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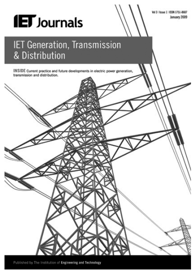

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Effect of customer worth of interrupted supply on the optimal design of small isolated power systems with increased renewable energy penetration

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Abstract: The analysis and design of a small isolated power system (SIPS) with renewable energy sources (RES) and storage can be challenging, because of the large number of design options and the uncertainty in key parameters. RES add further complexity because their power output may be intermittent, seasonal and non-dispatchable. Owing to this characteristic, reliability evaluation of a RES-based SIPS cannot be implemented using the traditional deterministic and analytical methods. Moreover, this evaluation has to be done within a cost-benefit framework. This study models and investigates the effect of customer worth of interrupted supply (customer damage cost) on the optimal design of SIPS with storage and increased RES penetration. The SIPS optimal design is implemented with a genetic algorithm combined with local search procedure. In addition, this study examines the effect of the forced outage rate of SIPS components on SIPS optimal design via Monte Carlo simulation. The performance of the proposed hybrid optimisation methodology is investigated for a large number of alternative scenarios via sensitivity analysis, which study the effect on the results because of the uncertainty on weather data, components efficiency and cost data. The results show that the optimal design of a RES-based SIPS depends largely on the consideration of customer damage cost as well as the inclusion of components forced outage rate. The method and results presented in this article should be valuable in planning and operating SIPS with RES.

1 Introduction

A small isolated power system (SIPS) 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 too expensive [1].

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.

Owing to the unique characteristics of SIPS, reliability evaluation is crucial in these systems. The most traditional methods for reliability evaluation of SIPS 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 recognise the chronological variation of intermittent sources, such as wind speed and solar energy. Moreover, the inclusion of battery storage complicates the problem considerably [5]. These factors can be incorporated using the Monte Carlo simulation (MCS), which however increases significantly the computation time.

This paper models and investigates the effect of customer worth of interrupted supply on the optimal design of SIPS that is based on RES technologies. The customer worth of interrupted supply, also called customer damage cost, is a function of user sector and duration of interruption, as Table 1 shows. The location of the studied system is in Chania, Greece. The SIPS optimal design is implemented with a genetic algorithm (GA) combined with a local search procedure. GA is a powerful optimisation technique that has been proposed for the solution of a variety of problems, including conventional SIPS optimal design (sizing) [6–8]. In the proposed SIPS optimal design, the objective function

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

is the minimisation of SIPS cost of energy (in €/kWh), and three scenarios are examined: (i) no consideration of customer worth of interrupted supply, (ii) consideration of customer worth of interrupted supply for agricultural load type and (iii) consideration of customer worth of interrupted supply for residential load type. In addition, this paper examines the effect of SIPS components forced outage rate on SIPS optimal design for the above three mentioned scenarios. This analysis, which is implemented via MCS, aims to highlight the difference between the results obtained from a conventional SIPS optimal design (e.g. [6–9]), and the results of the proposed approach that takes into account reliability issues (i.e. customer worth of interrupted supply and forced outage rate) 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.

This paper is organised as follows. Section 2 deals with reliability analysis of SIPS with RES. Section 3 presents the proposed formulation of SIPS optimal design, and Section 4 provides SIPS modelling details. Section 5 describes the examined test system as well as discusses and compares the results provided by the conventional and the proposed SIPS optimal design. Section 6 presents the results of sensitivity analysis and Section 7 concludes the paper.

2 SIPS 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

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

where $t_{\mathrm{outage}}(i)$ 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

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

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

For calculation of the expected customer damage cost, 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. The methods that are used to evaluate customer damage costs can be divided into three categories: (i) indirect analytical methods, (ii) case studies and (iii) customer surveys. Usually, customer surveys are the most common method [10]. In the bibliography, there are a few studies that contain interruption cost data. Council of European Energy Regulators (CEER) [11] estimates the costs because of electricity interruptions and voltage disturbances for a number of European countries, and Billinton and Allan [3] and Kariuki *et al.* [12] contain data for the power utilities of Canada and United Kingdom, respectively. Similar studies in Greece [13] have shown coincidence with the Canadian results. The values of CDFs (in €/kW), 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. To compute the IEAR, the expected customer interruption cost (ECOST) in €/year must be estimated first [14], 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

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

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

1. LOLE
2. LOEE
3. Energy index of unreliability (EIU) that normalises LOEE by dividing it with the annual energy demand.
4. Frequency of interruptions (FOI), that is, 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.

3 Proposed formulation of SIPS optimal design

The SIPS optimal design problem has to fulfil the objective defined by (4) subject to the constraints (6)–(9). This problem is solved for three different scenarios: (i) no consideration of customer worth of interrupted supply, (ii) consideration of customer worth of interrupted supply for

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agricultural load type and (iii) consideration of customer worth of interrupted supply for residential load type.

3.1 Objective function

Minimisation of system's cost of energy, COE

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

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

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

where C_{antot} (€) is the total annualised cost and $E_{\mathrm{anloadserved}}$ (kWh) is the total annual electric energy production that serves load, that is, $E_{\mathrm{anloadserved}}$ takes into account the amount of load demand that cannot be satisfied, which means that in case of unmet load, $E_{\mathrm{anloadserved}}$ is smaller than the total annual electric energy demand. 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 ECOST if considering customer worth of interrupted supply.

3.2 Constraints

3.2.1 Unmet load constraint

$$f_{\mathrm{UL}} = \frac{\sum_{\Delta t}^{\mathrm{year}} \mathrm{UL}_{\Delta t}\Delta t}{E_{\mathrm{anload}}} \le f_{\mathrm{UL\ max}} \tag{6}$$

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. By its definition, f_{UL} is identical to EIU. In this paper, the value of $f_{\mathrm{UL\ max}}$ has been taken equal to 5%.

3.2.2 Minimum RES penetration constraint

$$f_{\mathrm{RES}} = \frac{E_{\mathrm{anRES}}}{E_{\mathrm{antot}}} \ge f_{\mathrm{RES\ min}} \quad \text{where } 0 \le f_{\mathrm{RES\ min}} \le 1 \tag{7}$$

where f_{RES} is the RES penetration 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 penetration. In this paper, the value of f_{RESmin} has been taken equal to 80%. As a result, the energy production of studied SIPS is based mainly on RES technologies.

3.2.3 Components' size constraints

$$\mathrm{size}_{\mathrm{comp}} \ge 0, \quad \forall\ \mathrm{comp} \tag{8}$$

$$\mathrm{size}_{\mathrm{comp}} \le \mathrm{size}_{\mathrm{compmax}}, \quad \forall\ \mathrm{comp} \tag{9}$$

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. The values of $\mathrm{size}_{\mathrm{compmax}}$ for the studied system are shown in Table 2.

4 SIPS components and modelling

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

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

The modelling of SIPS components is implemented as follows. The WT modelling is implemented using a power curve profile that is based on manufacturer's data. The selected WT has the following characteristics: rated power 10 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, whereas it presents exclusively positive values for the generated power in the interval [$V_{\mathrm{in}}V_{\mathrm{out}}$].

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

$$P_{\mathrm{PV}} = f_{\mathrm{PV}}\, P_{\mathrm{STC}} \frac{G_{\mathrm{A}}}{G_{\mathrm{STC}}} \left(1 + \left(T_{\mathrm{C}} - T_{\mathrm{STC}}\right) C_{\mathrm{T}}\right) \tag{10}$$

where f_{PV} is the PV derating factor, P_{STC} is the nominal PV array power in $\mathrm{kW_p}$ under standard test conditions (STC), G_{A} is the global solar radiation incident on the PV array in $\mathrm{kW/m^2}$, G_{STC} is the solar radiation under STC ($1\ \mathrm{kW/m^2}$), 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, ageing 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 global solar radiation on a horizontal plane G (in $\mathrm{kW/m^2}$) using (11) [16]

$$T_{\mathrm{C}} = T_{\mathrm{a}} + \frac{(\mathrm{NOCT} - 20)}{0.8} G \tag{11}$$

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 [17]

$$F = 0.08415 P_{\mathrm{rated}} + 0.246 P \tag{12}$$

where P_{rated} is the generator's rated power and P is the generator's output power. Lead-acid batteries have been modelled assuming 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 (8) and (9). Then, 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 of fully serving the load, the remaining electric

Table 2 Component characteristics

Component	$size_{compmax}$	Increment	Capital cost	Replacement cost	O&M cost	Fuel cost	Lifetime
WTs (10 kW rated)	6 WT	1 WT	25 000 €/WT	20 000 €/WT	500 €/year	–	20 years
PVs	20 kW_p	0.5 kW_p	3000 €/kW_p	2500 €/kW_p	0	–	25 years
diesel generator	20 kW	variable	300 €/kW	300 €/kW	0.01 €/h/kW	1.5 €/l (diesel)	20 000 oper. hours
batteries (1250 Ah, 6 V)	160 bat.	8 bat.	600 €/bat.	600 €/bat.	10 €/bat.	–	9000 kWh
converter	20 kW	1 kW	1000 €/kW	1000 €/kW	0	–	15 years

load has to be supplied by the diesel generator and/or batteries. From all possible combinations, the one that supplies the load at the least cost is selected. When the whole year's simulation has been completed, it is determined whether the system is feasible, that is, it is checked if it satisfies the constraints (6) and (7). After the end of the simulation, the 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 customer worth of interrupted supply), (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 paper, three alternative values of SOC_a have been considered: 80, 90 and 100%, hence the total number of examined dispatch strategies is 4. CC strategy tends to be optimal in systems with little or no renewable power.

5 Results and discussion

5.1 Case study system

In the considered SIPS, 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 estimation of WT and PV performance refer to measurements for the mountainous region of Keramia (altitude 500 m), in Chania, Crete, Greece. The annual SIPS peak load has been considered equal to 20 kW, whereas the necessary SIPS 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% (SIPS). It should be noted that the proposed methodology is general and it can be also applied to different geographical locations using the following data: (i) wind, solar, ambient temperature and load time-series, (ii) the longitude, latitude and time zone of the region (needed for calculation of global solar radiation incident on the PV array G_A) and (iii) the altitude of the region (needed for correction of WT output because of atmospheric pressure variation).

The WT hub height has been considered 25 m, and the PVs do not include a tracking system. 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 the diesel generator, all the components have constant increment of their size, as Table 2 shows. The considered sizes for the diesel generator are 0, 3, 5, 8, 10, 12, 15 and 20 kW. For the optimal design problem of the SIPS of Table 2, the complete enumeration method requires

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

that is, approximately 4 million evaluations in order to find the optimal COE; in (13) 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 3 months, for each one of the three considered scenarios. That is why it is essential to develop an alternative optimisation method in order to solve the SIPS optimal design problem in a fast and effective way.

5.2 GA implementation for SIPS optimal design

GAs mimic natural evolutionary principles and constitute powerful search and optimisation 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 SIPS component can take only discrete values, hence the binary GA is proposed for the solution of SIPS optimal design 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 SIPS component sizes (WT, PV, diesel generator, batteries and converters), whereas the sixth gene refers to the adopted dispatch strategy (LF or CC). For handling of constraints, the penalty function approach is adopted, in which an exterior penalty term is used that penalises infeasible solutions. Since different constraints may take different orders of magnitude, prior to the calculation of the overall penalty function, all constraints are normalised.

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Table 3 Optimal solutions of GA combined with local search

Scenario	WTs	PVs, kW_p	Dsl, kW	Batteries	Converter, kW	Dispatch strategy	COE, €/kWh	LOLE, h/year	LOEE, kWh/year	EIU, %	FOI, int/year	DOI, h/int	ENSI, kWh/int
no customer damage cost	3	11	3	48	13	LF	0.2156	895.0	3882.9	4.99	435	2.0575	8.9264
agricultural CDFs	3	7.5	15	56	15	LF	0.2478	10.67	10.18	0.013	46	0.2319	0.2214
residential CDFs	3	7	15	48	16	LF	0.2462	13.83	13.20	0.017	56	0.2470	0.2358

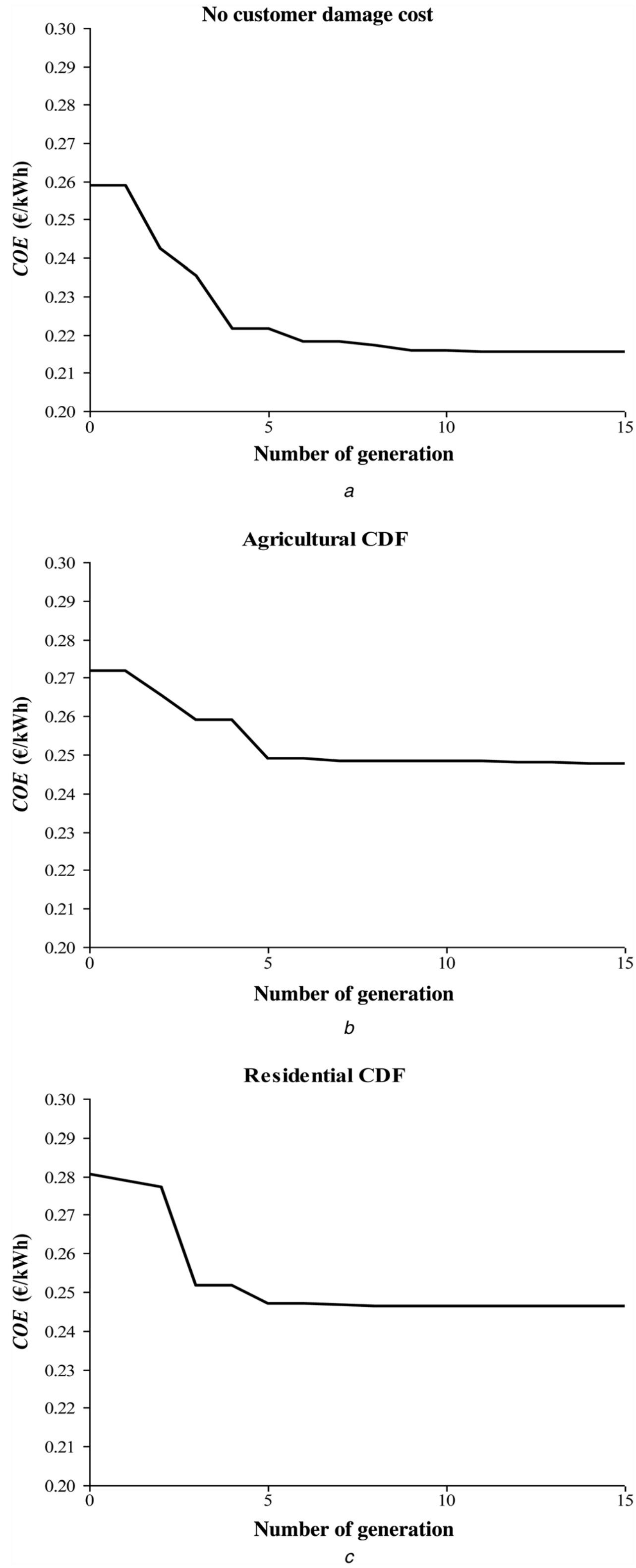

Fig. 1 *GA convergence considering*

a No customer damage cost
b Agricultural CDF
c Residential CDF

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

1. Evaluation of objective function.

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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 of a small portion of population members.

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 [7]. In addition, the proposed GA is combined with the local search procedure, in order to ensure that the selected solution is optimal compared with its neighbour solutions. Table 3 presents the optimal configurations and the six reliability indices for the three examined scenarios. As can be seen, the consideration of no customer damage cost leads to a solution that presents the lowest COE. However, the scenario of not considering CDFs is much less reliable than the other two scenarios that consider CDFs. It can be also seen from Table 3 that the EIU is marginally below the limit of 5% that constraint (6) imposes. 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 for small interruptions (e.g. 20 min and 1 h), the agricultural CDF values are larger than the residential CDF values, whereas the opposite exists for larger interruptions (e.g. 4 and 8 h), 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, because of 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 3.

5.3 Consideration of components forced outage rate

In the analysis of Section 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 SIPS, 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, an MCS is applied for a total number of 1000 simulation years.

The consideration of forced outage rate is applied to the two SIPS 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)

Table 4 MCS results considering no customer damage cost

Index	Min	Max	Average	Standard deviation	Coefficient of variation
COE, €/kWh	0.2163	0.2273	0.2208	0.0014	0.0063
LOLE, h/year	1047.5	1566.2	1213.0	81.98	0.0676
LOEE, kWh/year	3895.2	6303.2	4611.0	371.66	0.0806
EIU, %	5.00	8.09	5.92	0.48	0.0811
FOI, int/year	350	704	463.28	53.13	0.1147
DOI, h/int	2.0678	3.0776	2.6339	0.1576	0.0598
ENSI, kWh/int	7.6293	12.2344	10.0096	0.6974	0.0697

Table 5 MCS results considering agricultural CDFs

Index	Min	Max	Average	Standard deviation	Coefficient of variation
COE, €/kWh	0.2481	0.3156	0.2716	0.0103	0.0379
LOLE, h/year	171.50	721.83	354.10	86.29	0.2437
LOEE, kWh/year	18.2	2931.7	825.7	397.9	0.4819
EIU, %	0.023	3.76	1.06	0.51	0.4811
FOI, int/year	790	1131	899.70	54.53	0.0606
DOI, h/int	0.2128	0.6952	0.3899	0.0743	0.1906
ENSI, kWh/int	0.0226	3.1222	0.9005	0.3945	0.4381

Table 6 MCS results considering residential CDFs

Index	Min	Max	Average	Standard deviation	Coefficient of variation
COE, €/kWh	0.2464	0.3877	0.2892	0.0222	0.0768
LOLE, h/year	166.33	685.00	321.79	81.98	0.2548
LOEE, kWh/year	25.44	2433.5	741.27	371.66	0.5014
EIU, %	0.032	3.12	0.95	0.48	0.5053
FOI, int/year	729	1083	842.28	53.13	0.0631
DOI, h/int	0.2173	0.6755	0.3901	0.0745	0.1910
ENSI, kWh/int	0.0305	2.3999	0.8623	0.3936	0.4565

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equal to 80 h. 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 interval [2 and 24 h]. Moreover, a starting failure of 1% is included in the evaluation, while the repairing process follows the same distribution with the maintenance process [19].

The MCS simulation type is sequential, which takes into account the chronology of the process, considering random generating unit failures and repairs [3]. For each WT, the probability of time to failure (TTF_{WT} – in h) and time to repair (TTR_{WT} – in h) follows an exponential distribution, so both variables can be calculated using the inverse transform method [20] as follows

$$TTF_{WT} = -MTTF \ln(\mathrm{rnd}(0,\ 1)) \tag{14}$$

$$TTR_{WT} = -MTTR \ln(\mathrm{rnd}(0,\ 1)) \tag{15}$$

where rnd(0, 1) is the uniformly distributed random number generation function in the interval (0, 1). After the calculation of TTF_{WT} and TTR_{WT}, the obtained values are rounded to the nearest multiple of time interval Δt. In case the number of WTs is >1, different simulations for each WT are executed.

For operation of the diesel generator, two counters are used: the first counts its operating hours and the second counts its state [working (1) or non-working (0)] for each

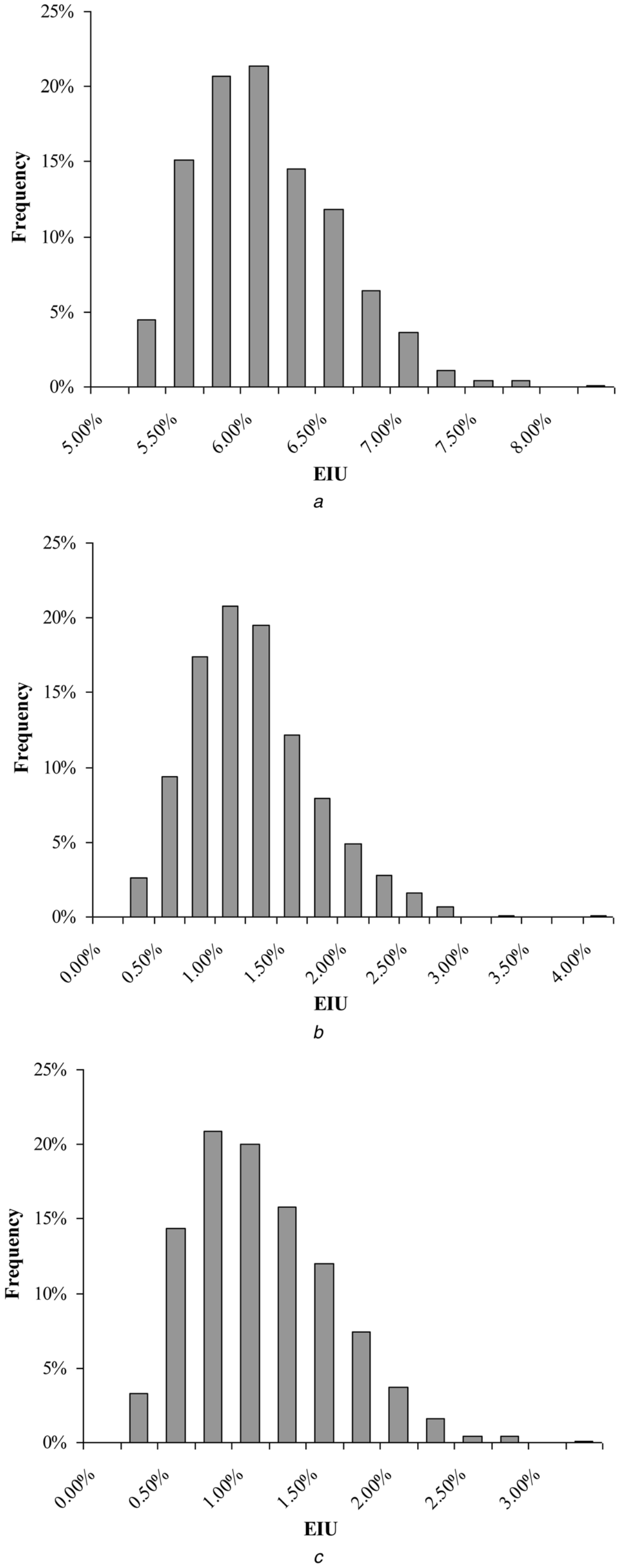

Fig. 2 *EIU histogram considering*

a No customer damage cost
b Agricultural CDF
c Residential CDF

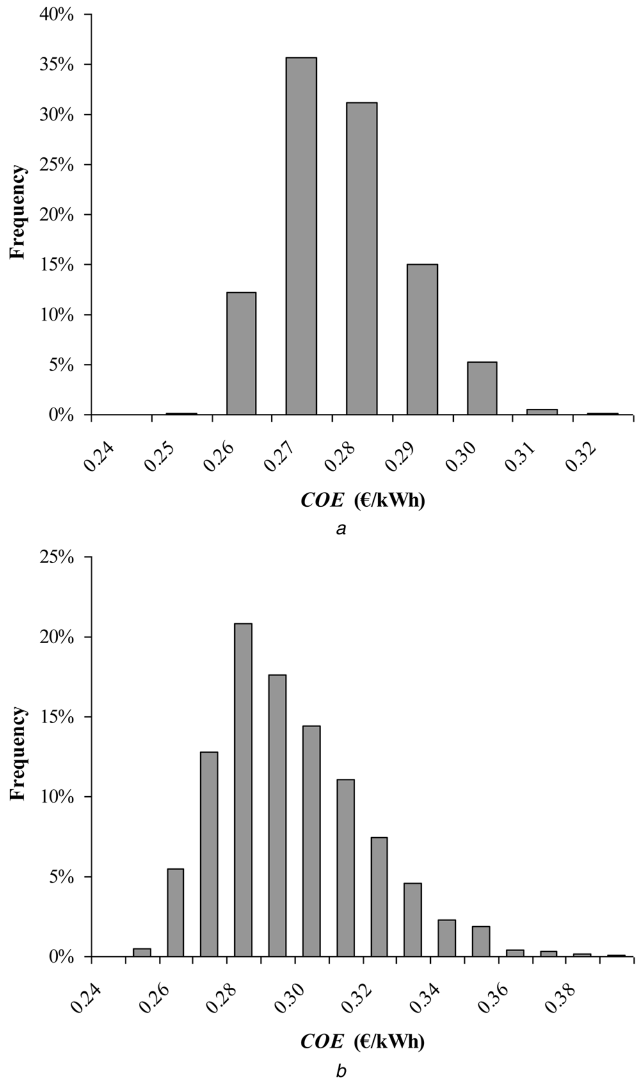

Fig. 3 *COE histogram considering*

a Agricultural CDF
b Residential CDF

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time interval. When the needed number of operating hours for service (1000 h) is fulfilled, then the diesel generator is under maintenance and cannot produce power. The time to repair (TTR_d – in h) is calculated from

$$\mathrm{TTR_d} = 2\,\mathrm{h} + [(24\,\mathrm{h} - 2\,\mathrm{h})\,(\mathrm{rnd}(0,\ 1))] \tag{16}$$

After the calculation of TTR_d, the obtained value is rounded to the nearest multiple of time interval Δt. Moreover, in case that the state of diesel generator is 1 for the current Δt and 0 for the previous Δt, a random number check is executed. If $\mathrm{rnd}(0,\ 1) \leq 0.01$, then the diesel generator is under maintenance, and time to repair is given by (16).

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, the (dimensionless) coefficient of variation is calculated, which is the ratio of the standard deviation to the mean, as a measure of variability. As can be seen, the consideration of forced outage rate increases significantly the values of the basic reliability indices (LOLE, LOEE and EIU) and COE. Considering the value of EIU, which also represents a constraint of the examined problem (6), it can be seen that for the case of considering no customer damage cost, the obtained values for all simulations surpass the maximum allowable value of 5%, that is, the solution is infeasible for all cases considering components forced outage rate. On the other hand, there is no simulation that EIU surpasses 4% for the scenarios of considering agricultural and residential CDFs. Fig. 2 depicts the variation of EIU for the three examined scenarios. In some simulation runs, the values of DOI and ENSI indicators may be smaller compared with those of Table 3, but this does not mean that the performance is better. In these simulation runs, the low values of DOI and ENSI are combined with the large values of FOI, resulting in much higher number of interruptions that have slightly lower duration.

Another interesting conclusion from the study of Tables 4–6 is higher variability (denoted by coefficient of variation) of the basic reliability indices (LOLE, LOEE and EIU) and COE, in the scenarios of considering customer damage costs. It can be seen from Tables 5 and 6 that agricultural and residential scenarios have no significant difference in indicators variability, 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 1), affecting concomitantly COE. Fig. 3 presents the variation of COE for the agricultural and residential scenario.

6 Sensitivity analysis

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

1. 10% increase of wind speed.
2. 10% decrease of wind speed.
3. 5% increase of solar radiation.
4. 5% decrease of solar radiation.
5. Installation of a two-axis PV tracking system (additional PV capital and replacement cost: 1000 €/kW$_p$, additional PV annual O&M cost: 25 €/kW$_p$).

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	11	3	48	13	LF	0.2156
	agricultural	3	7.5	15	56	15	LF	0.2478
	residential	3	7	15	48	16	LF	0.2462
wind +10%	no CDF	2	8	5	40	16	LF	0.1898
	agricultural	2	8.5	15	40	14	LF	0.2264
	residential	2	8.5	15	40	14	LF	0.2247
wind –10%	no CDF	3	12.5	5	40	14	LF	0.2382
	agricultural	3	11	15	64	15	LF	0.2773
	residential	3	9	15	64	15	LF	0.2742
solar +5%	no CDF	3	4	5	48	14	LF	0.2172
	agricultural	3	8	15	48	15	LF	0.2466
	residential	3	7	15	48	15	LF	0.2452
solar –5%	no CDF	3	5.5	5	40	14	LF	0.2134
	agricultural	3	7.5	15	56	15	LF	0.2490
	residential	3	6	15	56	16	LF	0.2474
two-axis PV	no CDF	2	8.5	5	56	13	LF	0.2143
	agricultural	3	5	15	56	15	LF	0.2483
	residential	3	4	15	56	18	LF	0.2480
diesel increased efficiency	no CDF	2	14	5	32	10	LF	0.2053
	agricultural	3	6.5	15	48	15	LF	0.2417
	residential	2	7.5	15	40	15	LF	0.2397
diesel 2 €/l	no CDF	3	5	5	40	15	LF	0.2277
	agricultural	3	8	15	80	16	LF	0.2663
	residential	3	9.5	12	72	16	LF	0.2636
RES –50%	no CDF	3	12	3	48	13	LF	0.1582
	agricultural	3	20	15	40	16	LF	0.1879
	residential	3	19	15	48	15	LF	0.1874
no O&M cost	no CDF	2	11.5	5	56	12	LF	0.1888
	agricultural	3	6.5	15	80	16	LF	0.2189
	residential	3	5.5	15	80	16	LF	0.2173

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Table 8 Sensitivity analysis results for GA-local search procedure and MCS

Case	CDF	GA – local search results							MCS results (average values)						
		COE, €/kWh	LOLE, h/year	LOEE, kWh/year	EIU, %	FOI, int/year	DOI, h/int	ENSI, kWh/int	COE, €/kWh	LOLE, h/year	LOEE, kWh/year	EIU, %	FOI, int/year	DOI, h/int	ENSI, kWh/int
initial	no CDF	0.2156	895.0	3882.9	4.99	435	2.0575	8.9264	0.2208	1213.0	4611.0	5.92	463.28	2.6339	10.0096
	agricultural	0.2478	10.67	10.18	0.013	46	0.2319	0.2214	0.2716	354.10	825.7	1.06	899.70	0.3899	0.9005
	residential	0.2462	13.83	13.20	0.017	56	0.2470	0.2358	0.2892	321.79	741.27	0.95	842.28	0.3901	0.8623
wind +10%	no CDF	0.1898	1140.8	3773.2	4.84	969	1.1773	3.8939	0.1949	1294.5	5063.4	6.50	995.81	1.2966	5.0685
	agricultural	0.2264	13.50	13.11	0.017	59	0.2288	0.2222	0.2612	504.92	1721.5	2.21	831.79	0.5962	1.9954
	residential	0.2247	13.50	13.11	0.017	59	0.2288	0.2222	0.2726	496.91	1704.2	2.19	808.50	0.6042	2.0361
wind −10%	no CDF	0.2382	1154.2	3806.3	4.89	963	1.1985	3.9525	0.2430	1375.3	4609.3	5.92	936.98	1.4686	4.9213
	agricultural	0.2773	20.17	18.52	0.024	87	0.2318	0.2128	0.3012	523.50	1755.8	2.25	804.07	0.6480	2.1586
	residential	0.2742	21.50	19.59	0.025	94	0.2287	0.2084	0.3178	549.34	1650.7	2.12	794.68	0.6897	2.0610
solar +5%	no CDF	0.2127	1090.8	3835.5	4.93	805	1.3551	4.7647	0.2180	1252.1	4806.3	6.17	839.45	1.4913	5.7218
	agricultural	0.2466	11.17	10.78	0.014	48	0.2326	0.2245	0.2669	490.16	1678.4	2.16	801.15	0.6085	2.0715
	residential	0.2452	12.50	12.02	0.015	52	0.2311	0.2452	0.2829	508.16	1689.4	2.17	661.68	0.7644	2.5220
solar −5%	no CDF	0.2172	1092.5	3737.4	4.80	842	1.2975	4.4387	0.2216	1265.4	4485.5	5.76	803.33	1.5767	5.5882
	agricultural	0.2490	11.50	10.95	0.014	49	0.2347	0.2235	0.2741	519.44	1795.9	2.31	734.28	0.7034	2.4134
	residential	0.2474	15.67	15.14	0.019	65	0.2410	0.2329	0.2924	509.78	1854.0	2.38	652.92	0.7764	2.8047
two-axis PV	no CDF	0.2143	1145.5	3853.4	4.95	1013	1.1308	3.8039	0.2208	1442.1	5208.1	6.69	1124.0	1.2812	4.6243
	agricultural	0.2483	12.67	11.87	0.015	55	0.2303	0.2158	0.2723	491.56	1617.9	2.08	727.07	0.6736	2.2047
	residential	0.2480	19.33	18.69	0.024	79	0.2447	0.2366	0.2884	491.16	1759.9	2.26	612.57	0.7983	2.8438
diesel increased	no CDF	0.2053	1214.2	3855.5	4.95	1214	1.0001	3.1758	0.2121	1441.0	4876.0	6.26	1075.1	1.3401	4.5312
efficiency	agricultural	0.2417	13.50	13.12	0.017	54	0.2500	0.2429	0.2688	537.97	1800.7	2.31	711.77	0.7518	2.4986
	residential	0.2397	25.33	25.02	0.032	111	0.2282	0.2254	0.2877	697.70	2264.6	2.91	933.08	0.7431	2.3935
diesel 2 €/l	no CDF	0.2277	1108.5	3826.6	4.91	833	1.3307	4.5937	0.2364	1326.3	4776.0	6.13	896.06	1.4806	5.3288
	agricultural	0.2663	9.00	9.25	0.019	38	0.2368	0.2434	0.2870	451.78	1713.4	2.20	583.85	0.7702	2.9061
	residential	0.2636	52.00	86.95	0.110	149	0.3490	0.5836	0.3093	435.94	1585.7	2.04	501.26	0.8660	3.1330
RES −50%	no CDF	0.1582	849.50	3639.6	4.67	448	1.8962	8.1242	0.1616	992.77	4313.0	5.54	630.22	1.5778	6.8573
	agricultural	0.1879	6.83	6.72	0.009	31	0.2204	0.2167	0.2016	371.27	1278.1	1.64	359.02	1.0346	3.5363
	residential	0.1874	6.67	6.54	0.008	30	0.2222	0.2181	0.2147	393.77	1298.6	1.67	338.04	1.1693	3.8034
no O&M cost	no CDF	0.1888	1177.0	3858.0	4.95	1018	1.1562	3.7898	0.1938	1487.0	5185.4	6.66	1180.1	1.2583	4.3847
	agricultural	0.2189	10.50	10.61	0.014	43	0.2442	0.2467	0.2369	459.90	1750.3	2.25	493.55	0.9288	3.5150
	residential	0.2173	12.50	13.00	0.017	52	0.2404	0.2500	0.2584	475.99	1741.7	2.24	576.37	0.8207	2.9789

6. Increase of diesel generator maximum efficiency from 31 to 36%.
7. Increase of diesel fuel price from 1.5 to 2.0 €/l.
8. 50% capital and replacement cost reduction of renewable energy technologies (WTs and PVs).
9. Consideration of zero O&M cost for each component.

The first four scenarios consider modified wind and solar data series compared with the initial scenario. Scenario 5 is a combination of increased efficiency and increased cost for the PVs. It should be noted that the PVs cost difference of scenario 5 is combined with an over 31% annual PVs energy production at the considered location. For scenario 6, the following equation is used for diesel generator fuel consumption F

$$F = 0.08\, P_{\text{rated}} + 0.20\, P \tag{17}$$

Compared with the initial scenario [that uses (12)], the diesel generator maximum efficiency (at rated power P_{rated}) is increased from 31 to 36%. In scenario 7, the effect of increased diesel fuel cost is examined. Scenario 8 considers a reduction of capital and replacement cost of RES that 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. Scenario 9 assumes that O&M costs are negligible for all components, in order to study their impact on the final results.

Tables 7 and 8 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, whereas Table 8 compares the results of the GA-local search procedure with the results of the MCS (average values). Regarding the comparison of GA-local search and MCS, the conclusions are identical with those mentioned in Section 5.3. It has to be emphasised that in all MCS for any specific scenario, the average COE values assuming residential CDF are significantly higher compared with agricultural CDF, because of the exponential increase of residential customer damage cost with the increase of interruption duration.

The study of Tables 7 and 8 draws the following main conclusions for the considered case study system:

1. The wind potential (scenarios 1 and 2) affects more the value of COE in comparison with the solar potential (scenarios 3 and 4).
2. The adoption of a two-axis PV tracking system (scenario 5) reduces the installed PV capacity (because of higher PV efficiency) and produces almost identical COE values for all cases.
3. The (negative) effect of increased diesel fuel price (scenario 7) surpasses the (positive) effect of increased diesel generator efficiency (scenario 6), especially in agricultural and residential customers because of the CDFs and the assumed diesel generator maintenance and reliability parameters (Section 5.3).
4. The lower cost of RES technologies (scenario 8) results in a low cost (COE) and a highly reliable system considering the constraints of Section 3.2.
5. The omission of O&M costs (scenario 9) changes significantly the obtained results.
6. The configurations in all the examined scenarios contain large number of batteries, converters of similar sizes and adoption of LF dispatch strategy.

7 Conclusions

The reliability evaluation of SIPS with storage and increased RES penetration is a complex and time consuming task, because of the intermittent nature of renewable resources, their variation, the high modularity of each part of the system and the considered assumptions for reliability analysis. In most cases, the optimal design 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 customer worth of interrupted supply as well as the forced outage rate of SIPS components. This paper shows that the consideration of the customer worth of interrupted supply and the forced outage rate in the analysis changes significantly the obtained results, and that it may transform a feasible solution of the conventional optimisation procedure to an infeasible one. Moreover, the performance of a real SIPS, as computed by considering the above two parameters, will be much different than the performance of SIPS ignoring both the customer worth of interrupted supply and the forced outage rate. This paper also shows that the type of load, which changes the customer worth of interrupted supply, may also affect the performance of SIPS. The uncertainty in key input parameters has been investigated through a detailed sensitivity analysis study.

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