions. Off-grid systems usually operate in isolated areas that are far from the grid. A fundamental characteristic of such systems is that they present low energy demand. A large portion of this demand is usually served by conventional generators such as diesel generators, although renewable energy sources (RES) technologies can be also used, as large amounts of RES are usually present in these areas. Conventional generators produce power on demand in an economic way, and when used in combination with RES technologies, they can provide backup power during times of insufficient renewable output. On the other hand, conventional generators emit large amounts of pollutants such as CO_2, either by taking into account only the direct emissions of system's operation, or by taking into account the emissions through the whole life cycle of these systems, as estimated through life cycle assessment (LCA) methodology. RES technologies do not emit during their operation, however, in their whole life cycle, they may produce significant amount of pollutant emissions.

In a multiobjective optimization problem, such as the one studied in this paper, any two solutions can have one of the following two possibilities: 1) one solution dominates the other or 2) none solution dominates the other. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set. After a set of such non-dominated solutions is found, a user can then use higher-level qualitative considerations to make a choice 0.

For the solution of multiobjective optimization problems numerous classical methods have been proposed, which can be classified into two distinct groups: direct methods and gradient-based methods 0. In direct search methods, only the objective function and the constraint values are used to guide the search strategy, whereas gradient-based methods use the first and/or second order derivatives of the objective function and/or constraints to guide the search process. However, in real-world problems, a number of complicating factors may occur, such as non-linearities, non-convexity, randomness, or non-standard constraints and feasibility conditions, which make the resulting model difficult to solve by these methods. In the last years, a large number of more appropriate algorithms for tackling such problems has been developed, mainly from the area of metaheuristics. Of these, the vast majority belongs to the category of evolutionary algorithms (EAs) 0. The main reason is that

EAs handle inherently a population of possible solutions, instead of a single solution, so they propose a set of alternative solutions in problems involving several objectives in one single simulation run.

Various methodologies have been proposed for the economic and environmental evaluation of off-grid power systems. In 0, a multiobjective EA is developed that minimizes cost and pollutant emissions of such a system. HOMER software 0 uses the weighted sum method, as it initially considers a cost penalty associated with the pollutant emissions, and then optimizes the overall cost objective function. However, the previous mentioned methodologies consider only the direct emissions of system's components. LCA analysis of off-grid power systems is implemented in 0 and 0, which however is not combined with economic analysis.

This paper proposes an economic and environmental multiobjective optimization of an off-grid power system using an EA. The economic objective function is the total net present cost (NPC), while the environmental objective function is the total CO_2 equivalent emissions. The main novelty of the proposed methodology is the consideration of LCA results for the calculation of CO_2 emissions. The different locations of a product's CO_2 emissions during its life cycle are unimportant, as the incremental impact on global warming will be the same 0. The minimization of the CO_2 emissions based on LCA of system's components, which is considered in this paper, is extremely important since it minimizes the impact of the considered off-grid power system on global warming of our planet.

2. Problem formulation

This paper deals with the economic and environmental evaluation of an off-grid power system, and belongs to the category of non-linear combinatorial multiobjective optimization problems. This multioblective optimization problem has to fulfill the two objectives defined by equations (1) and (4) subject to the constraints (5), (6), and (7). In particular, the problem is formulated as follows.

2.1 First objective

Minimization of system's net present cost:

$$Minimize \quad f_1(x) = \text{NPC} \tag{1}$$

NPC is calculated according to the following equation:

$$\text{NPC} = \frac{C_{tot,ann}}{\text{CRF}(d,N)} \tag{2}$$

where $C_{tot,ann}$ is the total annualized cost, which is equal to the sum of the annualized costs of each system component, and CRF(d,N) is the capital recovery factor:

$$\text{CRF}(d,N) = \frac{d\cdot(1+d)^N}{(1+d)^N - 1} \tag{3}$$

CRF(d,N) is a ratio used to calculate the present value of an annuity. In eq. (3) d is the discount rate and N is the lifetime of the project.

2.2 Second objective

Minimization of CO_2 emissions based on life cycle assessment of system's components:

$$Minimize \quad f_2(x) = \text{CO}_2 \quad \text{emissions} \quad \text{(LCA)} \tag{4}$$

2.3 Constraints

Initial cost constraint:

$$IC \le IC_{\max} \tag{5}$$

Unmet load constraint:

$$\sum_{t=1}^{8760} UL_t \le UL_{\max} \tag{6}$$

Non-negative components size:

$$x_i \ge 0 \quad \forall i \tag{7}$$

where IC is the initial installation cost of the system; IC_{max} is the maximum allowable initial cost of the system, t is the hourly time step index, UL_t is the unmet load of the system at time step t; UL_{max} is the maximum allowable annual unmet load; and x_i is the size of each system's component i.

3. Life cycle assessment in power systems

LCA is usually limited to environmental issues only, although it could also imply the assessment of other issues, such as social or economic. LCA is divided into four phases:

1. Goal definition and scoping.
2. Inventory analysis.
3. Impact assessment.
4. Interpretation.

In the power systems sector, LCA considers not only emissions from each component's construction, operation, and decommissioning, but also the environmental burdens associated with the entire lifetime of all relevant upstream and downstream processes within the energy chain. This includes exploration, extraction, processing, and transport of the energy carrier, as well as waste treatment and disposal. The direct emissions include releases from the operation of power system's components, processing factories, and transport systems. Moreover, it includes indirect emissions originating from manufacturing and transport of materials, from energy inputs to all steps of the chain, and from infrastructure.

Electricity generation from conventional sources is a major source of CO_2, SO_2, NO_x, and particulate matter; it also produces large quantities of solid waste and contributes to water pollution. On the other hand, in renewable energy technologies, power generation emits negligible quantities of pollutants; however, there are considerable emissions that are associated with the material procurement, manufacture and transportation. Moreover, high levels of intermittent supply sources, such as solar or wind, require the installation of storage options, which should also be included in the LCA of the overall system.

The LCA results that are focused on assessing greenhouse gas emissions of energy systems are expressed in terms of CO_2 equivalent emissions. This means that CO_2 and other greenhouse gases, such as CH_4 and N_2O, have been included in the assessment. However, other greenhouse gases have different effects on the climate and may have a different atmospheric life span. To take into account these differences, each greenhouse gas is converted to an equivalent of CO_2 and is added to the inventory. For example, a gram of CH_4 has a global warming potential of 21 and a gram of N_2O has a global warming potential of 310, relative to a gram of CO_2 over a 100-year period 0.

4. Evolutionary algorithms

4.1 Overview

EAs mimic natural evolutionary principles to constitute search and optimization procedures. The most widely used type of EAs is the genetic algorithms (GAs). GAs can be classified in two categories:

1. *Binary GAs*: They borrow their working principle directly from natural genetics, as the variables are represented by bits of zeros and ones. Binary GAs are preferred when the problem consists of discrete variables.
2. *Continuous GAs*: Although they present the same working principle with binary GAs, the variables here are represented by floating-point numbers over whatever range is deemed appropriate. Continuous GAs are ideally suited to handle problems with a continuous search space.

The first step of a GA is the random generation of the initial population. Then a GA follows an iterated procedure that contains the following steps:

1. Evaluation of objective(s) function(s).
2. Reproduction of population, which makes duplicates of good solutions and eliminates bad solutions.
3. Crossover, in which existing population members (parents) are mated in order to produce new population members (offspring).
4. Mutation, which randomly changes the values at a portion of population members.

In a single objective optimization, there is one goal: the search for an optimum solution. However, in multiobjective optimization there are two goals that are equally important:

1. To find a set of solutions as close as possible to the Pareto-optimal set.
2. To find a set of solutions as diverse as possible.

Numerous GAs have been proposed in the literature for the solution of multiobjective optimization problems 0. The approach adopted in this paper is the non-dominated sorting GA (NSGA-II) 0.

4.2 NSGA-II

The NSGA-II procedure includes the following steps:

1. Combination of parent and offspring population in order to create the entire population set R_t, and execution of a non-dominated sorting to R_t. In case of constraints existence, a solution *x* dominates solution *y* if any of the following conditions are true:
   a) Solution *x* is feasible and solution *y* is not.
   b) Solutions *x* and *y* are both infeasible, but solution *x* has a smaller constraint violation.
   c) Solutions *x* and *y* are feasible and solution *x* dominates solution *y*.
2. Descending sorting of each produced non-dominated set population according to crowding distance criterion, which estimates the diversity of each solution.
3. Creation of offspring population from parent population by using the reproduction, crossover and mutation operators.

5. Proposed methodology

5.1 Chromosome representation

The considered off-grid power system has to serve electrical load, and it can contain four component types:

1. Wind turbines (WTs) of a specific type.
2. Photovoltaic (PV) modules.
3. Diesel Generator.
4. Batteries of a specific type.

The minimum size of each component is considered to be zero. The increment in each component's size is constant; it is equal to 1 unit for WTs and batteries, 1 kW_p for PVs, and 1kW rated power for the diesel generator. Due to the discrete formulation of components size increment, the type of the GA is selected to be binary. The encoding of the GA chromosome is shown in Fig. 1. It can be seen that the chromosome is divided into four parts; each one shows the size (in bits) of a system's component. The length of the chromosome is determined by the maximum allowable number of components. The calculation procedure of this number differs according to component type, and it is estimated as follows:

1. For WTs and PVs it is equal to the maximum number that does not violate the initial cost constraint:

$$x_{WT\max} = \text{int}(IC_{\max} / CC_{WT}) \quad (8)$$

$$x_{PV\max} = \text{int}(IC_{\max} / CC_{PV}) \quad (9)$$

where $x_{WT\max}$ is the maximum number of WTs, $x_{PV\max}$ is the maximum size of PVs in kW_p, int(x) is the function that rounds x down to its nearest integer, CC_{WT} is the capital cost of the WT, and CC_{PV} is the capital cost of PVs per kW_p.

2. For the diesel generator, its maximum allowable installed capacity $x_{Dsl\max}$ (in kW) is the minimum value of a) the rated power that does not violate the initial cost constraint, and b) the minimum value that can satisfy exclusively the annual peak load AL_p:

$$x_{Dsl\max} = \min(\text{int}(IC_{\max} / CC_{Dsl}),\ \ \text{int}(AL_p) + 1) \quad (10)$$

where CC_{dsl} is the capital cost of diesel generator per kW.

3. For the batteries, their maximum allowable quantity is the minimum value of a) the battery units number that does not violate the initial cost constraint, and b) the minimum number of batteries that can satisfy exclusively a 4 day (96 h) average load, if the batteries are fully charged at the beginning of this period and without taking into account battery's minimum state of charge:

$$x_{bat\max} = \min(\text{int}(IC_{\max} / CC_{bat}),\ \ \text{int}(\sum_{t=1}^{96} \overline{AL} / Cap_{Bat}) + 1) \quad (11)$$

where CC_{bat} is the capital cost of one battery, $\overline{AL}$ is the mean hourly value of load demand, and Cap_{Bat} is the battery capacity.

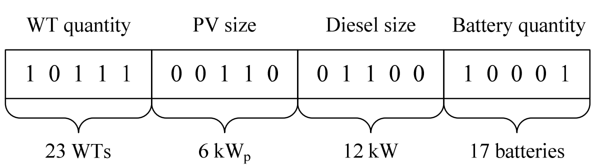


Fig. 1. Example of a chromosome representation for an off-grid power system.

5.2 Normalization of constraints

In order to apply effectively the NSGA-II algorithm, the values of constraints (5) and (6) have to be normalized in the case that they are violated. The normalized violation of the initial cost constraint (5), *ICV*, is calculated by:

$$ICV = \begin{cases} 0, & \text{if} \quad IC \le IC_{\max} \\ \dfrac{IC - IC_{\max}}{IC_{\max}}, & \text{if} \quad IC > IC_{\max} \end{cases} \quad (12)$$

while the normalized violation of the unmet load constraint (6), *ULV*, is equal to:

$$ULV = \begin{cases} 0, & \text{if} \quad \sum_{t=1}^{8760} UL_t \le UL_{\max} \\ \dfrac{\sum_{t=1}^{8760} UL_t - UL_{\max}}{\sum AL}, & \text{if} \quad \sum_{t=1}^{8760} UL_t > UL_{\max} \end{cases} \quad (13)$$

where $\sum AL$ is the total annual energy demand of the system.

5.3 Economic evaluation

The economic evaluation of the system is implemented through the calculation of NPC, which includes all costs that occur within the project lifetime, with future cash flows discounted to the present. The total net present cost includes the initial capital cost of each system component, the cost of any component replacements that occur within the project lifetime, as well as the cost of fuel for the case of diesel generator.

The fuel cost for diesel generator is calculated by multiplying the diesel fuel price with fuel consumption. It is assumed that the diesel generator fuel consumption F (in lt/kWh) is a linear function of its electrical power output 0:

$$F = 0.08415 \cdot P_{rated} + 0.246 \cdot P \quad (14)$$

where P_{rated} is generator's rated power and P is generator's output power.

The calculation of WT's power output is managed through the fitting of the Power Curve by a polynomial curve. The PV power output is analogous to the radiation that strikes the PV panel, and it is estimated by global solar radiation data and geographic location data. The adopted dispatch strategy is the cycle charging strategy, whereby whenever the diesel generator needs to operate to serve the primary load, it operates at full output power 0.

5.4 Environmental evaluation

The LCA CO_2 equivalent emissions of power generation components (WTs, PVs and diesel generator) are calculated per amount of energy produced (kg/kWh). This approach is more appropriate than the kg/kW approach, as some power plants are used at full capacity for most of the year, while other are not present such a high availability 0. For batteries, the LCA CO_2 equivalent emissions are given in kg/kWh·y. The values that were adopted in this paper are shown in Table 1.

Table 1. CO_2 equivalent emissions of system's components.

Component	CO_2 emissions
WT 0	0.017 kg/kWh
PV (Mono-crystalline) 0	0.23 kg/kWh
Diesel generator 0	0.85 kg/kWh
Battery 0	62 kg/kWh·y

6. Results and discussion

6.1 Case study system

In the considered off-grid power system, the project lifetime *N* is assumed to be 20 years and the discount rate *d* has been taken equal to 5%. The constraints parameters IC_{max} and UL_{max} have been set equal to 200,000 € and 100 kWh, respectively. The annual peak load has been taken equal to 60 kW, while the wind and solar data needed for the estimation of WT and PV performance refer to the Chania region, Crete, Greece. The price of diesel fuel is assumed to be 0.6 €/lt. Batteries have been modeled according to the following technical characteristics per unit: efficiency equal to 85%, capacity equal to 7.5 kWh, minimum state of charge equal to 30%.

The cost and lifetime characteristics of each component are shown in Table 2. The replacement cost is assumed to be equal with the capital cost.

Table 2. Component characteristics.

Component	Capital cost	Lifetime
WT, with rated power equal to 10 kW	7500 €/WT	20 years
PV	5000 €/kW$_p$	20 years
Diesel generator	150 €/kW	20,000 oper. hours
Battery	850 €/bat	10,000 kWh

The obtained values for maximum components sizes are (eqs. (8)-(11)): x_{WTmax} = 26, x_{PVmax} = 40, x_{Dslmax} = 60, x_{batmax} = 235. This implies that the WT quantity is coded in 5 bits, PV and diesel generator sizes are coded in 6 bits, and battery quantity is coded in 8 bits. The total length of each binary chromosome is therefore 25 bits.

6.2 NSGA-II parameter optimization

For the implementation of the NSGA-II, a computer code in MATLAB was developed. The tests were performed at a laptop computer with Intel Pentium M 1.73 GHz processor, 512 MB RAM memory in Microsoft Windows XP environment. The average time for the convergence of the GA was 63 minutes.

For all simulations the population size of the GA was kept constant and equal to 100, as further increase in its size does not improve neither the quality nor the diversity of the obtained solutions, while a decrease in its size results in a significant reduction of the non-dominated solutions population. Moreover, after trial and error, a crossover probability of 0.9 is used in all simulations.

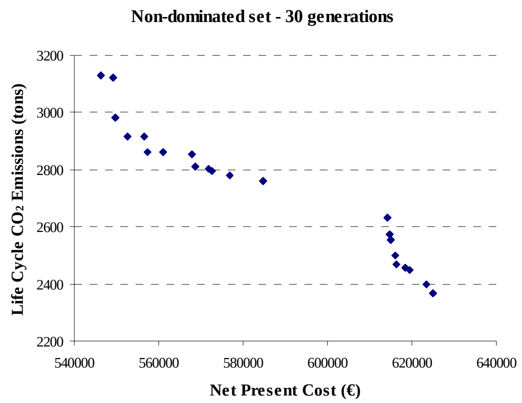
The performance of the GA was tested according to number of generations, crossover type and mutation rate. Fig. 2 shows the effect of generation number in the non-dominated set, when uniform crossover and mutation rate equal to 0.08 have been used. In both Figs. 2(a) and 2(b), it can be observed that the comparison of whichever two solutions of the non-dominated set is resulting a better value in one objective function and a worse value in the other objective function. Although there are no significant differences between the non-dominated sets of Fig. 2(a) and Fig. 2(b), the quality of the solutions in the 60th generation is slightly better. After this generation, no notable differences are observed.

In Fig. 3, a comparison of uniform crossover (Fig. 3(a)) and single-point crossover (Fig. 3(b)) has been done. It can be seen that for the same generation number and mutation rate, the uniform crossover operator presents better diversity of solutions. Fig. 4 depicts the effect of mutation rate in GA performance. A low mutation rate drives to a very poor non-dominated set, which cannot explore the entire range of solutions.

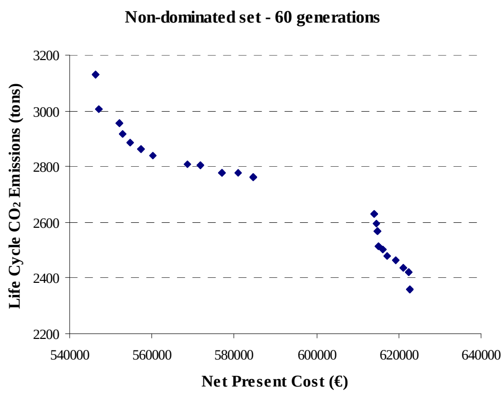
The NSGA-II optimum configuration is presented in Table 3, while Table 4 shows the corresponding non-dominated set members, as well as their objective functions values. Table 4 shows that all 22 non-dominated solutions combine a diesel generator with large rated power (48 kW in all cases, compared to 60 kW peak load) and a large WT number, which varies between 11 and 25. In the majority of solutions there are no PV panels, while their maximum size does not exceed 1 kW$_p$. The absence of solutions in the range a) 585,000€ to 615,000€ for NPC, and b) 2,630 to 2,760 tons for CO_2 emissions is explained from batteries presence. More specifically, the solutions that present higher net present cost (over 615,000€) and lower CO_2 emissions (below 2,630 tons) contain batteries whose number varies between 9 and 30, while the remaining solutions do not contain any batteries.

Table 3. NSGA-II optimum configuration.

Parameter	Value
Population size	100
Number of generations	60
Crossover probability	0.9
Crossover type	Uniform
Mutation rate	0.08

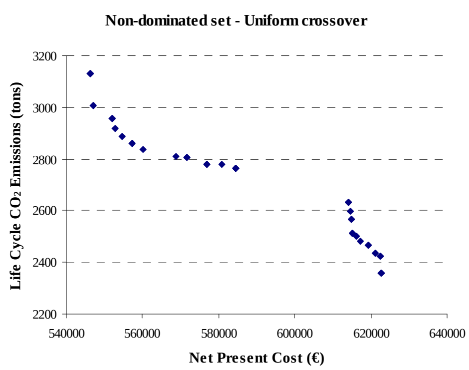


a

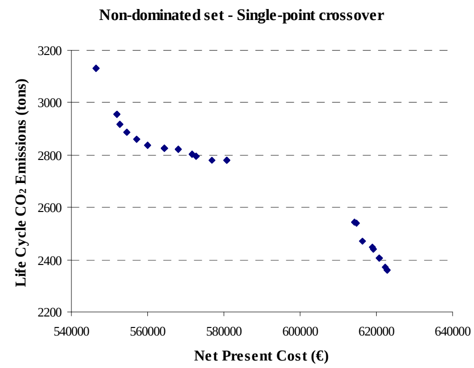


b

Fig. 2. Effect of generation number in the non-dominated set (uniform crossover, 0.08 mutation rate). (a) 30 generations, (b) 60 generations.

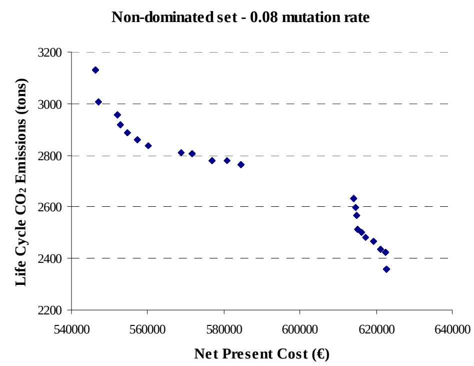


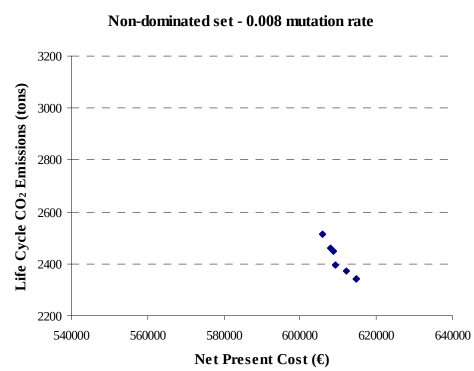
a



b

Fig. 3. Effect of crossover operator in the non-dominated set (60 generations, 0.08 mutation rate). (a) uniform crossover, (b) single-point crossover.





(a)

(b)

Fig. 4. Effect of mutation rate in the non-dominated set (60 generations, uniform crossover). (a) 0.08 mutation rate, (b) 0.008 mutation rate.

Table 4. Non-dominated set members for optimum NSGA-II performance.

Non-dominated set member	Components size				Objective functions values	
	WTs	PVs (kW_p)	Diesel (kW)	Batteries	NPC (€)	CO_2 emissions (tons)
1	11	0	48	0	546,412	3,131.6
2	14	0	48	0	547,031	3,007.5
3	16	0	48	0	552,068	2,955.8
4	17	0	48	0	552,752	2,917.5

Non-dominated set member	Components size				Objective functions values	
	WTs	PVs (kW_p)	Diesel (kW)	Batteries	NPC (€)	CO_2 emissions (tons)
5	18	0	48	0	554,570	2,886.5
6	19	0	48	0	557,244	2,861.5
7	20	0	48	0	560,092	2,837.8
8	22	0	48	0	568,715	2,809.8
9	22	1	48	0	571,766	2,804.3
10	24	0	48	0	576,927	2,779.2
11	24	1	48	0	580,845	2,779.1
12	25	1	48	0	584,617	2,761.8
13	15	0	48	9	614,143	2,631.4
14	16	0	48	9	614,650	2,596.5
15	17	0	48	9	614,750	2,566.8
16	18	0	48	14	615,195	2,513.5
17	19	0	48	9	616,115	2,500.7
18	19	0	48	17	617,187	2,480.4
19	20	0	48	16	619,296	2,465.4
20	21	0	48	17	621,106	2,436.3
21	21	0	48	25	622,511	2,422.2
22	22	0	48	30	622,739	2,358.8

6.3 Sensitivity analysis

Due to the fact that the PV panels manufacturing is a rapid evolving procedure, an optimistic scenario has been considered, which combines lower CO_2 emissions with lower prices. For future conditions, the emissions of mono-crystalline PVs may decrease to 0.046 kg CO_2 equivalent/kWh 0. Moreover, a 50% reduction of PVs initial cost has been assumed.

Using the GA parameter values of Table 3, the non-dominated set for the new scenario is depicted in Fig. 5. It can be seen that the resulted solutions present lower NPC and CO_2 emissions. After mapping the obtained results in a Table similar to Table 4, it can be observed that the cost and CO_2 emissions reduction for PVs improve their penetration, which varies between 0 kW_p (in only one solution) and 27 kW_p. The diesel generator rated power ranges from 44 kW to 48 kW, while the number of WTs has been restricted in the range of 16 to 18. The batteries number does not differ significantly from the base case.

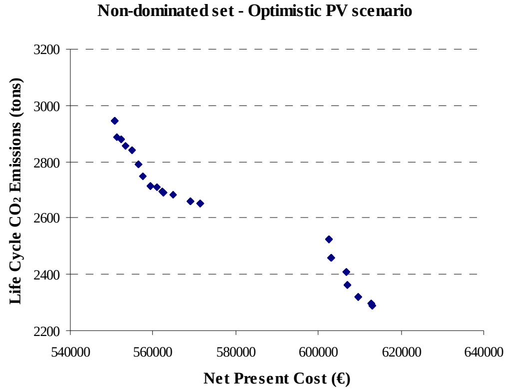


Fig. 5. Non-dominated set for the optimistic PV scenario.

7. Conclusions

A multiobjective evolutionary algorithm approach for the optimum economic and environmental performance of an off-grid power system that contains renewable energy sources technologies is presented in this paper, taking into account as environmental criterion the CO_2 emissions during the life cycle of each system's component. The obtained results proved the necessity of such an analysis. Although the photovoltaics does not emit during their operation, the large amounts of energy needed for their manufacturing result in high economic and environmental costs. On the other hand, wind turbines present much better performance than photovoltaics in both objectives and thus they have a significant portion in systems' energy production. However, the fundamental component for the reliable and economic operation of such a system is the diesel generator, although it presents the highest CO_2 emissions. A future improvement in photovoltaics manufacturing may improve their contribution to the energy supply of such systems.

Acknowledgment

This work has been performed within the European Commission (EC) funded RISE project (contract number FP6-INCO-CT-2004-509161). The authors wish to thank the RISE project partners for their contributions and the EC for partially funding this project.

References

[1] K. Deb, Multi-objective optimization using evolutionary algorithms, John Wiley & Sons, 2001.
[2] K. Deb, Optimization for engineering design: algorithms and examples, Prentice-Hall, 1995.
[3] D. F. Jones, S. K. Mirrazavi, M. Tamiz, Multi-

objective meta-heuristics: an overview of the current state-of-art, European Journal of Operational Research **137**, 1-9 (2002).
[4] J. L. Bernal-Agustin, R. Dufo-Lopez, D. M. Rivas-Ascaso, Renewable Energy **31**, 2227-2244 (2006).
[5] Hybrid Optimization Model for Electric Renewables (HOMER). Website: www.nrel.gov/homer.
[6] F. I. Khan, K. Hawboldt, M. T. Iqbal, Renewable Energy **30**, 157-177 (2005).
[7] Y. Kemmoku, K. Ishikawa, S. Nakagawa, T. Kawamoto, T. Sakakibara, Electrical Energy in Japan, **138**(2), 14-23 (2002).
[8] B. F. Hobbs, P. Meier, Kluwer Academic Publishers, 2000.
[9] L. Gagnon, C. Belanger, Y. Uchiyama, Energy Policy **30**, 1267-1278 (2002).
[10] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation **6**(2), 182-197 (2002).
[11] O. Skarstein, K. Uhlen, Design considerations with respect to long-term diesel saving in wind/diesel plants, Wind Engineering **13**, 72-87 (1989).
[12] C. D. Barley, C. B. Winn, Solar Energy **58**, 165-179 (1996).
[13] T. Ackermann, G. Andersson, L. Soder, Distributed generation: a definition, Electric Power Systems Research **57**, 195-204 (2001).
[14] R. Dones, T. Heck,d S. Hirschberg, Greenhouse gas emissions from energy systems, comparison and overview, Elsevier Encyclopedia of Energy **3**, 77-95 (2004).

* Corresponding author: ikatsigiannis@yahoo.gr