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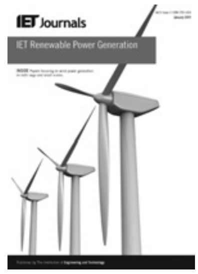

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Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables

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Abstract: The overall evaluation of small autonomous hybrid power systems (SAHPS) that contain renewable and conventional power sources depends on economic and environmental criteria, which are often conflicting objectives. The solution of this problem belongs to the field of non-linear combinatorial multiobjective optimisation. In a multiobjective optimisation problem, the target is not to find an optimal solution, but a set of non-dominated solutions called Pareto-set. The present article considers as an economic objective the minimisation of system's cost of energy (COE), whereas the environmental objective is the minimisation of the total greenhouse gas (GHG) emissions of the system during its lifetime. The main novelty of this article is that the calculation of GHG emissions is based on life cycle analysis (LCA) of each system's component. In LCA, the whole life cycle emissions of a component are taken into account, from raw materials extraction to final disposal/recycling. This article adopts the non-dominated sorting genetic algorithm (NSGA-II), which in combination with a proposed local search procedure effectively solves the multiobjective optimisation problem of SAHPS. Two main categories of SAHPS are examined with different energy storage: lead-acid batteries and hydrogen storage. The results indicate the superiority of batteries under both economic and environmental criteria.

1 Introduction

The aim of the optimisation procedure is to find and compare feasible solutions according to one or more objective functions. When the examined problem involves one objective function, the optimisation procedure aims to find the best feasible solution under the given criterion. However, the majority of real-world problems involve simultaneous optimisation 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 small autonomous hybrid power systems (SAHPS), mainly two conflicting objectives are important: system cost and pollutant emissions. SAHPS usually operate in isolated areas that are far from the grid. A fundamental characteristic of such systems is that they have low energy demand [1]. A large portion of this demand is usually served by conventional generators such as diesel generators, although renewable energy sources (RES) technologies combined with electricity storage 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 production. On the other hand, conventional generators emit large amounts of pollutants such as CO_2 through direct emissions from system operation (e.g. fuel consumption), and through emissions generated during the whole life cycle of these systems, as estimated through life cycle analysis (LCA) methodology. RES and electricity storage technologies do not emit during their operation; however, in their whole life cycle, they may produce significant amounts of pollutant emissions.

In a multiobjective optimisation problem, such as the one addressed in this paper, the comparison of two solutions x and y can lead to the following three results: (i) x dominates y (i.e. x is better than y in at least one objective, and no worse in all the others), (ii) y dominates x or (iii) no solution dominates the other (x is better than y on some objectives, but y is better than x on other objectives). 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 [2].

For the solution of multiobjective optimisation problems numerous conventional methods have been proposed, such as the weighted sum method [3, 4], the ε-constraint method [5], goal programming methods [6, 7] and so on. These methods convert the moltiobjective optimisation problem into a single objective optimisation problem by either aggregating the objective functions or optimising the most important objective and treating the others as constraints. 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. Moreover, all conventional methods require some problem knowledge, such suitable weights, the value of ε or target values. The application of these methods to the economic and environmental evaluation of SAHPS is often viewed as contradictory, because of the failure of mainstream economics to properly account for the environmental and health costs of conventional power sources, the opportunity costs of conventional energy, the trade-offs between cost and price fluctuation and so on.

Recently, various algorithms have been developed, mainly from the area of metaheuristics, which efficiently tackle the above-mentioned problems. Metaheuristics orchestrate an interaction between local improvement procedures and higher level strategies to create a process capable of escaping from local optima and performing a robust search of a solution space, and they are often inspired by the study of natural processes. The vast majority of multiobjective metaheuristic algorithms belongs to the category of genetic algorithms (GAs) [8]. The main reason is that GAs 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 [2].

Various methodologies have been proposed for the multiobjective evaluation of small hybrid power systems. A multiobjective GA is proposed in [9] in order to minimise six objective functions related to system's performance and CO_2 emissions. In [10], a multiobjective GA is developed that minimises cost, pollutant emissions and unmet load of such a system. The authors of [10] have also developed HOGA software [11], which uses a multiobjective GA in order to minimise the net present cost, the CO_2 emissions and the unmet load of a hybrid power system. In [12], a multiobjective GA has been used for the optimisation of the cost and CO_2 emissions of an isolated system of a network in which three hotels and a town were thermally and electrically supplied. HOMER software [13] uses the weighted sum method for the multiobjective optimisation of a hybrid power system, as it initially considers a penalty cost associated with the pollutant emissions, and then minimises the overall net present cost. However, all these methodologies [9–13] consider only the direct emissions of system's components because of system operation. LCA analysis of SAHPS is implemented in [14, 15]; however, LCA is not combined with economic analysis in a multiobjective optimisation framework.

This paper proposes an economic and environmental multiobjective formulation of SAHPS evaluation. The economic objective function is system's cost of energy (COE), whereas the environmental objective function is the total CO_2 equivalent (CO_2-eq.) emissions. The main novelty of the proposed methodology is the consideration of LCA results for the calculation of CO_2-eq. emissions. The different locations of a product's CO_2-eq. emissions during its life cycle are unimportant, as the incremental impact on global warming will be the same [16]. This paper adopts the non-dominated sorting genetic algorithm (NSGA-II), which in combination with a proposed local search procedure effectively solves the multiobjective optimisation problem of SAHPS.

The paper is organised as follows. Section 2 formulates the multiobjective optimisation problem of SAHPS. Section 3 provides a brief description of LCA in power systems, whereas Section 4 presents the main characteristics of multiobjective GA. Section 5 describes the proposed multiobjective GA methodology for the solution of the multiobjective optimisation problem of SAHPS. Section 6 presents and discusses the obtained results and shows how the results are improved because of the proposed local search procedure that is combined with NSGA-II. Section 7 concludes the paper.

2 Problem formulation

This paper deals with the economic and environmental evaluation of a SAHPS, and belongs to the category of non-linear combinatorial multiobjective optimisation problems. This multioblective optimisation problem has to fulfil the two objectives defined by (1) and (3) subject to constraints (4)–(10). In particular, the problem is formulated as follows.

2.1 First objective

Minimisation of system's COE (€/kWh)

$$\min(\mathrm{COE}) \tag{1}$$

The COE of SAHPS is calculated as follows

$$\mathrm{COE} = \frac{C_{\mathrm{antot}}}{E_{\mathrm{anloadserved}}} \tag{2}$$

where C_{antot} (€) is the total annualised cost and $E_{\mathrm{anloadserved}}$ (kWh) is the total annual useful electric energy production. C_{antot} takes into account the annualised capital costs, the annualised replacement costs, the annual operation and maintenance (O&M) costs, the annual fuel costs (if applicable) of system's components, and the discount rate utilised. The discount rate represents the opportunity cost of capital, and is probably the most important of the above-mentioned factors, as it greatly affects the whole economics of the project and the decision making [17]. Typical discount rate values for electricity generation projects range from 5 to 10% [18]. In this paper, a value of 8% has been adopted for a project lifetime of 20 years.

2.2 Second objective

Minimisation of system's components total GHG emissions $\mathrm{GHG}_{\mathrm{tot}}$ (tn CO_2-eq.), based on LCA during the lifetime of the system

$$\min(\mathrm{GHG}_{\mathrm{tot}}) \tag{3}$$

2.3 Constraints

1. *Initial cost constraint:* The available budget (total initial cost at the beginning of system's lifetime) is limited

$$\mathrm{IC} \leq \mathrm{IC}_{\max} \tag{4}$$

where IC (€) is the initial installation cost of the system, and $\mathrm{IC}_{\max}$ (€) is the maximum acceptable initial cost of the system.

2. *Unmet load constraint:* The annual unmet load (which was not served because of insufficient generation), expressed as a percentage of the total annual electrical load, cannot exceed a fixed value

$$f_{\mathrm{UL}} = \frac{\sum_{\Delta t}^{\mathrm{year}}(\mathrm{UL}_{\Delta t}\Delta t)}{E_{\mathrm{anload}}} \leq f_{\mathrm{ULmax}} \tag{5}$$

where f_{UL} is the annual unmet load fraction, $\mathrm{UL}_{\Delta t}$ (kW) is the unmet load during the simulation time step Δt (h), E_{anload} (kWh) is the total annual electric energy demand, and f_{ULmax} is the maximum allowable annual unmet load fraction.

3. *Capacity shortage constraint:* The annual capacity shortage fraction, which is the total annual capacity shortage divided by the total annual electric energy demand, cannot exceed a fixed value. Capacity shortage is defined as a shortfall that occurs between the required amount of operating capacity (load plus required operating reserve) and the actual operating capacity the system can provide. Operating reserve in a SAHPS with renewables is the surplus electrical generation capacity (above that required to meet the current electric load) that is operating and is able to respond instantly to a sudden increase in the electric load or a sudden decrease in the renewable power output

$$f_{\mathrm{CS}} = \frac{\sum_{\Delta t}^{\mathrm{year}}(\mathrm{CS}_{\Delta t}\Delta t)}{E_{\mathrm{anload}}} \leq f_{\mathrm{CSmax}} \tag{6}$$

where f_{CS} is the annual capacity shortage fraction, $\mathrm{CS}_{\Delta t}$ (kW) is the capacity shortage during Δt, and f_{CSmax} is the maximum allowable annual capacity shortage fraction.

4. *Fuel consumption constraint:* The maximum amount of each fuel that is consumed throughout a year cannot exceed a specific limit

$$\sum_{\Delta t}^{\mathrm{year}} \mathrm{FCo}_{\mathrm{gen}\Delta t} \leq \mathrm{FCo}_{\mathrm{angenmax}} \tag{7}$$

where $\mathrm{FCo}_{\mathrm{gen}\Delta t}$ is the fuel consumption of a generator during Δt, and $\mathrm{FCo}_{\mathrm{angenmax}}$ is the maximum allowable annual fuel consumption of the generator.

5. *Minimum renewable fraction constraint:* The portion of system's total energy production originating from RES technologies must be greater than or equal a specified minimum limit

$$f_{\mathrm{RES}} = \frac{E_{\mathrm{anRES}}}{E_{\mathrm{antot}}} \geq f_{\mathrm{RESmin}} \quad \text{where} \quad 0 \leq f_{\mathrm{RESmin}} \leq 1 \tag{8}$$

where f_{RES} is the RES fraction of the system, E_{anRES} (kWh) is the total annual renewable energy production, E_{antot} (kWh) is the total annual energy production of the system, and f_{RESmin} is the minimum allowable RES fraction.

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6. *Components' size constraints:* The sizes of each system's component must lie between specific limits

$$\mathrm{size}_{\mathrm{comp}} \geq 0 \quad \forall \ \mathrm{comp} \tag{9}$$

$$\mathrm{size}_{\mathrm{comp}} \leq \mathrm{size}_{\mathrm{compmax}} \quad \forall \ \mathrm{comp} \tag{10}$$

where $\mathrm{size}_{\mathrm{comp}}$ is the size of system's component comp, and $\mathrm{size}_{\mathrm{compmax}}$ is the maximum allowable size of comp.

3 LCA of 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: (i) goal definition and scoping, (ii) inventory analysis, (iii) impact assessment and (iv) interpretation.

In the power systems area, 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 [19].

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, manufacturing 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 (GHG) emissions of energy systems are expressed in terms of CO_2-eq. emissions. This means that CO_2 and other GHGs, such as CH_4 and N_2O, have been included in the assessment. However, other GHGs have different effects on the climate and may have a different atmospheric life span. To take into account these differences, each GHG 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 [20].

4 Overview of GAs and NSGA-II methods

4.1 Genetic algorithms

GAs mimic natural evolutionary principles to constitute search and optimisation procedures, and 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 consists of 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 optimisation, there is one goal: the search for an optimum solution. However, in multiobjective optimisation 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.

4.2 NSGA-II method

Numerous GAs have been proposed in the literature for the solution of multiobjective optimisation problems [2]. The approach adopted in this paper is the non-dominated sorting GA (NSGA-II) [21]. In this algorithm, the population is sorted into different non-domination levels, and in each solution is assigned a fitness equal to its non-domination level (1 is the best level). 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

In order to evaluate the economic and environmental performance of SAHPS, two different types of systems have been modelled that contain different options for electricity storage. More specifically, the first type uses batteries as a storage means and can contain wind turbines (WTs), fixed mono-Si photovoltaics (PVs), generator with diesel fuel, generator with biodiesel fuel, fuel cells (FC) combined with reformer with natural gas as a fuel, lead-acid batteries and converter. The second type of system uses hydrogen for storage and can contain WTs, PVs, diesel and biodiesel generators, FC with hydrogen fuel, electrolyser, hydrogen tank and converter.

The considered sizes of each component can take only discrete values, so the binary GA is selected. Two alternative GA coding schemes are examined: conventional binary coding and gray coding. Moreover, for the constraint handling of the proposed GA the penalty function approach is adopted, in which an exterior penalty term that penalises infeasible solutions is used. Since different constraints may take different orders of magnitude, prior to the calculation of the overall penalty function all constraints are normalised.

The SAHPS component modelling is implemented as follows. The WT power output estimation is managed through its power curve fitting by a seventh-order polynomial curve. For the calculation of PV power, solar radiation data, ambient temperature data and geographic location data are taken into account. The diesel generator fuel consumption F (L/kWh) is assumed to be a linear function of its electrical power output [22]

$$F = 0.08415P_{\text{rated}} + 0.246P \qquad (11)$$

where P_{rated} is generator's rated power and P is generator's output power. When biodiesel is used instead of diesel, fuel consumption is increased [23]. In this paper, a 10% increase in fuel consumption has been considered. Moreover, a 30% minimum allowable load ratio of P_{rated} has been assumed for each type of generator. The FC and electrolyser efficiencies have been considered 50 and 65%, respectively [24]. Lead-acid batteries have been modelled assuming maximum charge and discharge current equal to $C/5$ [25]. Finally, converter efficiency has been taken equal to 90%.

Renewable power sources (WTs and PVs) have a priority in supplying the electric load. If they are not capable to fully serve the load, the remaining electric load has to be supplied by generators and/or electricity storage technologies. From all possible combinations, it is selected the one that supplies the load at the least cost. An additional aspect of system operation is whether (and how) the generators should charge the storage means. In this paper, the load following strategy is adopted, in which the storage technologies are charged by renewable power sources and not by generators.

The LCA CO_2 equivalent emissions of the considered SAHPS components are calculated per amount of energy produced or stored (kg CO_2-eq./kWh). The normalisation of GHG emissions over energy units is more appropriate than the normalisation of GHG emissions over component capacity, since some components are used at full capacity for most of the year, whereas others do not present such a high availability [26]. The values that are adopted in this paper are shown in Table 1. It has to be noted that the LCA GHG emissions of power systems' converters are not examined individually in the bibliography. The only related information is included in the LCA GHG emissions analysis of PV systems, in which the contribution of the inverter (part of the converter) is less than 1% of the overall PV system [27]. For this reason, in this paper the emissions of converters are considered negligible.

The NSGA-II of Section 4.2 in combination with a proposed local search procedure (Section 6.2) effectively solves the multiobjective optimisation problem of SAHPS of Section 2 as will be shown in Section 6.

6 Results and discussion

6.1 *Case study system*

In the considered SAHPS, the annual peak load has been taken equal to 50 kW, while the wind, solar and temperature data needed for the estimation of WT and PV performance refer to the Chania region, Crete, Greece. The average wind speed is 6.14 m/s at 10 m, the Weibull shape parameter is 1.54 and the Weibull scale parameter is 7.10 m/s. The average daily global solar radiation is 4.62 kWh/(m^2 d) and the average temperature is 17.07°C. The height above sea level of the studied SAHPS is considered to be 500 m and the related atmospheric

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Table 1 LCA CO_2 equivalent emissions of system's components

Component	GHG emissions ($kg\ CO_2$-eq./kWh)
WT (mean wind speed 6.5 m/s) [28]	0.011
PV (mono-Si) [29]	0.045
diesel generator [30]	0.880
biodiesel generator [31]	0.191
fuel cell (hydrogen production through natural gas reforming) [26]	0.664
fuel cell (hydrogen production through electrolysis) [14]	0.020
electrolyser and hydrogen tank [14]	0.011
lead-acid battery [32]	0.028
converter	0

pressure is considered 95.5 kPa. The simulation time step Δt is taken equal to 10 min (1/6 h), while the operating reserve inputs, needed for the calculation of system's capacity shortage, have been considered as 7% of the average 10 min load, 40% of the average 10 min WT output and 20% of the average 10 min PV output. The values of parameters involved in constraints (4)–(8) are: $IC_{max} = 300\,000$ €, $f_{ULmax} = 0.5\%$, $f_{CSmax} = 1.0\%$, $f_{RESmin} = 50\%$, maximum allowable annual biodiesel consumption 10 000 L/year, unlimited fuel consumption for diesel and natural gas.

The cost, lifetime and size characteristics for each component of the two case studies are presented in Table 2. For each component, the minimum size is equal to zero. Batteries have been modelled according to the following technical characteristics per component: efficiency 85%, capacity 625 Ah, voltage 12 V and minimum state of charge 30%. Moreover, with the exception of diesel and biodiesel generators, all components have constant increment of their size, as Table 2 shows. The considered sizes for the generators are 0, 3, 5, 7.5, 10, 15, 20, 25, 30, 35, 40 and 50 kW.

6.2 NSGA-II optimal setting and results for SAHPS with lead-acid battery storage

During the investigation of the parameter values that ensure optimum performance of NSGA-II, the population N_{pop} was kept equal to 100, as the decrease of population has resulted in a significant decrease in the number and the diversity of the optimal set of non-dominated solutions. On the other hand, the population growth of the GA may improve its performance after a large number of generations, but it is also leading to a significant increase in the number of performed simulations. For this reason,

Table 2 Component characteristics

Component	$size_{compmax}$	Increment	Capital cost	Replacement cost	O&M cost	Fuel cost	Lifetime
WT (hub height 30 m, rated power 10 kW)	10 WTs	1 WT	15 000 €/WT	12 000 €/WT	300 €/WT/year	—	20 years
PV	60 kW_p	1 kW_p	5000 €/kW_p	4500 €/kW_p	0	—	25 years
generator (diesel fuel)	50 kW	variable	200 €/kW	200 €/kW	0.01 €/h/kW	1.0 €/L	20 000 h of operation
generator (biodiesel fuel)	50 kW	variable	200 €/kW	200 €/kW	0.01 €/h/kW	1.4 €/L	20 000 h of operation
FC + reformer (natural gas fuel)	40 kW	4 kW	2000 €/kW	2000 €/kW	0.02 €/h/kW	0.3 €/m^3	40 000 h of operation
battery	150 Bat	10 Bat	700 €/Bat	700 €/Bat	0	—	9000 kWh
FC (hydrogen fuel)	40 kW	4 kW	2000 €/kW	2000 €/kW	0.02 €/h/kW	—	40 000 h of operation
electrolyser	60 kW	4 kW	1200 €/kW	1200 €/kW	30 €/kW/year	—	15 years
hydrogen tank	60 kg	4 kg	800 €/kg	800 €/kg	10 €/kg/year	—	25 years
converter	60 kW	2 kW	1000 €/kW	1000 €/kW	0	—	10 years

at the end of this section there is a comparison between the performance of a GA with $N_{pop} = 100$ combined with a local search procedure, and the performance of a GA with $N_{pop} = 200$.

The performance of the GA was tested according to crossover type, mutation rate, coding type and number of generations. The optimal results are obtained for uniform crossover and mutation rate equal to 0.01. Moreover, Fig. 1 shows that the gray coding increases the number and the diversity of non-dominated solutions and improves their quality.

Fig. 2 shows the non-dominated solutions set for different numbers of GA generations. As can be seen, a satisfactory set of solutions arises from the 50th generation, which is improved slightly in the following generations, but with a concomitant increase in computational burden. For this reason, the non-dominated set of the 50th generation will be used as the basis for the local search procedure.

In order to further improve the quality of NSGA-II results, a methodology that combines local search and classification of non-dominated solutions is used. Initially, a local search procedure is applied in each member of the non-dominated solutions set, and then classification takes place, thereby resulting in a new set of non-dominated solutions (first generation of local search). In the new set, a new local search procedure and reclassification is applied. The process continues until no new members are entering the non-dominated set. Fig. 3 shows the results for different GA populations and different stages of local search. The consideration of double GA population (Fig. 3*b*) compared to the initial solution (Fig. 3*a*) provides better results (as Fig. 3*e* shows), larger number of non-dominated solutions, but also a significant increase in the number of simulations performed (5200 against 2600). The first generation of the local search procedure of the initial solution (Fig. 3*c*) produces a wider set of non-dominated solutions compared to Fig. 3*a*, without increasing significantly the number of simulations (2971). The last generation of the local search procedure (Fig. 3*d*) provides better results than Fig. 3*b* for the vast majority of solutions (see also Fig. 3*e*), while the number of simulations increases from 5200 to 6561. If the local search procedure is applied to the results of Fig. 3*b*, it will also produce the non-dominated set of Fig. 3*d*. However, the number of required simulations will be increased from 6561 to 7053. The computational time needed for NSGA-II without local search is 138.7 min, whereas the NSGA-II with local search requires 317.2 min. The final results of the local search procedure are presented in Table 3, while Table 4 shows the optimal GA parameters.

The study of Table 3 shows that all non-dominated solutions include a large number of WTs and batteries,

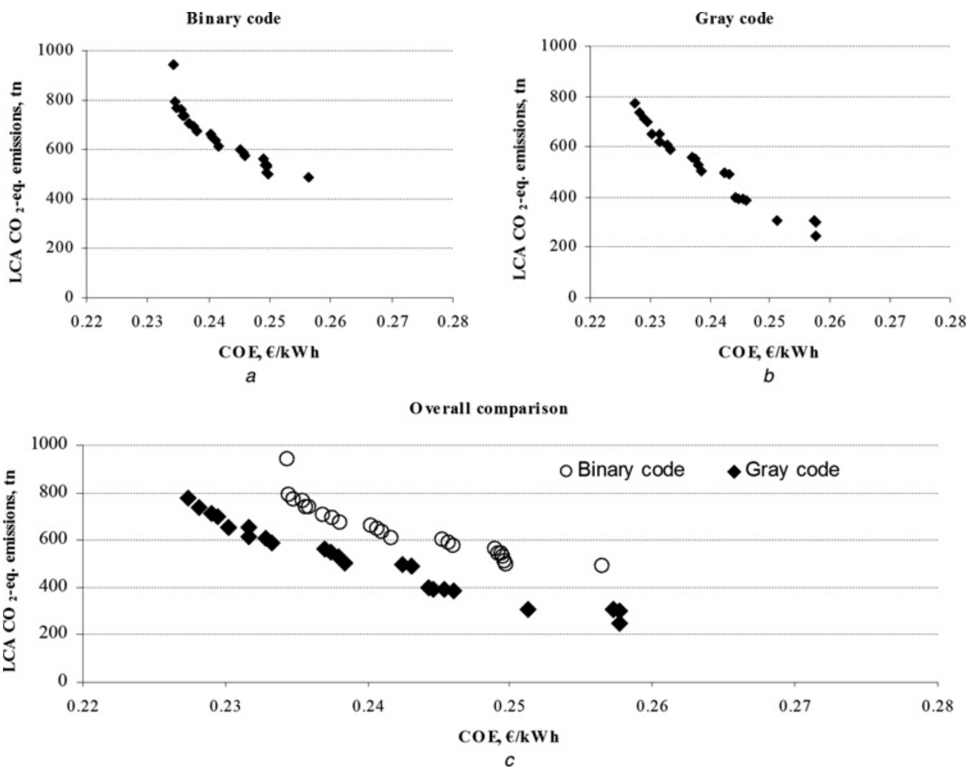

Figure 1 *Effect of coding type on the non-dominated set (50 generations, uniform crossover, 0.01 mutation rate)*

a Conventional binary code
b Gray code
c Comparison of the two coding types

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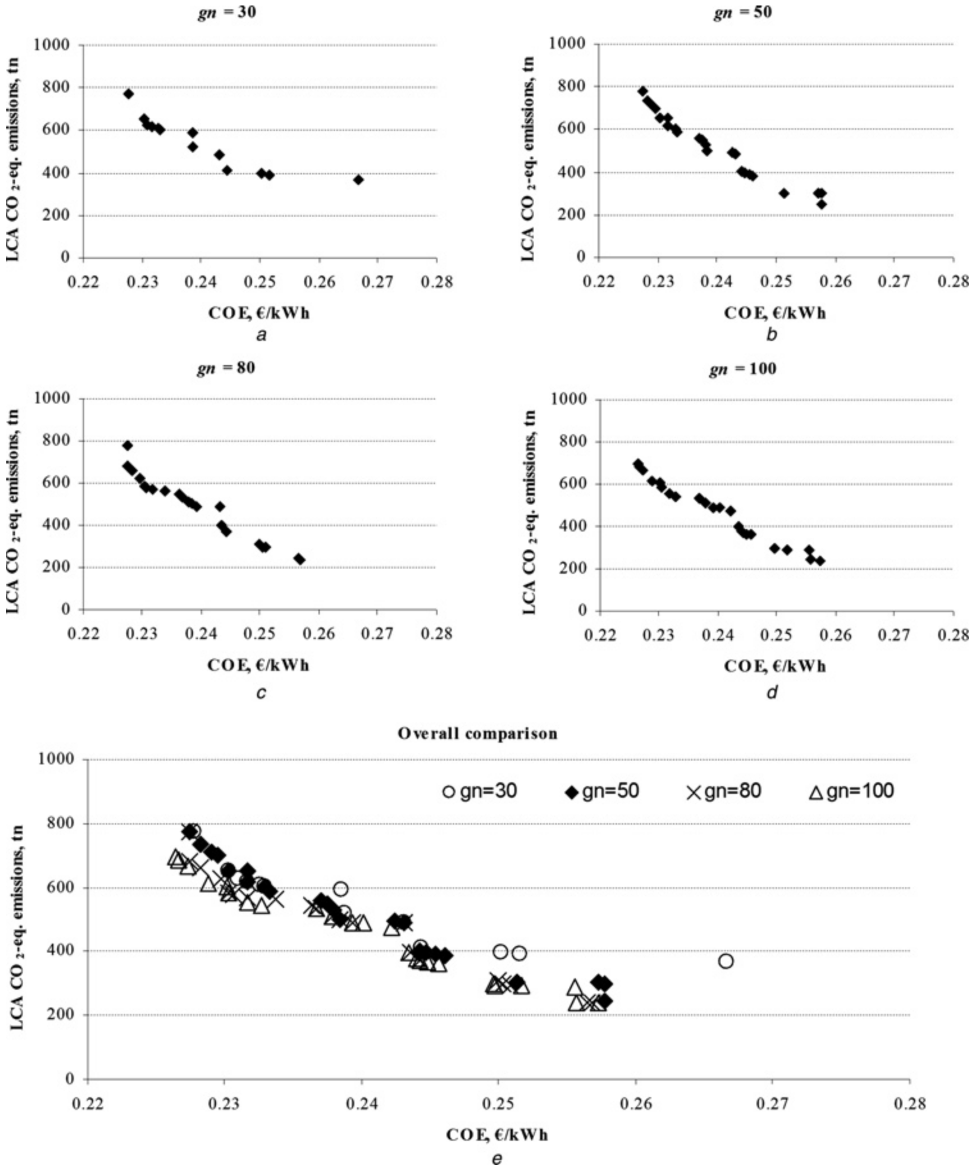

Figure 2 *Effect of generation number gn on the non-dominated set (uniform crossover, 0.01 mutation rate, gray code)*

a $gn = 30$
b $gn = 50$
c $gn = 80$
d $gn = 100$
e Comparison of the four generation numbers

similar capacity of converters (in the range of 40 kW), PV arrays and FCs with small or zero power. The main criterion that affects the performance of the two objective functions is the fuel of generators. More specifically, diesel fuel presents lower costs and higher CO_2-eq. emissions, whereas biodiesel fuel presents higher costs and lower of CO_2-eq. emissions. WTs present the best combination of low cost and low CO_2-eq. emissions from all available RES technologies, while the large number of batteries is essential for the proper operation of SAHPS, in which a large amount of energy is produced by non-dispatchable units. The lack of PV arrays can be explained by their high cost, whereas the lack of FCs with natural gas as a fuel is explained because of the combination of their high costs and their high CO_2-eq. emissions, as reflected by the LCA methodology. The consideration of higher WT hub heights is not changing significantly the results because of WT size constraint ($size_{compmax} = 10$ WTs), whereas the installation of a PV tracking system (one axis or two axis) cannot increase the negligible sizes of the PVs because of the high additional cost of the tracking systems.

Having knowledge of the Pareto-optimal set, higher level information can be used for the selection of one non-dominated solution. The simplest way is to consider a

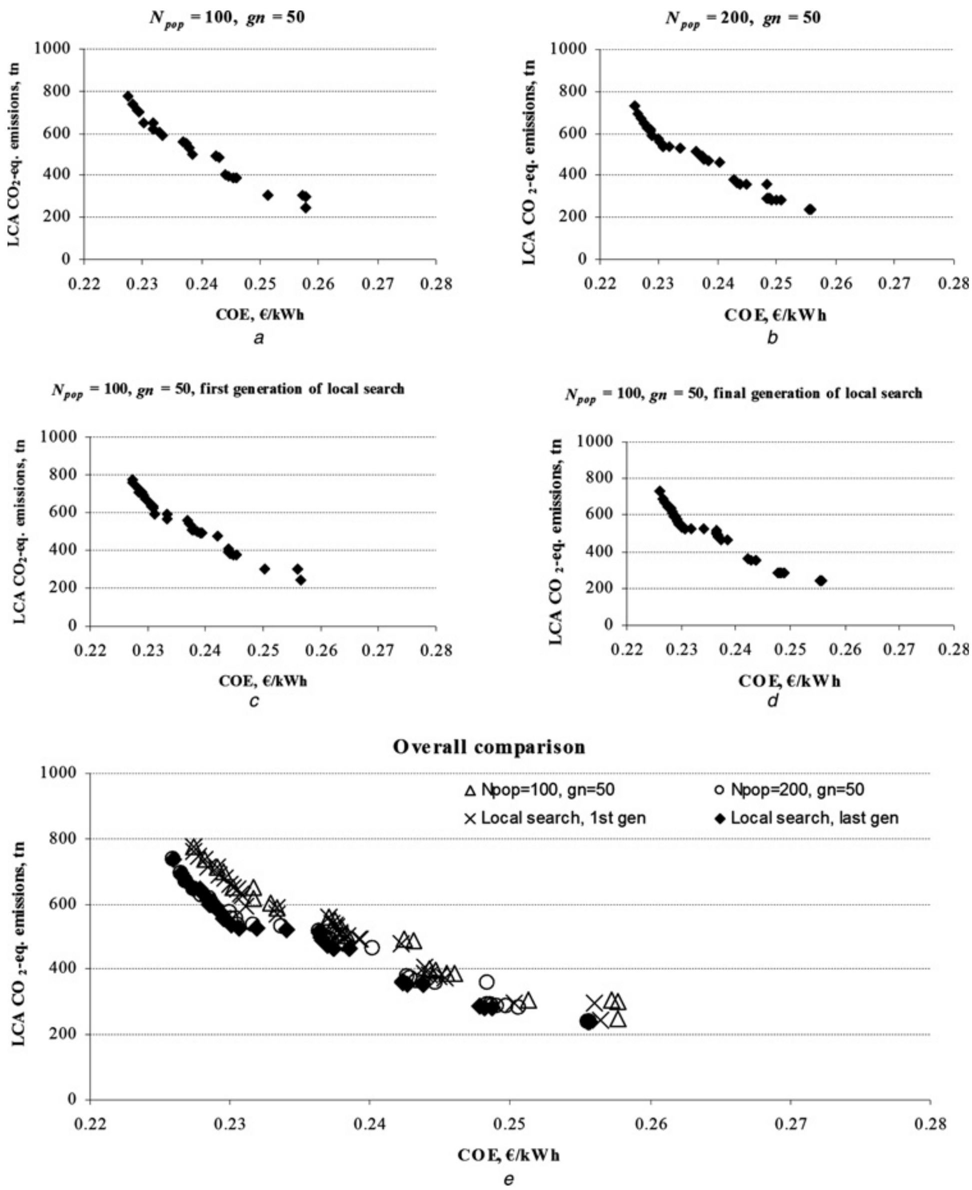

Figure 3 *Effect of population size N_{pop} and local search procedure on the non-dominated set (gn = 50, uniform crossover, 0.01 mutation rate, gray code)*

a $N_{pop} = 100$
b $N_{pop} = 200$
c First local search generation of *a*
d Last local search generation of *a*
e Comparison of the four examined cases

CO_2-eq. emission cost (in €/tn), and then calculate the updated COE value. In any case, the optimal solution will be contained in the non-dominated set, as each other feasible solution is dominated by at least one Pareto-optimal solution. Table 5 presents the optimal solutions and their related updated COE for five values of CO_2-eq. emission cost. For zero emission cost, the second objective is not taken into account, so solution 1 of Table 3 is selected. The increase of the CO_2-eq. cost leads to solutions with lower CO_2-eq. emissions, until the last solution of Table 3 (that minimises CO_2-eq. emissions) is reached.

6.3 NSGA-II optimal setting and results for SAHPS with hydrogen tank storage

For the economic and environmental evaluation of a SAHPS with hydrogen tank, the NSGA-II algorithm is used with parameter values presented in Table 4. The results obtained from the GA are depicted in Fig. 4*a*, the overall results after local search are depicted in Fig. 4*b*, whereas Fig. 4*c* depicts these results in the same graph. These results prove the necessity of the local search procedure, as it increases significantly not only the number of non-dominated solutions but also their

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Table 3 Final non-dominated set for SAHPS with lead-acid battery storage

Solution number	Component sizes							Objective function values	
	WT	PV (kW_p)	Dsl (kW)	Bio (kW)	FC (kW)	Bat	Conv (kW)	COE (€/kWh)	CO_2-eq. emissions (tn)
1	9	2	25	3	0	110	36	0.225991	734.906
2	9	2	25	3	0	110	42	0.226492	692.165
3	9	2	25	3	0	120	42	0.226870	668.465
4	9	1	25	3	0	140	42	0.227357	647.528
5	9	4	20	7.5	0	100	40	0.227855	644.319
6	9	4	20	7.5	0	110	38	0.227940	635.057
7	9	4	20	7.5	0	110	40	0.228246	622.168
8	9	4	20	7.5	0	120	38	0.228444	614.800
9	9	3	20	7.5	0	130	40	0.228579	598.455
10	9	3	20	7.5	0	140	38	0.228906	594.359
11	10	1	20	7.5	0	110	42	0.228998	594.079
12	9	3	20	7.5	0	130	42	0.229014	586.649
13	10	1	20	7.5	0	120	40	0.229032	585.040
14	9	3	20	7.5	0	140	40	0.229163	580.639
15	10	1	20	7.5	0	120	42	0.229339	571.926
16	10	0	20	7.5	0	130	44	0.229523	555.013
17	10	0	20	7.5	0	140	42	0.229719	549.783
18	10	0	20	7.5	0	140	44	0.230077	536.866
19	10	0	20	7.5	0	140	46	0.230710	527.063
20	10	1	20	7.5	0	130	48	0.231881	524.365
21	10	1	20	10	0	130	48	0.234017	523.170
22	10	0	15	15	0	120	42	0.236352	515.731
23	10	0	15	15	0	130	40	0.236429	512.493
24	10	0	15	15	0	130	42	0.236439	499.271
25	10	0	15	15	0	130	44	0.236648	488.586
26	10	0	15	15	0	140	42	0.236685	484.372
27	10	0	15	15	0	140	44	0.236895	473.507
28	10	0	15	15	0	140	46	0.237421	465.097
29	10	1	15	15	0	130	48	0.238507	462.949
30	10	0	7.5	20	0	140	42	0.242320	365.568
31	10	0	7.5	20	0	140	44	0.242321	358.584
32	10	0	7.5	20	0	140	46	0.242666	353.211
33	10	1	7.5	20	0	130	48	0.243795	352.328
34	10	1	3	25	0	130	44	0.247778	286.369

Continued

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Table 3 *Continued*

Solution number	Component sizes							Objective function values	
	WT	PV (kW_p)	Dsl (kW)	Bio (kW)	FC (kW)	Bat	Conv (kW)	COE (€/kWh)	CO_2-eq. emissions (tn)
35	10	2	3	25	0	130	42	0.247839	286.008
36	10	1	3	25	0	130	46	0.248195	283.524
37	10	1	3	25	0	130	48	0.248760	281.040
38	9	6	0	30	0	120	42	0.255535	239.498
39	9	6	0	30	0	120	44	0.255640	237.808

Abbreviations used: Dsl = diesel, Bio = biodiesel, Bat = battery, Conv = converter

Table 4 NSGA-II optimum configuration

Parameter	Value
population size, N_{pop}	100
number of generations, *gn*	50, followed by local search
coding type	gray code
crossover type	uniform
mutation rate	0.01

Table 5 Optimal solution for SAHPS with battery storage considering CO_2-eq. emission costs

CO_2-eq. price (€/tn)	Number of optimum solution (see Table 3)	COE (€/kWh)
0	1	0.225991
10	18	0.257652
20	34	0.277195
30	36	0.291883
40	39	0.304498

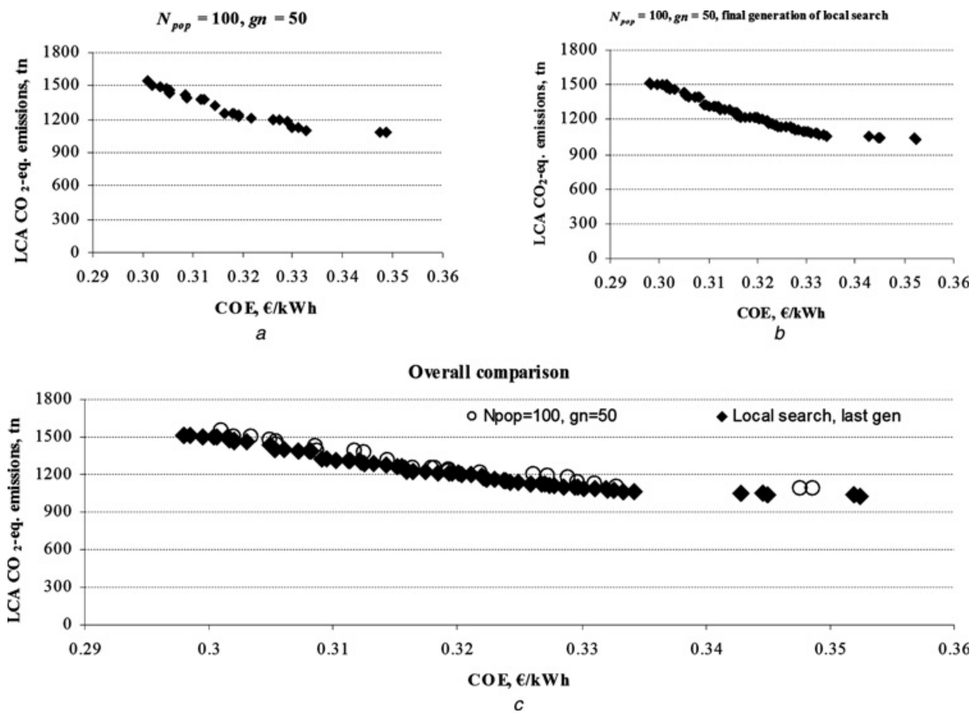

Figure 4 *Non-dominated set for SAHPS with hydrogen storage (N_{pop} = 100, gn = 50, uniform crossover, 0.01 mutation rate, gray code)*

a NSGA-II results
b Last generation of local search
c Comparison of the two examined cases

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Table 6 Final non-dominated set for SAHPS with hydrogen tank storage

Solution number	Component sizes								Objective function values	
	WT	PV (kW_p)	Dsl (kW)	Bio (kW)	FC (kW)	Elctls (kW)	H_2 tank (kg)	Conv (kW)	COE (€/kWh)	CO_2-eq. emissions (tn)
1	9	0	20	10	12	20	12	20	0.297938	1517.477
2	9	0	20	10	12	20	16	20	0.298429	1507.687
3	9	0	20	10	12	20	20	20	0.299478	1502.522
4	9	1	20	10	12	20	16	20	0.300391	1501.585
5	9	0	20	10	12	20	24	20	0.300655	1497.532
6	9	1	20	10	12	20	20	20	0.301445	1496.344
7	10	0	20	10	12	20	8	20	0.301466	1493.239
8	10	0	20	10	12	20	12	20	0.301588	1478.120
9	9	0	20	10	12	24	16	24	0.302032	1477.976
10	10	0	20	10	12	20	16	20	0.302045	1468.013
11	10	0	20	10	12	20	20	20	0.302983	1461.658
12	9	1	20	10	16	24	20	24	0.304885	1434.335
13	10	0	20	10	16	24	16	24	0.305261	1404.882
14	10	0	20	10	16	24	20	24	0.306049	1396.990
15	10	0	20	10	16	24	24	24	0.307123	1391.926
16	10	1	20	10	16	24	20	24	0.308052	1391.031
17	10	0	20	10	16	24	28	24	0.308254	1387.255
18	9	0	15	15	12	20	12	20	0.309121	1326.525
19	9	0	15	15	12	20	16	20	0.309406	1319.740
20	9	0	15	15	12	20	20	20	0.310278	1316.152
21	9	1	15	15	12	20	16	20	0.311241	1315.411
22	9	0	15	15	12	20	24	20	0.311364	1311.890
23	9	1	15	15	12	20	20	20	0.312114	1311.791
24	10	0	15	15	12	20	12	20	0.312244	1294.867
25	10	0	15	15	12	20	16	20	0.312433	1287.813
26	10	0	15	15	12	20	20	20	0.313220	1283.310
27	10	0	15	15	12	20	24	20	0.314212	1279.240
28	10	0	15	15	12	24	16	24	0.315121	1264.047
29	10	0	15	15	12	24	20	24	0.315483	1256.503
30	9	1	15	15	16	24	20	24	0.315815	1253.688
31	10	0	15	15	16	24	16	24	0.315900	1229.543
32	10	0	15	15	16	24	20	24	0.316449	1223.698
33	10	0	15	15	16	24	24	24	0.317367	1219.980
34	10	0	15	15	16	24	28	24	0.318430	1216.512

Continued

Table 6 *Continued*

Solution number	Component sizes								Objective function values	
	WT	PV (kW_p)	Dsl (kW)	Bio (kW)	FC (kW)	Elctls (kW)	H_2 tank (kg)	Conv (kW)	COE (€/kWh)	CO_2-eq. emissions (tn)
35	10	1	15	15	16	24	24	24	0.319354	1215.585
36	10	0	15	15	16	24	32	24	0.319605	1212.780
37	9	0	15	15	16	32	20	32	0.320110	1212.098
38	9	0	15	15	16	32	24	32	0.320371	1204.603
39	9	0	15	15	16	32	28	32	0.321044	1198.187
40	9	0	15	15	16	32	32	32	0.321968	1193.232
41	10	0	15	15	16	32	20	32	0.322069	1174.037
42	10	0	15	15	16	32	24	32	0.322391	1167.101
43	10	0	15	15	16	32	28	32	0.322966	1159.325
44	10	0	15	15	16	32	32	32	0.323686	1153.577
45	10	0	15	15	20	32	20	32	0.323858	1148.839
46	10	0	15	15	20	32	24	32	0.324189	1140.493
47	10	0	15	15	20	32	28	32	0.324881	1134.911
48	10	0	15	15	20	32	32	32	0.325884	1130.995
49	10	0	15	15	16	36	32	36	0.326790	1130.159
50	10	0	15	15	20	32	36	32	0.326976	1126.496
51	10	0	15	15	20	36	24	36	0.327435	1117.432
52	10	0	15	15	20	36	28	36	0.327744	1109.577
53	10	0	15	15	20	36	32	36	0.328491	1103.832
54	10	0	15	15	20	36	36	36	0.329449	1098.686
55	10	0	15	15	24	36	24	36	0.329655	1097.042
56	10	0	15	15	24	36	28	36	0.330234	1090.341
57	10	0	15	15	24	36	32	36	0.331070	1085.378
58	10	0	15	15	20	40	32	40	0.331932	1081.574
59	10	0	15	15	24	36	36	36	0.332058	1081.134
60	10	0	15	15	20	40	36	40	0.332601	1073.691
61	10	0	15	15	20	40	40	40	0.333386	1068.172
62	10	0	15	15	24	40	32	40	0.334209	1060.776
63	10	0	15	20	20	40	36	40	0.342832	1054.705
64	10	0	15	20	24	40	28	40	0.344527	1047.467
65	10	0	15	20	24	40	32	40	0.345012	1041.116
66	10	0	15	25	20	40	32	40	0.351947	1037.211
67	10	0	15	25	20	40	36	40	0.352370	1030.182

Abbreviations used: Dsl = diesel, Bio = biodiesel, Elctls = electrolyser, Conv = converter

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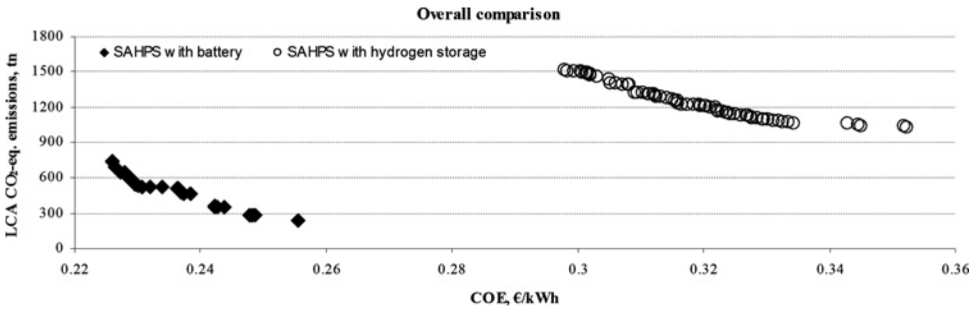

Figure 5 *Comparison of the non-dominated sets for SAHPS with different energy storage technologies (batteries and hydrogen storage)*

Table 7 Optimal solution for SAHPS with hydrogen storage considering CO_2-eq. emission costs

CO_2-eq. price (€/tn)	Number of optimum solution (see Table 6)	COE (€/kWh)
0	1	0.297938
10	2	0.375868
20	46	0.441346
30	62	0.497662
40	62	0.552146

quality. The total number of performed simulations in the two cases is 2600 and 5983, respectively. The results obtained from the local search procedure are presented in Table 6.

Table 6 shows that the non-dominated solutions set of a SAHPS containing hydrogen tank continues to include a large number of WTs. The main difference compared to the SAHPS containing lead-acid batteries is the significant increase in the FC size. This is explained by the non-polluting FC fuel (H_2), as well as by the fact that this fuel is not purchased, but it is produced by the excess electricity of the system (usually from WTs). Because of the negligible size of the PV arrays, the electrolyser is powered mainly from AC generators, and this explains the equality between the electrolyser and converter sizes in each non-dominated solution. The comparison of Tables 3 and 6 is depicted in Fig. 5, and shows that there is a significant increase in both COE and CO_2-eq. emissions in the SAHPS with hydrogen tank. The increased COE is explained from the higher electricity storage costs, whereas the increased CO_2-eq. emissions are explained mainly by the increased fuel consumption of the diesel generator. More specifically, although the nominal power of the diesel generators remains in the same order of magnitude, as Tables 3 and 5 show, their capacity factor is increased significantly in the SAHPS with hydrogen storage, because of the significantly lower efficiency of the overall storage system (electrolyser, hydrogen tank and FC) compared to lead-acid batteries. Finally, Table 7 presents the optimal solutions (with respect to Table 6) and their related updated COE considering five values of CO_2-eq. emission cost.

7 Conclusions

A multiobjective evolutionary algorithm approach for the optimum economic and environmental performance of SAHPS is proposed in this paper, taking into account as environmental criterion the GHG emissions during the life cycle of each system's component. Two types of systems are examined, related to their electricity storage technology: lead-acid batteries and hydrogen tank combined with fuel cell. The analysis of each system type has resulted in a large number of non-dominated solutions, which present common features as well as significant differences. Regarding the common features, all solutions include a large number of wind turbines, PV arrays of small size and adequate capacity of electricity storage technologies. The most important factor that affects the economic and the environmental performance of a solution is the size of diesel-fuelled generators compared to biodiesel-fuelled generators. More specifically, large sizes of diesel-fuelled generators lead to smaller COE and larger CO_2-eq. emissions, whereas large sizes of biodiesel-fuelled generators lead to opposite results. Furthermore, the use of FC with natural gas as a fuel is not recommended, because of their high costs and the high CO_2-eq. emissions they present.

The comparison of the examined electricity storage technologies shows that there is a significant advantage of using lead-acid batteries in both the economic and the environmental criterion. Moreover, in all examined types of hybrid systems it was proved that the addition of the proposed local search procedure in the multiobjective genetic algorithm significantly improves the obtained results, as it combines the excellent quality and the wide range of non-dominated solutions, while it is not increasing prohibitively the computational time.

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