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

Y. A. Katsigiannis
Department of Natural Resources & Environment
Technological Educational Institute of Crete
Chania, Crete, Greece
katsigiannis@chania.teicrete.gr

P. S. Georgilakis, S. C. Papadopoulos
School of Electrical and Computer Engineering
National Technical University of Athens (NTUA)
Athens, Greece
pgeorg@power.ece.ntua.gr

M. N. Moschakis
Department of Electrical Engineering
Technological Educational Institute of Larissa
Larissa, Greece
mmoschakis@teilar.gr

***Abstract*—The analysis and design of a small autonomous power system (SAPS) that contains renewable energy sources (RES) technologies can be challenging, due to the large number of design options and the uncertainty in key parameters. Renewable power sources add further complexity because their power output may be intermittent, seasonal, and non dispatchable. Due to this characteristic, reliability evaluation of a RES based SAPS cannot be implemented using the traditional deterministic and analytical methods. Moreover, in order to be complete, this evaluation has to be done within a cost-benefit framework. This paper investigates the effect of reliability worth in the optimal economic operation of a SAPS that is based on RES technologies, considering different scenarios. The optimization procedure is implemented with a combined genetic algorithm (GA) and local search procedure. In addition, this paper examines the effect of considering SAPS components forced outage rate in the obtained optimal solutions via Monte Carlo simulation (MCS). The main conclusion of this paper is that the optimal operation of a RES based SAPS depends largely on the consideration of reliability worth as well as the inclusion of components forced outage rate.**

Keywords-small autonomous power systems; renewable energy sources; power systems reliability; reliability worth; Monte Carlo simulation; customer damage functions; optimization; genetic algorithms

I. 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. Grid electrification costs more than $3000 per connection [1], while the cost of fossil fuel delivery in these areas may be greater than the cost of the fuel itself.

Renewable energy sources (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 [2]. The basic way to solve this problem is to use storage and/or dispatchable generators, such as diesel generators.

Due to the unique characteristics of SAPS, reliability evaluation is crucial in these systems. 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 [3]. In addition, these techniques cannot be extended to include intermittent sources, such as wind energy [4]. 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 us wind speed and solar energy. These factors can be incorporated using the Monte Carlo simulation (MCS), which however increases significantly the computation time.

This paper investigates the effect of reliability worth on the optimal economic operation of a 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 [5]-[6]. In the optimization procedure, the objective function is the minimization of SAPS cost of energy (in €/kWh), and three scenarios are examined: (1) no consideration of reliability worth, (2) consideration of reliability worth for agricultural load type, and (3) consideration of reliability worth for residential load type. In addition, this paper 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, and the results of an approach that takes into account reliability issues related to the operation of the studied system.

The paper is organised as follows. Section II presents information about reliability analysis of power systems, as well as details about the calculation of reliability worth. Section III formulates the optimization problem, whereas Section IV presents SAPS modelling details. Section V provides a brief description of the examined system and compares the results of the optimization procedure and the MCS. Section VI concludes the paper.

II. 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). LOLE is defined as the average number of hours for which the load is expected to exceed the available capacity. On an annual basis, LOLE can be expressed mathematically as:

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

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:

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

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 [3] contains data for the power utilities of Canada. Similar studies in Greece [7] 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 I. Interruption costs for durations different than the values shown in Table I were estimated using the same slope of the straight line joining the two nearest duration values of Table I.

TABLE I. 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

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 €/yr 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:

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

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

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

III. Problem Formulation

The SAPS optimal sizing problem has to fulfill the objective defined by (4) subject to the constraints (6)-(9). This problem is solved for three different scenarios: (1) no consideration of reliability worth, (2) consideration of reliability worth for agricultural load type, and (3) consideration of reliability worth for residential load type.

A. Objective Function

Minimization of system's cost of energy, COE:

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

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

$$COE = \frac{C_{antot}}{E_{anloadserved}} \quad (5)$$

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. In case of considering customer damage costs, the value of COE includes IEAR.

B. Constraints

1. Unmet load constraint:

$$f_{UL} = \frac{\sum_{\Delta t}^{year} UL_{\Delta t} \cdot \Delta t}{E_{anload}} \leq f_{UL\max} \quad (6)$$

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 paper, the value of $f_{UL\max}$ has been taken equal to 5%.

2. Minimum renewable fraction constraint:

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

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 paper, 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.

3. Components' size constraints:

$$size_{comp} \geq 0 \quad \forall \ comp \quad (8)$$

$$size_{comp} \leq size_{comp\max} \quad \forall \ comp \quad (9)$$

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 II.

IV. SAPS Components and Modeling

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

1. WTs.
2. Polycrystalline silicon (poly-Si) PVs.
3. Generator with diesel fuel.
4. Lead-acid batteries.
5. Converter.

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 10kW 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 $[V_{in}\ V_{out}]$.

In the PV modeling, the output of the PV array P_{PV} (in kW) is calculated from [8]:

$$P_{PV} = f_{PV} \cdot P_{STC} \cdot \frac{G_A}{G_{STC}} \cdot (1 + (T_C - T_{STC}) \cdot C_T) \quad (10)$$

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 (10) [9]:

$$T_C = T_a + \frac{(NOCT - 20)}{0.8} \cdot G \quad (11)$$

where $NOCT$ is the normal operating cell temperature, which is usually obtaining the value of 48°C.

The diesel generator fuel consumption F (L/kWh) is assumed to be a linear function of its electrical power output [10]:

$$F = 0.08415 \cdot P_{rated} + 0.246 \cdot P \quad (12)$$

where P_{rated} is generator's rated power and P is generator's output power. Lead-acid batteries have been modeled assuming maximum charge and discharge current equal to C/5. 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 batteries. From all possible combinations, it is selected the one that supplies the load at the least cost.

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 [11] 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 paper, three alternative values of SOC_a have been considered: 80%, 90% and 100%, so the total number of examined dispatch strategies is 4. CC strategy tends to be optimal in systems with little or no renewable power.

TABLE II. COMPONENT CHARACTERISTICS

Component	$size_{compmax}$	Increment	Capital cost	Replacement cost	O&M cost	Fuel cost	Lifetime
WTs (10kW rated)	6 WT	1 WT	25,000 €/WT	20,000 €/WT	500 €/y	-	20 y
PVs	20 kW_p	0.5 kW_p	3,000 €/kW_p	2,500 €/kW_p	0	-	25 y
Diesel generator	20 kW	Variable	300 €/kW	300 €/kW	0.01 €/h per kW	1.5 €/L (diesel)	20,000 oper. hours
Batteries (1250Ah, 6V)	160 bat.	8 bat.	600 €/bat.	600 €/bat.	10 €/bat.	-	9,000 kWh
Converter	20 kW	1 kW	1,000 €/kW	1,000 €/kW	0	-	15 y

TABLE III. OPTIMAL SOLUTIONS OF GA COMBINED WITH LOCAL SEARCH

Scenario	WTs	PVs (kW_p)	Dsl (kW)	Batteries	Converter (kW)	Dispatch strategy	COE (€/kWh)	LOLE (h/y)	LOEE (kWh/y)	EIU	FOI (int./y)	DOI (h/int.)	ENSI (kWh/int.)
No customer damage cost	3	11	3	48	13	LF	0.2156	895	3882.92	4.986%	435	2.057	8.926
Agricultural CDF	3	7.5	15	56	15	LF	0.2478	10.67	10.18	0.013%	46	0.232	0.221
Residential CDF	3	7	15	48	16	LF	0.2462	13.83	13.20	0.017%	56	0.247	0.236

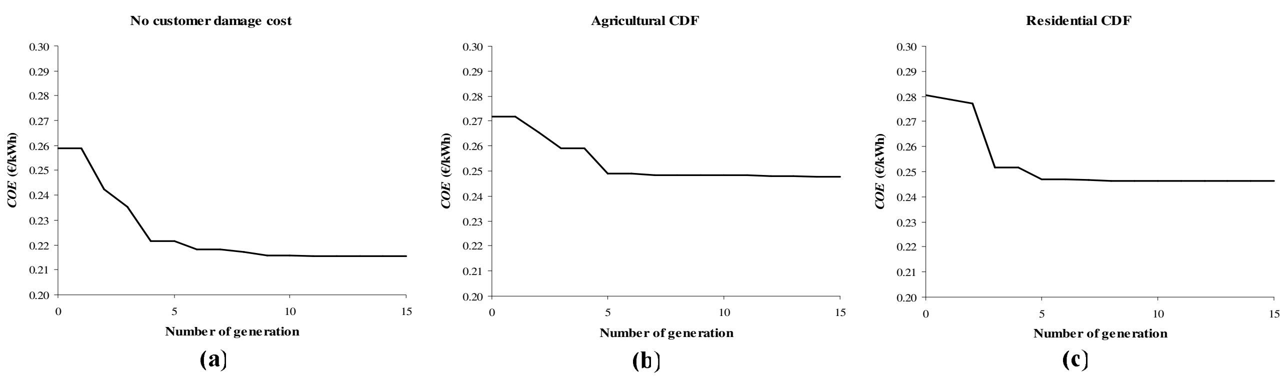

Figure 1. GA convergence considering: (a) no customer damage cost, (b) agricultural CDF, (c) residential CDF

V. RESULTS AND DISCUSSION

A. Case Study System

In the considered SAPS, the project lifetime and the discount rate are assumed to be 25 years and 6%, respectively. The simulation time step Δt 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 has been considered equal to 20 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 WT hub height has been considered 25 m, and the PVs do not include tracking system. The cost, lifetime, and size characteristics for each component are presented in Table II. 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 II shows. The considered sizes for the diesel generator are 0, 3, 5, 8, 10, 12, 15, and 20 kW. For the SAPS sizing problem of Table II, the complete enumeration method requires:

$$\underbrace{7}_{\text{WTs}} \cdot \underbrace{41}_{\text{PVs}} \cdot \underbrace{8}_{\text{Dsl}} \cdot \underbrace{21}_{\text{Bat.}} \cdot \underbrace{21}_{\text{Conv.}} \cdot \underbrace{4}_{\text{Disp.}} = 4{,}050{,}144 \tag{13}$$

i.e., approximately 4 million evaluations in order to find the optimal *COE*; in (12) Disp. denotes the number of dispatch strategies. The computational time for each *COE* evaluation is 2.1 seconds. Consequently, the evaluations of the complete enumeration method require more than 3 months, 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.

B. 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 6 genes, of which the first 5 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 [6]. 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 III 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 I shows. The optimal state is a compromise between these two situations, as reliability indices of Table III 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-local search procedure was 930 for all scenarios. Fig. 1 shows the GA convergence for the three examined scenarios of Table III.

TABLE IV. MCS RESULTS CONSIDERING NO CUSTOMER DAMAGE COST

Index	Min	Max	Average	Standard deviation	Coef. of variation
COE (€/kWh)	0.2169	0.2246	0.2208	0.0015	0.0068
LOLE (h/y)	1055.3	1410.7	1221.8	81.097	0.0664
LOEE (kWh/y)	3896.1	5825.3	4663.6	378.19	0.0811
EIU	5.00%	7.48%	5.99%	0.49%	0.0818
FOI (int./y)	377	612	473.60	51.87	0.1095
DOI (h/int.)	2.3028	2.9156	2.5941	0.1572	0.0606
ENSI (kWh/int.)	8.4702	11.9126	9.8983	0.7057	0.0713

TABLE V. MCS RESULTS CONSIDERING AGRICULTURAL CDFS

Index	Min	Max	Average	Standard deviation	Coef. of variation
COE (€/kWh)	0.2481	0.2975	0.2693	0.0103	0.0382
LOLE (h/y)	174.83	596.17	353.75	87.05	0.2461
LOEE (kWh/y)	20.5	1839.9	803.5	387.4	0.4821
EIU	0.026%	2.36%	1.03%	0.50%	0.4854
FOI (int./y)	788	1062	901.01	57.27	0.0636
DOI (h/int.)	0.2119	0.5782	0.3888	0.0741	0.1906
ENSI (kWh/int.)	0.0249	1.9129	0.8747	0.3835	0.4384

TABLE VI. MCS RESULTS CONSIDERING RESIDENTIAL CDFS

Index	Min	Max	Average	Standard deviation	Coef. of variation
COE (€/kWh)	0.2464	0.3858	0.2930	0.0241	0.0823
LOLE (h/y)	176.33	641.00	361.98	89.51	0.2473
LOEE (kWh/y)	29.38	2331.8	863.64	407.89	0.4723
EIU	0.038%	2.99%	1.11%	0.52%	0.4685
FOI (int./y)	766	1034	876.13	57.87	0.0661
DOI (h/int.)	0.2172	0.6501	0.4090	0.0778	0.1902
ENSI (kWh/int.)	0.0362	2.3697	0.9659	0.4101	0.4246

C. Consideration of Components Forced Outage Rate

In the analysis of Section V.B, 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 on Table III. For each one of them, a MCS is applied for a total number of 100 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 1920 h and mean time to repair (MTTR) equal to 80 h [4]. For the diesel generator, it is assumed that it needs scheduled maintenance every 1000 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 [2].

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

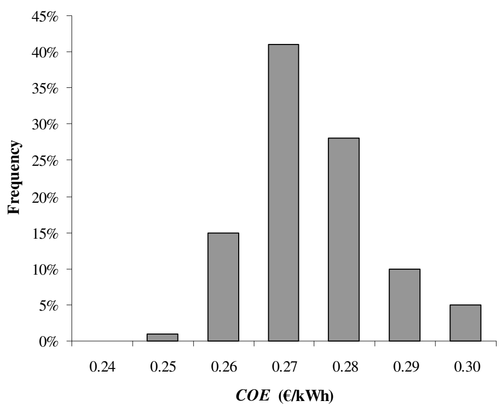

Figure 2. COE histogram for agricultural load.

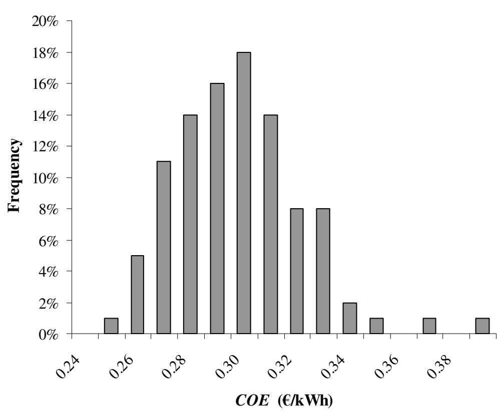

Figure 3. COE histogram for residential load.

Another interesting conclusion drew from the results shown in Table IV to VI is the higher variability (denoted by coefficient of variation) of the basic reliability indices (LOLE, LOEE, EIU) and *COE*, in the scenarios of considering customer damage costs. These two scenarios (agricultural and residential) have no significant difference in variability between them, with the exception of *COE*. This exception can be explained by the fact that the residential customer damage cost is increased exponentially with the increase of interruption duration (see Table I), affecting concurrently *COE*. Figs. 2 and 3 present the variation of *COE* for these two scenarios.

VI. Conclusions

The reliability evaluation of a 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 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 paper 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 paper also shows that the type of load, which changes the reliability worth, may also affect the performance of a SAPS.

References

[1] T. Ackermann, Wind power in power systems, Chichester: John Wiley & Sons, 2005.

[2] Y.A. Katsigiannis, P.S. Georgilakis, and G.J. Tsinarakis, "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, vol. 40, no. 6, pp. 1296–1309, Nov. 2010.

[3] R. Billinton and R. N. Allan, Reliability Evaluation of Power Systems, 2nd ed., New York: Plenum, 1996.

[4] R. Karki and R. Billinton, "Cost effective wind energy utilization for reliable power supply," IEEE Trans. Energy Convers., vol. 19, no. 2, pp. 435–440, Jun. 2004.

[5] E. Koutroulis, D. Kolokotsa, A. Potirakis, and K. Kalaitzakis, "Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms," Solar Energy, vol. 80, pp. 1072–1088, 2006.

[6] Y. A. Katsigiannis, P. S. Georgilakis, and E. S. Karapidakis, "Genetic algorithm solution to optimal sizing problem of small autonomous hybrid power systems," Lecture Notes in Artif. Intell., vol. 6040, pp. 327–332, 2010.

[7] N. C. Koskolos, S. M. Megaloconomos, and E. N. Dialynas, "Assessment of power interruption costs for the industrial customers in Greece," in Proc. ICHQP '98, Athens, Greece, 1998.

[8] M. Thomson and D. G. Infield, "Impact of widespread photovoltaics generation on distribution systems," IET Ren. Power Gen., vol. 1, pp. 33–40, 2007.

[9] T. Markvart and L. Castañer, Practical handbook of photovoltaics: fundamentals and applications, UK: Elsevier, 2003.

[10] O. Skarstein and K. Uhlen, "Design considerations with respect to long-term diesel saving in wind/diesel plants," Wind Eng., vol. 13, pp. 72–87, 1989.

[11] C. D. Barley and C. B. Winn, "Optimal dispatch strategy in remote hybrid power systems," Solar Energy, vol. 58, pp. 165–179, 1996.