Evaluating the Performance of Small Autonomous Power Systems Using Reliability Worth Analysis

Y. A. Katsigiannis, P. S. Georgilakis and M. N. Moschakis

1 Introduction

A small autonomous power system (SAPS) is a system that generates electricity in order to serve a nearby low energy demand, and it usually operates in areas that are far from the grid. Generally, there are three methods of supplying energy in rural areas: grid extension, use of fossil fuel generators, and hybrid power systems with renewable energy sources (RES). In isolated or remote areas, the first two methods can be very expensive [1]. The typical cost of a low-voltage distribution line is about US$ 3,000/km for the plains and it increases by 10–25 % for remote hilly regions [2], whereas the cost of fossil fuel delivery in these areas may be greater than the cost of the fuel itself.

RES can often be used as a primary source of energy in such a system, as they are usually present in geographically remote and demographically sparse areas. However, since renewable technologies such as wind turbines (WTs) and photovoltaics (PVs) are dependent on a resource that is not dispatchable, there is an impact on the reliability of the electric energy of the system, which has to be considered [3]. The basic way to solve this problem is to use storage and/or dispatchable generators, such as diesel generators.

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Due to the unique characteristics of SAPS, reliability evaluation is crucial in these systems [1, 4]. The most traditional methods for the reliability evaluation of SAPS are mainly deterministic techniques. However, these techniques do not define consistently the true risk of the system, as they can lead to very divergent risks even for systems that are very similar [5]. In addition, these techniques cannot be extended to include intermittent sources, such as wind energy [6]. A second approach for reliability evaluation of power systems is direct analytical methods. These methods overcome the problems of deterministic techniques, but they cannot completely recognize the chronological variation of intermittent sources, such as wind and solar energy. These factors can be incorporated using the Monte Carlo simulation (MCS), which however increases significantly the computation time.

This chapter investigates the effect of reliability worth on the optimal economic operation of SAPS that is based on RES technologies. The location of the studied system is in Chania region, Greece. The optimization procedure is implemented with a combined genetic algorithm (GA) and local search procedure. GA is a powerful optimization technique that has been proposed for the solution of a variety of problems, including optimal SAPS sizing [7–9] and distributed generator placement in power distribution networks [10]. In the optimization procedure, the objective function is the minimization of SAPS cost of energy (in €/kWh), and three scenarios are examined: (i) no consideration of reliability worth, (ii) consideration of reliability worth for agricultural load type, and (iii) consideration of reliability worth for residential load type. In addition, this chapter examines the effect of considering SAPS components forced outage rate in the obtained optimal solutions for the above three examined scenarios. This analysis, which is implemented via MCS, aims to highlight the difference between the results obtained from a typical SAPS optimization procedure (e.g., [7–9, 11]), and the results of an approach that takes into account reliability issues related to the operation of the studied system. This procedure is repeated for a large number of alternative scenarios, in order to study the effects for a large number of key and uncertain parameters.

The chapter is organized as follows. Section 2 presents information about reliability analysis of power systems, as well as details about the calculation of reliability worth. Section 3 formulates the optimization problem, whereas Sect. 4 presents SAPS modeling details. Section 5 provides a brief description of the examined system and compares the results of the optimization procedure and the MCS. Section 6 presents the results of sensitivity analysis and Sect. 7 concludes the chapter.

2 SAPS Reliability Analysis

A variety of probabilistic indices can be calculated, in order to evaluate the performance of a power system in a reliability framework. The two basic probabilistic indices used are the loss of load expectation (LOLE) and the loss of energy expectation (LOEE) [5]. LOLE is defined as the average number of hours for which the

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Table 1 CDF values (€/kW)

User sector	Interruption duration			
	20 min	1 h	4 h	8 h
Agricultural	0.2541	0.4807	1.5289	3.0519
Residential	0.0689	0.3570	3.6400	11.6222

load is expected to exceed the available capacity. On an annual basis, LOLE can be expressed mathematically as:

$$\mathrm{LOLE} = \Delta t \bullet \sum_{\Delta t} t_{outage}(i) \tag{1}$$

where $t_{outage}(i)$ is equal to 1 for the case that the load in time step i is greater than the generating capacity plus the battery storage level and 0 otherwise. LOEE is defined as the expected energy (in kWh) that will not be supplied when the load exceeds the available generation, and can be expressed as:

$$\mathrm{LOEE} = \Delta t \bullet \sum_{\Delta t} e_{unserved}(i) \tag{2}$$

where $e_{unserved}(i)$ is the energy not supplied in the time step i of the year. However, the actual benefits of a power system's operation can only be assessed by conducting relevant cost and reliability studies. It is therefore important to determine the optimal reliability level at which the reliability investment achieves the best results in reducing the customer damage costs due to power supply interruptions. This approach can be expressed mathematically as the minimization of total cost, which is equal to the sum of life cycle cost and customer damage cost.

For the calculation of the expected customer damage cost, the customer damage functions (CDFs) have been used. The CDF is an index (expressed mainly in $/kW) that depends on the type of user and the interruption duration. There are a few studies that contain interruption cost data. Reference [4] contains data for the power utilities of Canada. Similar studies in Greece [12] have shown coincidence with the Canadian results. The values of CDFs, limited for the type of users that are considered in our study, are presented in Table 1. Interruption costs for durations different than the values shown in Table 1 were estimated using the same slope of the straight line joining the two nearest duration values of Table 1.

The CDF values can be converted into an extended index that links system reliability with customer interruption costs. One suitable form is the interrupted energy assessment rate (IEAR), expressed in €/kWh of unsupplied energy. The estimation of the IEAR indicates the severity, frequency and generation of the expected states of the generation model. In order to compute the IEAR, the expected customer interruption cost (ECOST) in €/year must be estimated first, taking into account the duration of interruption, the value of CDF and the unserved energy of each interruption. Then, IEAR can be calculated as follows:

$$\text{IEAR} = \frac{\text{ECOST}}{\text{LOEE}}. \tag{3}$$

For the investigation of SAPS performance, six reliability indices have been selected:

- LOLE.
- LOEE.
- Energy index of unreliability (EIU) that normalizes LOEE by dividing it with the annual energy demand.
- Frequency of interruptions (FOI), i.e., the expected number of times that loss of load occurs per year.
- Duration of interruptions (int), DOI, which is equal to LOLE/FOI, expressed in h/int.
- Energy not supplied index (ENSI) that is equal to LOEE/FOI, expressed in kWh/int.

3 Problem Formulation

The SAPS optimal sizing problem has to fulfill the objective defined by (Eq. 4) subject to the constraints (Eq. 6)–(Eq. 9). This problem is solved for three different scenarios: (i) no consideration of reliability worth, (ii) consideration of reliability worth for agricultural load type, and (iii) consideration of reliability worth for residential load type.

3.1 Objective Function

Minimization of system's cost of energy, $\min(COE).:$

$$\min(COE). \tag{4}$$

The COE (€/kWh) of SAPS is calculated as follows:

$$COE = \frac{C_{antot}}{E_{anloadserved}} \tag{5}$$

where C_{antot} (€) is the total annualized cost and $E_{anloadserved}$ (kWh) is the total annual useful electric energy production. C_{antot} takes into account the annualized capital costs, the annualized replacement costs, the annual operation and maintenance (O&M) costs, and the annual fuel costs (if applicable) of system's components [11]. In case of considering customer damage costs, the value of COE includes IEAR.

3.2 Constraints

- Unmet load constraint [11]:

$$f_{UL} = \frac{\sum_{\Delta t}^{year} UL_{\Delta t} \bullet \Delta t}{E_{anload}} \leq f_{UL\max} \tag{6}$$

where f_{UL} is the annual unmet load fraction, $UL_{\Delta t}$ (kW) is the unmet load during the simulation time step Δt (h), E_{anload} (kWh) is the total annual electric energy demand, and $f_{UL\max}$ is the maximum allowable annual unmet load fraction. By its definition, f_{UL} is identical with EIU. In this chapter, the value of $f_{UL\max}$ has been taken equal to 5 %.

- Minimum renewable fraction constraint:

$$f_{RES} = \frac{E_{anRES}}{E_{antot}} \geq f_{RES\min} \quad \text{where } 0 \leq f_{RES\min} \leq 1 \tag{7}$$

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 $f_{RES\min}$ is the minimum allowable RES fraction. In this chapter, the value of $f_{RES\min}$ has been taken equal to 80 %. As a result, the energy production of studied SAPS is based mainly on RES technologies.

- Components' size constraints:

$$size_{comp} \geq 0 \quad \forall \ comp \tag{8}$$

$$size_{comp} \leq size_{comp\max} \quad \forall \ comp \tag{9}$$

where $size_{comp}$ is the size of system's component $comp$, and $size_{comp\max}$ is the maximum allowable size of $comp$. The values of $size_{comp\max}$ are shown in Table 2.

4 SAPS Components and Modeling

The considered SAPS has to serve electrical load, and it can contain the following component types:

- WTs.
- Polycrystalline silicon (poly-Si) PVs.
- Generator with diesel fuel.
- Lead-acid batteries.
- Converter.

Table 2 Component characteristic

Component	$size_{compmax}$	Increment	Capital cost	Replacement cost	O&M cost	Fuel cost	Lifetime
WTs (20 kW rated)	7 WT	1 WT	50,000 €/WT	40,000 €/WT	1,000 €/year	–	20 years
PVs	50 kW_p	1 kW_p	2,500 €/kW_p	2,000 €/kW_p	0	–	25 years
Diesel generator	50 kW	Variable	300 €/kW	300 €/kW	0.01 €/h per kW	1.5 €/L (diesel)	20,000 oper. hours
Batteries (1500 Ah,4V)	300 bat.	12 bat.	1,000 €/bat.	1,000 €/bat.	10 €/bat.	–	10,000 kWh
Converter	50 kW	1 kW	1,000 €/kW	1,000 €/kW	0	–	15 years

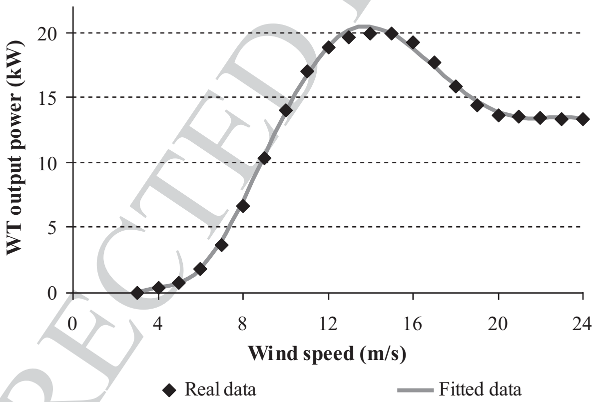

Fig. 1 Correlation between real and fitted data of WT power curve

The modeling of SAPS components is implemented as follows. The WT modeling is implemented using a power curve profile that is based on manufacturer's data. The selected WT has the following characteristics: rated power 20 kW AC, cut-in speed (V_{in}) 3 m/s, and cut-out speed (V_{out}) 24 m/s. For the WT power curve fitting, a seventh order polynomial expression has been selected, as it provides accurate correlation with real data, while it presents exclusively positive values for the generated power in the interval $[V_{in}\ V_{out}]$. The correlation between power curve's real and fitted data is shown in Fig. 1.

The WT power curve refers to standard conditions at sea level, corresponding to a temperature of 15 °C (288.15°K) and air pressure of 101.325 kPa, resulting in a standard sea density ρ_{air0} = 1.225 kg/m³ [13]. If the pressure and temperature conditions at the area of WT installation are different from those corresponding to the standard conditions, the resulting power from the WT power curve needs to be adjusted, multiplied by the following density ratio [14]:

$$\frac{\rho_{air}}{\rho_{air0}} = \left(\frac{Pr}{101.325}\right) \bullet \left(\frac{288.15}{273.15+T}\right) \tag{10}$$

where ρ_{air} is the air density of the site (in kg/m^3), Pr is the air pressure of the site (in kPa), and T is the air temperature of the site (in °C). Air pressure decreases with elevation above sea level, and for an altitude up to 5,000 m can be approximated by [13]:

$$Pr = 101.29 - 0.011837 \bullet z + 4.793 \bullet 10^{-7} \bullet z^2 \tag{11}$$

where z is the altitude (in m).

In the PV modeling, the output of the PV array P_{PV} (in kW) is calculated from [15]:

$$P_{PV} = f_{PV} \bullet P_{STC} \bullet \frac{G_A}{G_{STC}} \bullet \left(1 + \left(T_C - T_{STC}\right) \bullet C_T\right) \tag{12}$$

where f_{PV} is the PV derating factor, P_{STC} is the nominal PV array power in kW$_p$ under standard test conditions (STC), G_A is the global solar radiation incident on the PV array in kW/m^2, G_{STC} is the solar radiation under STC (1 kW/m^2), T_C is the temperature of the PV cells, T_{STC} is the STC temperature (25 °C), and C_T is the PV temperature coefficient (−0.004/°C for poly-Si). The PV derating factor is a scaling factor applied to the PV array output to account for losses, such as dust cover, aging and unreliability of the PV array, and is considered to be equal to 0.80. T_C can be estimated from the ambient temperature T_a (in °C) and the global solar radiation on a horizontal plane G (in kW/m^2) using (Eq. 13) [16]:

$$T_C = T_a + \frac{(NOCT - 20)}{0.8} \bullet G \tag{13}$$

where $NOCT$ is the normal operating cell temperature, which is considered equal to 45 °C.

The diesel generator fuel consumption F (L/kWh) is assumed to be a linear function of its electrical power output [17]:

$$F = 0.08415 \bullet P_{rated} + 0.246 \bullet P \tag{14}$$

where P_{rated} is generator's rated power and P is generator's output power. Lead-acid batteries have been modeled assuming: (i) overall efficiency of 80 %, (ii) nominal voltage of 4V, (iii) nominal capacity (per unit) of 1,500 Ah (6 kWh), (iv) lifetime of 10,000 kWh, (v) minimum state of charge equal to 20 % of their nominal capacity, and (vi) maximum charge and discharge current equal to C/5. Finally, converter efficiency has been taken equal to 90 %.

The simulation process examines a particular system configuration, in which components sizes satisfy constraints (Eq. 8) and (Eq. 9). The necessary inputs for the simulation are: (i) annual time series data for wind speed, solar radiation, ambient temperature and load, (ii) component characteristics, (iii) constraint bounds, and (iv) general parameters (project lifetime, interest rate). The specific values for these data are described in Sect. 5.1. In the simulation, for every time step Δt, the available renewable power (from WTs and PVs) is calculated and then is compared with the load. In case of excess, the surplus renewable energy is charging the batteries, if they are not fully charged. If renewable power sources are not capable to fully serve the load, the remaining electric load has to be supplied by controllable generators and/or batteries. From all possible combinations, it is selected the one that supplies the load at the least cost. When the whole year's simulation has been completed, it is determined whether the system is feasible, i.e., it is checked if it satisfies the constraints (Eq. 6) and (Eq. 7). After the end of simulation, *COE* is calculated by taking into account: (i) the annual results of the simulation, (ii) the capital, replacement, O&M and fuel cost (if applicable) of each component, (iii) the ECOST (if considering CDFs), (iv) the components' lifetime, (v) the project lifetime, and (vi) the discount rate.

An additional aspect of system operation arises, which is whether (and how) the diesel generator should charge the battery bank. Two common control strategies that can be used are load following (LF) strategy and cycle charging (CC) strategy. It has been found [18] that over a wide range of conditions, the better of these two strategies is virtually as cost-effective as an ideal predictive strategy, which assumes the existence of perfect knowledge in future load and wind conditions. In the LF strategy, batteries are not charged at all with diesel-generated energy; the diesel operating point is set to match the instantaneous required load. LF strategy tends to be optimal in systems with a lot of renewable power, when the renewable power output sometimes exceeds the load. In the CC strategy, whenever the diesel generator needs to operate to serve the primary load, it operates at full output power. A setpoint state of charge, SOC_a, has also to be set in this strategy. The charging of the battery by the diesel generator will not stop until it reaches the specified SOC_a. In this chapter, three alternative values of SOC_a have been considered: 80 %, 90 % and 100 %, so the total number of examined dispatch strategies is four. CC strategy tends to be optimal in systems with little or no renewable power.

5 Results and Discussions

5.1 Case Study System

In the considered SAPS, the project lifetime and the discount rate are assumed to be 25 years and 5 %, respectively. The simulation time step is taken equal to 10 min (1/6 h). The annual wind, solar and ambient temperature data needed for the estimation of WT and PV performance refer to measurements for the mountainous region of Keramia (altitude 500 m), in Chania, Crete, Greece. The annual SAPS peak load

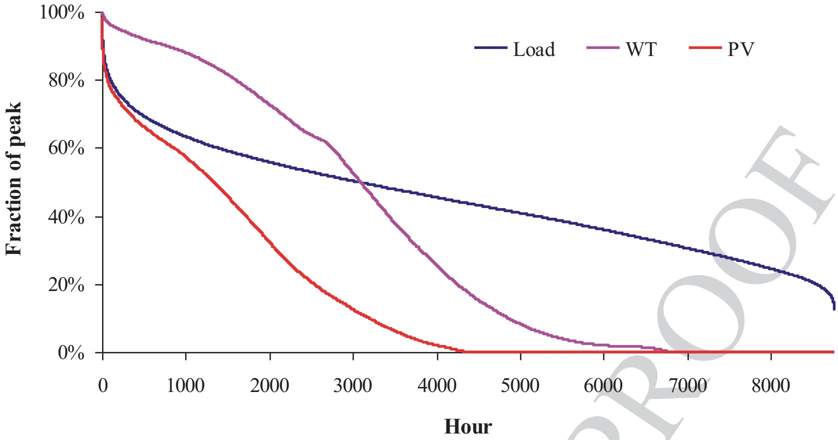

Fig. 2 Load, WT production, and PV production duration curves

has been considered equal to 50 kW, whereas the necessary SAPS load profile was computed by downscaling the actual annual load profile of Crete Island, which is the largest autonomous power system of Greece, with 600 MW peak load and 17 % min/max annual load. An additional noise has been added in the load profile, in order to reduce the min/max annual load ratio from 17 % (Crete power system) to 12 % (SAPS).

The considered values for anemometer height and WT hub height are 10 m and 35 m, respectively, assuming that power law exponent is equal to 0.20. Regarding PVs, it is considered that they do not include tracking system. The duration curves for load, WT production and PV production are depicted in Fig. 2.

The cost, lifetime, and size characteristics for each component are presented in Table 2. For each component, the minimum size is equal to zero. Moreover, with the exception of diesel generator, all components have constant increment of their size, as Table 2 shows. The considered sizes for the diesel generator are 0, 5, 10, 15, 25, 30, 40, and 50 kW. For the SAPS sizing problem of Table 2, the complete enumeration method requires:

$$\underbrace{8}_{\text{WTs}} \cdot \underbrace{51}_{\text{PVs}} \cdot \underbrace{8}_{\text{Dsl}} \cdot \underbrace{26}_{\text{Bat.}} \cdot \underbrace{51}_{\text{Conv.}} \cdot \underbrace{4}_{\text{Disp.}} = 17{,}312{,}256 \qquad (15)$$

i.e., over 17 million evaluations in order to find the optimal *COE*; in (Eq. 15) Disp. denotes the number of dispatch strategies. The computational time for each *COE* evaluation is 2.1 s. Consequently, the evaluations of the complete enumeration method require more than one year, for each one of the three considered scenarios. That is why it is essential to develop an alternative optimization method in order to solve the SAPS sizing problem in a fast and effective way.

5.2 GA Implementation for SAPS Optimal Sizing

Genetic algorithms (GAs) mimic natural evolutionary principles and constitute powerful search and optimization procedures. More specifically, binary GAs 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. The considered sizes of each SAPS component can take only discrete values, so the binary GA is proposed for the solution of SAPS optimal sizing problem.

In the binary GA, two alternative GA coding schemes can be used: conventional binary coding and Gray coding. In the proposed GA, each chromosome consists of six genes, of which the first five genes represent the SAPS component sizes (WT, PV, diesel generator, batteries, and converters), while the sixth gene refers to the adopted dispatch strategy (LF or CC). For the handling of constraints, the penalty function approach is adopted, in which an exterior penalty term is used that penalizes infeasible solutions. Since different constraints may take different orders of magnitude, prior to the calculation of the overall penalty function, all constraints are normalized.

The optimum configuration parameters of the adopted GA are: population size $N_{pop}=50$, number of generations $gn=15$, Gray coding, tournament selection, uniform crossover, and 0.01 mutation rate [8]. Additionally, the proposed GA is combined with local search procedure, in order to ensure that the selected solution is optimal compared to its neighbor solutions. Table 3 presents the optimal configurations and the six reliability indices for the three examined scenarios. As it can be seen, the consideration of no customer damage cost leads to a solution that presents the lowest *COE*. On the other hand, in this case the operation of SAPS is not the most reliable, since all reliability indices have their highest possible values in order the SAPS operation to be feasible, according to the problem constraints. The consideration of CDF increases the *COE* and improves significantly the reliability of the system by decreasing the PV size and increasing the diesel generator size. It can be seen that the consideration of either agricultural CDF or residential CDF provides almost identical results. This can be explained by the fact that agricultural CDF values are larger for small interruptions, but significantly lower for larger interruptions (more than 1 hour), as Table 1 shows. The optimal state is a compromise between these two situations, as reliability indices of Table 3 show. In all cases, the adopted dispatch strategy is LF, due to the large portion of RES technologies in energy production. The total number of performed objective function (*COE*) evaluations for the combined GA and local search procedure was 930 for all scenarios. Figure 3 shows the GA convergence for the three examined scenarios of Table 3.

Table 3 Optimal solutions of GA combined with local search

Scenario	WTs	PVs (kW_p)	Dsl(kW)	Batteries	Converter (kW)	Dispatch strategy	COE (€/kWh)
No customer damage cost	3	35	10	108	35	LF	0.2214
Agricultural CDF	3	50	40	144	40	LF	0.2659
Residential CDF	3	50	30	120	39	LF	0.2635
Scenario	LOLE (h/year)	LOEE (kWh/year)	EIU	FOI (int./year)	DOI (h/int.)	ENSI (kWh/int.)	
No customer damage cost	1053	9708.73	4.987 %	689	1.529	14.091	
Agricultural CDF	2.50	6.22	0.003 %	13	0.192	0.478	
Residential CDF	55.50	224.92	0.116 %	148	0.375	1.520	

5.3 Consideration of Components Forced Outage Rate

In the analysis of Sect. 5.2, no forced outage rate for any component of the system has been taken into account, in order to focus on the interruptions driven by the incapability of the system to meet the load demand. However, in order to evaluate more realistically the performance of the system, an analysis of components forced outage rate has to be included. This task is crucial especially for a SAPS, because there is no other way to supply its load other than by itself. The analysis is applied to the three optimal solutions shown in Table 3. For each one of them, a sequential MCS [19] is applied for a total number of 500 runs.

The consideration of forced outage rate is applied to the 2 SAPS components that contain rotating parts: WTs and diesel generator. For the WTs, a forced outage rate of 4 % for each WT has been considered, with mean time to failure (MTTF) equal to 1,920 h and mean time to repair (MTTR) equal to 80 h [6]. For the diesel generator, it is assumed that it needs scheduled maintenance every 1,000 h of operation. The duration of the maintenance follows uniform distribution in the hour interval [2, …, 24]. Moreover, a starting failure of 1 % is included in the evaluation, while the repairing process follows the same distribution with the maintenance process [3].

The obtained results of MCS for the three examined cases are shown in Tables 4–6. These results include the minimum, maximum and average values, as well as the standard deviation of the six reliability indices and *COE*. Moreover,

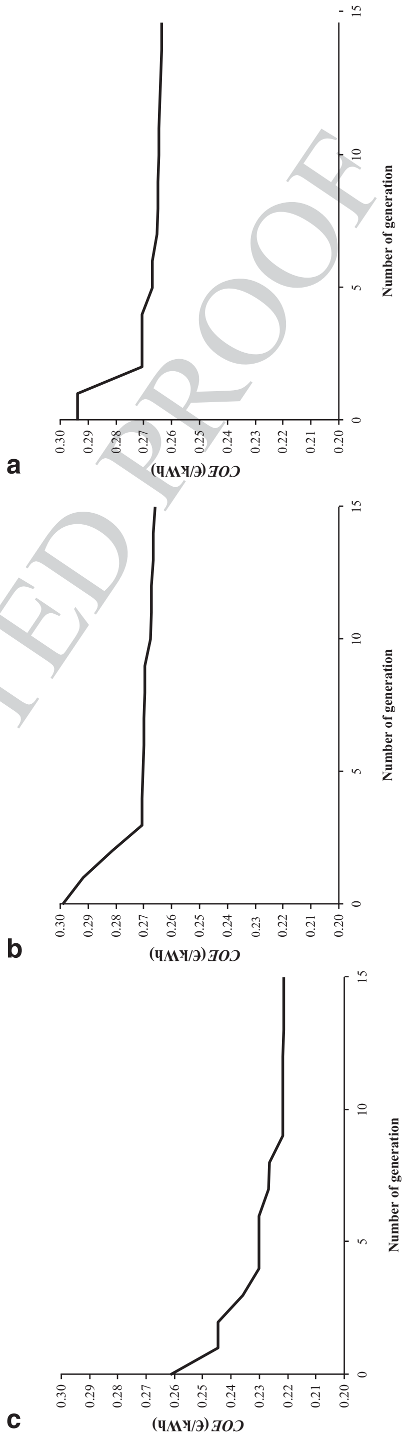

Fig. 3 GA convergence considering: **a** no customer damage cost, **b** agricultural CDF, **c** residential CDF

Table 4 MCS results considering no customer damage cost

Index	Min	Max	Average	Standard deviation	Coeffcient of variation
COE (€/kWh)	0.2228	0.2366	0.2286	0.0023	0.0102
LOLE (h/year)	1102.33	1654.67	1303.61	92.83	0.0712
LOEE (kWh/year)	9757.55	16478.74	11850.02	990.62	0.0836
EIU	5.012 %	8.464 %	6.086 %	0.509 %	0.0836
FOI (int./year)	669	1078	798.80	63.21	0.0791
DOI (h/int.)	1.437	1.849	1.634	0.0599	0.0367
ENSI (kWh/int.)	12.127	18.290	14.850	0.7894	0.0532

the (dimensionless) coefficient of variation is calculated, which is the ratio of the standard deviation to the mean, as a measure of variability. As it can be seen, the consideration of forced outage rate increases significantly the values of the basic reliability indices (LOLE, LOEE, EIU) and *COE*. In some cases, the values of the remaining reliability indices may be smaller compared to these of Table 2, but this does not mean that the performance is better. For example, the low values of FOI are combined with the large values of DOI and ENSI, resulting in lower number of interruptions that have higher duration.

Another interesting conclusion, drawn from the results shown in Table 4–6, is the higher variability (expressed by the coefficient of variation) of the basic reliability indices (LOLE, LOEE, EIU) and *COE*, in the scenarios of considering customer damage costs. In these two scenarios (agricultural and residential), the highest difference in variability is presented in *COE*, which can be explained by the fact that the residential customer damage cost is increased exponentially with the increase of interruption duration (see Table 1), affecting concurrently *COE*. Figures 4 and 5 present the variation of *COE* for these two scenarios.

6 Sensitivity Analysis

The uncertainty in many SAPS variables over which the designer has no control makes essential the need for sensitivity analysis. The uncertain parameters may contain weather data, and/or cost data. In this section, six alternative scenarios have been developed and analyzed. These scenarios are based on the following modifications of the case study system of Sect. 5.1 (initial scenario):

- 10 % increase of wind speed. In this scenario, the annual energy production of the WTs is increased by 9.08 %.
- 10 % decrease of wind speed. In this scenario, the annual energy production of the WTs is decreased by 11.67 %.
- 5 % increase of solar radiation. In this scenario, the annual energy production of the PVs is increased by 5.09 %.
- 5 % decrease of solar radiation. In this scenario, the annual energy production of the PVs is decreased by 5.27 %.

Table 5 MCS results considering agricultural CDFs

Index	Min	Max	Average	Standard deviation	Coefficient of variation
COE (€/kWh)	0.2673	0.3174	0.2867	0.0091	0.0319
LOLE (h/year)	94.50	443.67	210.16	63.64	0.3028
LOEE (kWh/year)	109.09	5479.53	1820.96	919.68	0.5051
EIU	0.056 %	2.814 %	0.935 %	0.472 %	0.5051
FOI (int./year)	450	793	566.40	62.51	0.1104
DOI (h/int.)	0.202	0.602	0.364	0.0720	0.1977
ENSI (kWh/int.)	0.221	7.579	3.098	1.2635	0.4078

Table 6 MCS results considering residential CDFs

Index	Min	Max	Average	Standard deviation	Coeffcient of variation
COE (€/kWh)	0.2649	0.3606	0.2965	0.0170	0.0573
LOLE (h/year)	139.50	501.17	266.44	64.72	0.2429
LOEE (kWh/year)	296.70	4930.19	1873.37	813.61	0.4343
EIU	0.152 %	2.532 %	0.962 %	0.418 %	0.4343
FOI (int./year)	445	773	560.41	55.72	0.0994
DOI (h/int.)	0.291	0.705	0.470	0.0733	0.1560
ENSI (kWh/int.)	0.619	7.287	3.261	1.1635	0.3567

- 20 % increase of diesel fuel price (from 1.5 to 1.8 €/L).
- 40 % capital and replacement cost reduction of renewable energy technologies (WTs and PVs). This reduction may be attributed either to technology improvement and economies of scale, or to a modification in the regulatory regime that promotes the installation of RES technologies by offering incentives that reduce the capital and replacement cost of RES.

Tables 7–9 present the results of the above mentioned sensitivity analyses, as well as the initial scenario results for comparison purposes. More specifically, Table 7 presents the minimum *COE* values and their corresponding optimal configurations, Table 8 shows the results of the combined GA and local search procedure (referred to as GA-local search), and Table 9 shows the results of the MCS (average values). Regarding the comparison of GA-local search and MCS, the conclusions are similar with those mentioned in Sect. 5.3. Figure 6 shows the variability of *COE* obtained from all MCS compared to *COE* values obtained from the A-local search procedure. From the study of Fig. 6 it can be concluded that: (Eq. 1) all MCS obtained *COE* values are higher compared to those obtained from GA-local search procedure, (Eq. 2) the highest variability of the MCS results appears when considering residential CDFs (because of the exponential increase of residential customer damage cost with the increase of interruption duration), whereas the lowest variability

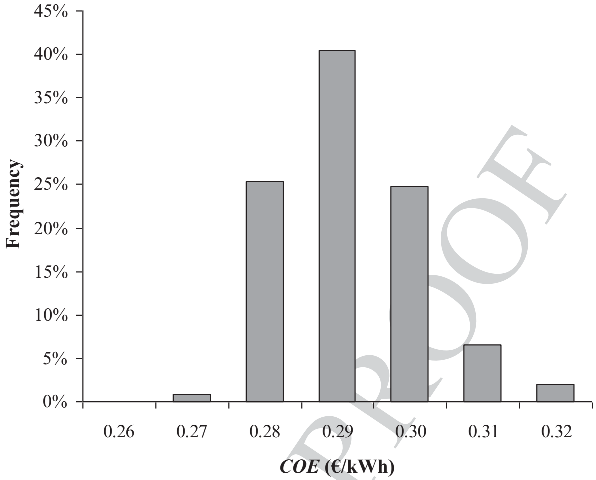

Fig. 4 *COE* histogram for agriculture

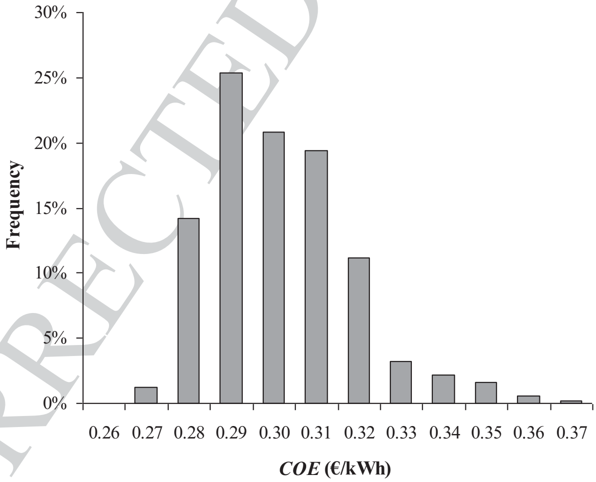

Fig. 5 *COE* histogram for residential load

appears when considering no customer damage cost, and (Eq. 3) in the majority of implemented MCSs, the average *COE* values assuming residential CDF are significantly higher compared to agricultural CDF.

The study of Tables 7–9 provides the following main conclusions for the considered case study system:

- The wind potential (scenarios 1 and 2) affects more the value of *COE* in comparison with the solar potential (scenarios 3 and 4).
- The optimal configurations of scenarios 3 and 4 (increased and decreased solar potential) are almost identical with the optimal configurations of the initial scenario.

Table 7 Optimal configuration for sensitivity analysis scenarios

Case	CDF	WTs	PVs (kW_p)	Dsl (kW)	Batteries	Converter (kW)	Dispatch strategy	*COE* (€/kWh)
Initial	No CDF	3	35	10	108	35	LF	0.2214
	Agricultural	3	50	40	144	40	LF	0.2659
	Residential	3	50	30	120	39	LF	0.2635
Wind +10%	No CDF	3	50	0	132	31	LF	0.2036
	Agricultural	3	42	40	120	39	LF	0.2466
	Residential	3	31	30	144	38	LF	0.2433
Wind −10%	No CDF	3	50	10	144	36	LF	0.2449
	Agricultural	4	50	40	144	41	LF	0.2918
	Residential	4	50	30	144	40	LF	0.2901
Solar +5%	No CDF	3	34	10	108	36	LF	0.2200
	Agricultural	3	50	40	132	40	LF	0.2627
	Residential	3	50	30	120	39	LF	0.2604
Solar −5%	No CDF	3	37	10	108	35	LF	0.2233
	Agricultural	3	50	40	156	40	LF	0.2693
	Residential	3	50	30	132	39	LF	0.2668
Diesel +20%	No CDF	3	39	10	96	37	LF	0.2287
	Agricultural	3	50	40	180	40	LF	0.2749
	Residential	3	50	30	168	40	LF	0.2721
RES −40%	No CDF	4	37	5	108	33	LF	0.1802
	Agricultural	4	50	40	108	41	LF	0.2197
	Residential	4	50	30	108	40	LF	0.2176

- The optimal configuration of scenario 1 (increased wind potential) considering no customer damage cost is the only case that does not contain the dispatchable diesel generator. As a result, the number of interruptions (FOI) is significantly increased.
- The (negative) effect of increased diesel fuel price (scenario 5) is marginally more severe than the (negative) effect of lower solar potential (scenario 4), but significantly less severe than the (negative) effect of lower wind potential (scenario 2).

Table 8 Sensitivity analysis results for GA—local search procedure

Case	CDF	GA—local search results						
		COE (€/kWh)	LOLE (h/year)	LOEE (kWh/year)	EIU (%)	FOI (int/year)	DOI (h/int)	ENSI (kWh/int)
Initial	No CDF	0.2214	1,053	9,708.73	4.987	689	1.529	14.091
	Agricultural	0.2659	2.50	6.22	0.003	13	0.192	0.478
	Residential	0.2635	55.50	224.92	0.116	148	0.375	1.520
Wind +10%	No CDF	0.2036	806	9,724.86	4.995	1,020	0.790	9.534
	Agricultural	0.2466	2.00	5.95	0.003	10	0.200	0.595
	Residential	0.2433	45.67	187.36	0.096	131	0.349	1.430
Wind −10%	No CDF	0.2449	1,044	9,708.60	4.987	650	1.606	14.936
	Agricultural	0.2918	3.50	7.65	0.004	16	0.219	0.478
	Residential	0.2901	56.83	237.55	0.122	147	0.387	1.616
Solar +5%	No CDF	0.2200	1,045	9,689.45	4.977	679	1.539	14.270
	Agricultural	0.2627	2.50	6.22	0.003	13	0.192	0.478
	Residential	0.2604	52.00	212.73	0.109	139	0.374	1.530
Solar −5%	No CDF	0.2233	1,055	9724.58	4.995	699	1.509	13.912
	Agricultural	0.2693	2.50	6.58	0.003	13	0.192	0.507
	Residential	0.2668	57.83	237.74	0.122	160	0.361	1.486
Diesel +20%	No CDF	0.2287	1,052	9,725.84	4.995	711	1.480	13.679
	Agricultural	0.2749	2.50	6.22	0.003	13	0.192	0.478
	Residential	0.2721	46.83	197.97	0.102	122	0.384	1.623
RES −40%	No CDF	0.1802	803	9680.81	4.972	519	1.546	18.653
	Agricultural	0.2197	2.17	5.93	0.003	11	0.197	0.539
	Residential	0.2176	35.83	149.76	0.077	94	0.381	1.593

- The lower cost of RES technologies (scenario 6) results in the system with the lowest cost (*COE*).
- Due to the minimum renewable fraction constraint value of 80%, all optimal configurations contain 3 to 4 WTs, whereas the PV installation is always greater that 30 kW_p, while in many cases the installed PV capacity is equal to its maximum possible value of 50 kW_p.

Table 9 Sensitivity analysis results for MCS

Case	CDF	MCS results (average values)						
		COE (€/kWh)	LOLE (h/year)	LOEE (kWh/year)	EIU (%)	FOI (int/year)	DOI (h/int)	ENSI (kWh/int)
Initial	No CDF	0.2286	1,303.61	11,850.02	6.086	798.80	1.634	14.850
	Agricultural	0.2867	210.16	1,820.96	0.935	566.40	0.364	3.098
	Residential	0.2965	266.44	1873.37	0.962	560.41	0.470	3.261
Wind +10%	No CDF	0.2057	1,067.53	11,591.58	5.954	1,357.88	0.786	8.537
	Agricultural	0.2648	214.11	1,852.61	0.952	582.52	0.360	3.056
	Residential	0.2879	312.79	2,390.13	1.228	610.26	0.507	3.826
Wind −10%	No CDF	0.2524	1,300.71	11,572.20	5.944	764.22	1.705	15.161
	Agricultural	0.3059	188.02	1604.03	0.824	488.63	0.379	3.193
	Residential	0.3155	221.96	1,566.89	0.805	436.75	0.502	3.497
Solar +5%	No CDF	0.2272	1,333.53	11,889.95	6.107	772.79	1.727	15.388
	Agricultural	0.2791	203.15	1726.46	0.887	556.09	0.360	3.011
	Residential	0.2920	267.11	1,952.32	1.003	540.73	0.489	3.525
Solar −5%	No CDF	0.2296	1,318.98	11,734.74	6.027	755.00	1.749	15.556
	Agricultural	0.2863	211.79	1,825.81	0.938	575.93	0.361	3.064
	Residential	0.3077	285.79	2101.94	1.080	586.30	0.479	3.458
Diesel +20%	No CDF	0.2360	1,297.18	11,773.18	6.047	780.61	1.664	15.096
	Agricultural	0.2946	194.82	1,807.78	0.929	489.78	0.389	3.538
	Residential	0.3077	251.56	2,042.88	1.049	455.23	0.544	4.348
RES −40%	No CDF	0.1859	994.18	10,839.14	5.567	877.58	1.133	12.357
	Agricultural	0.2307	132.06	963.78	0.495	411.33	0.317	2.283
	Residential	0.2367	206.00	1,372.09	0.705	420.37	0.485	3.189

- In all cases, when agricultural or residential CDFs are considered, the systems are notably more reliable (due to customer damage costs consideration). As a result, their optimal configuration contains significant higher capacity of the dispatchable diesel generator.
- In all the examined scenarios, the optimal configurations contain large number of batteries, converters of similar sizes, and adoption of LF dispatch strategy.

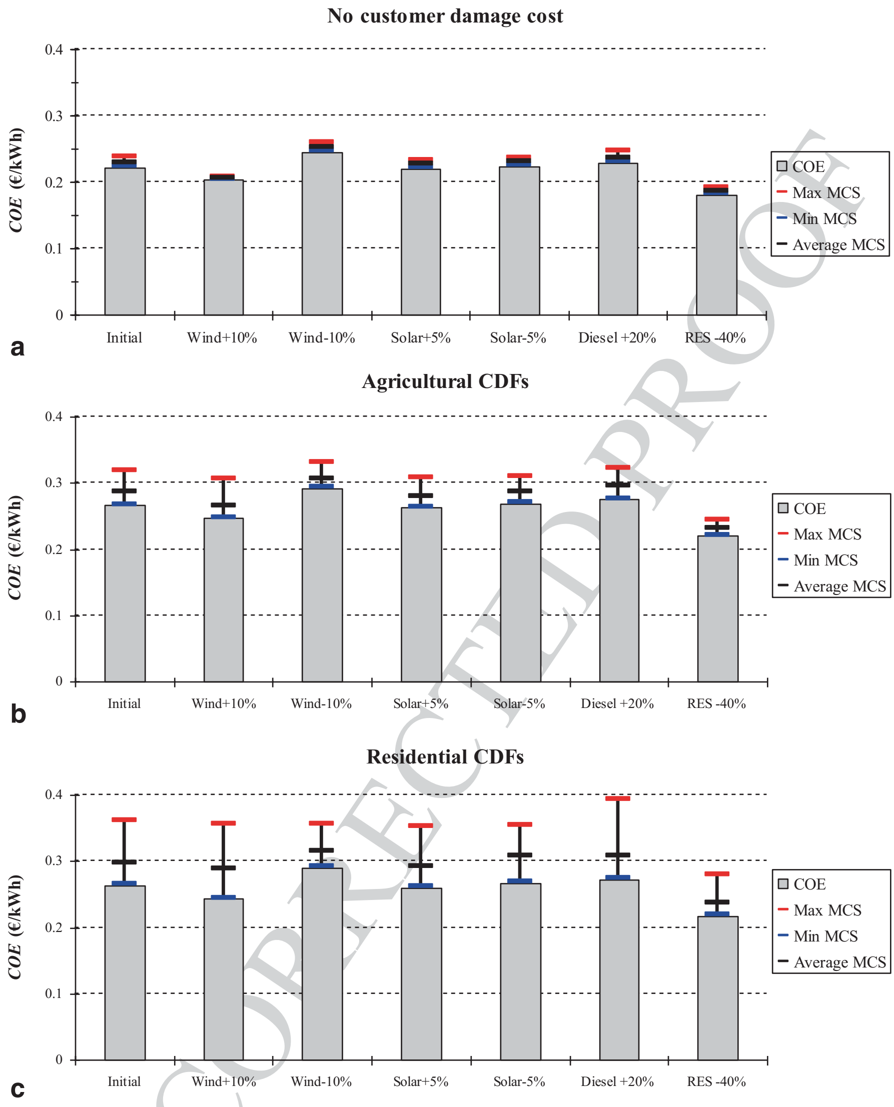

Fig. 6 Variability of obtained *COE* from MCS compared to GA-local search *COE* considering: **a** no customer damage cost, **b** agricultural CDF, and **c** residential CDF

7 Conclusions

The reliability evaluation of SAPS that is based on renewable energy technologies is a complex and time consuming task, due to the intermittent nature of renewable resources, their variation, the high modularity of each part of the system, and the considered assumptions for the reliability analysis. In most cases, the optimal

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sizing procedure of such systems takes into account reliability issues in a generic framework, using general constraints (such as maximum unmet load constraint). However, in order to be complete, this analysis has to take into account the effect of two more parameters: the reliability worth as well as the forced outage rate of SAPS components. This chapter shows that the consideration of the reliability worth and the forced outage rate in the analysis changes significantly the obtained results. Moreover, the operation of a real SAPS, as computed by considering the above two parameters, will be much different than the operation of a SAPS ignoring both the reliability worth and the forced outage rate. This chapter also shows that the type of load, which changes the reliability worth, may also affect the performance of SAPS. The above conclusions have been drawn using sensitivity analysis considering a large number of alternative scenarios that take into account the uncertainty of weather and cost data.

References

1. Katsigiannis YA, Georgilakis PS, Papadopoulos SC, Moschakis MN (2012) Evaluating the performance of small autonomous power systems using reliability worth analysis. in Proc. PMAPS 2012, Istanbul, Turkey, June 2012
2. Kishore VVN, Jagu D, Gopal EN (2013) Technology choices for off-grid electrification. In: Bhattacharyya S. (ed) Rural electrification through decentralised off-grid systems in developing countries. Springer-Verlag, London, pp 39–72
3. Katsigiannis YA, Georgilakis PS, Tsinarakis GJ (2010) A novel colored fluid stochastic petri net simulation model for reliability evaluation of Wind/PV/Diesel small isolated power systems. IEEE Trans Syst Man and Cybern, Part A 40(6):1296–1309
4. Katsigiannis YA, Georgilakis PS (2013) Effect of customer worth of interrupted supply on the optimal design of small isolated power systems with increased renewable energy penetration. IET Gener Transm Distrib 7(3):265–275
5. Billinton R, Allan RN (1996) Reliability evaluation of power systems, 2nd ed. Plenum, New York
6. Karki R, Billinton R(2004) Cost effective wind energy utilization for reliable power supply." IEEE Trans Energy Convers 19(2):435–440
7. Koutroulis E, Kolokotsa D, Potirakis A, Kalaitzakis K (2006) Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms. Sol Energy 80:1072–1088
8. Katsigiannis YA, Georgilakis PS, Karapidakis ES (2010) Genetic algorithm solution to optimal sizing problem of small autonomous hybrid power systems. Lecture Notes in Artif Intell 6040:327–332
9. Katsigiannis YA, Georgilakis PS, Karapidakis ES (2010) Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables. IET Ren Power Gen 4:404–419
10. Georgilakis PS, Hatziargyriou ND (2013) Optimal distributed generation placement in power distribution networks: Models, methods, and future research. IEEE Trans. Power Syst 28(3)3420–3428
11. Katsigiannis YA, Georgilakis PS, Karapidakis ES (2012) Hybrid simulated annealing–tabu search method for optimal sizing of autonomous power systems with renewables. IEEE Trans Sustain Energy 3:330–338

12. Koskolos NC, Megaloconomos SM, Dialynas EN (1998)Assessment of power interruption costs for the industrial customers in Greece. in Proc. ICHQP '98, Athens, Greece, 1998
13. Manwell JF, McGowan JG, Rogers AL (2009) Wind energy explained, 2nd ed. Wiley, Chichester
14. Manwell JF, Rogers A, Hayman G, Avelar CT, McGowan JG (1998, November 2). HYBRID2– a hybrid system simulation model, theory manual. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.27.8793
15. Thomson M, Infield DG (2007) Impact of widespread photovoltaics generation on distribution systems. IET Renew Power Gener 1:33–40
16. Markvart T, Castañer L (2003) Practical handbook of photovoltaics: fundamentals and applications. Elsevier, UK
17. Skarstein O, Uhlen K (1989) Design considerations with respect to long-term diesel saving in wind/diesel plants. Wind Eng 13:72–87
18. Barley CD, Winn CB (1996) Optimal dispatch strategy in remote hybrid power systems. Sol Energy 58:165–179
19. Billinton R, Li W (1994) Reliability assessment of electric power systems using Monte Carlo methods. Plenum, New York