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Assessment of probabilistic distributed factors influencing renewable energy supply for hotels using Monte-Carlo methods

Abstract

This paper investigates the use of renewable energies to supply hotels in island regions. The aim is to evaluate the effect of weather and occupancy fluctuations on the sensitivity of investment criteria. The sensitivity of the chosen energy system is examined using a Monte Carlo simulation considering stochastic weather data, occupancy rates and energy needs. For this purpose, algorithms based on measured data are developed and applied to a case study on the Canary Islands.

The results underline that electricity use in hotels is by far the largest contributor to their overall energy cost. For the invested hotel on the Canary Islands, the optimal share of renewable electricity generation is found to be 63 %, split into 67 % photovoltaic and 33 % wind power. Furthermore, a battery is used to balance the differences between day and night. It is found, that the results are sensitive to weather fluctuations as well as economic parameters to about the same degree. The results underline the risk caused by using reference time series for designing energy systems. The Monte Carlo method helps to define the mean of the annuity more precisely and to rate the risk of fluctuating weather and occupancy better.

Keywords: *Renewable energy systems, Monte Carlo methods, hotels, Canary Islands*

Abbreviations

	annuity
	surface area
amb	ambiance
	annuity factor
	heat transition coefficient solar collector
	temperature depending heat transition coefficient solar collector
CCM	Compression chiller
	collector
	investment cost
	maintenance cost
	specific heat capacity
	cognitive parameter
	social parameter
det	deterministic
DHW	domestic hot water
	cooling energy
	electric energy
	energy efficient ratio
	fuel demand

	fluid
	occupancy ratio
	daily solar factor
	chiller performance factors
	monthly solar factor
	Hellman exponent
	irradiance on tilted surface
	extra-terrestrial irradiance
	hub height
	daily irradiance
	monthly irradiance
	reference height
	hour of year
	global irradiance
	nominal interest rate
	inflation-adjusted interest rate
	inflation rate
KPI	key performance indicator
	clearness index
LCOE	levelised costs of electricity
	fluid mass flow
	mass of steam
	Normal distribution with mean value m and variance s^2
	number of years
NOCT	nominal operating cell temperature
NPV	net present value
	occupancy of the day
O&M	operation and maintenance
	electric power
PDF	probability density function
	global best position
	particle's best position
PV	photovoltaic
	heat flow
	unified random number
S	Storage
STC	standard testing conditions
sto	stochastic
	temperature
TPM	transition probability matrix
TWS	thermal water storage
	heat transition coefficient
	volume
	wind speed
	particle's velocity
	washing days per week
WT	wind turbine
	particle position
	absorbtion coefficient
	efficiency ratio
	cell efficiency temperature coefficient

transmission coefficient
constriction factor

1 Introduction

Islands cover approximately 5.3 % of the global landmass and are inhabited by 740 million people, which is about 10% of the planets population. Considering only islands with between 100 and 100,000 inhabitants, 3,828 islands can be found which are populated by 19.4 Mio inhabitants [1]. On most of these smaller islands, the energy supply is based on diesel power plants. As a result these islands are dependent on fossil fuel imports and the cost variations associated with these limited resources [2]. For this reason, the energy supply on the large majority of small islands is characterised by high levelised costs of electricity (LCOE) [3].

Fossil fuels do not only have economic disadvantages resulting from a high LCOE, they also cause high greenhouse gas emissions which increase anthropogenic climate change. The impacts of climate change have a particularly large effect on islands and small developing island states. To counteract climate change, the United Nation Framework Convention on Climate Change, 21st Conference of the Parties (COP21) has decided to prevent global warming from causing an average global temperature increase of 2°C. One step to achieve this objective is to work towards an energy supply based on a variety of renewable energies.

Most islands are located in regions with a potential for renewable energies. Two commonly faced solutions to meet the challenges of islands' energy systems are increasing the use of this potential and making the energy demand more flexible. Scientific literature highlights a variety of ways to investigate and optimise renewable energy systems on islands. Different research projects stress the economic advantages of renewable energy systems. The researches of Kuang et al. [4] and Neves et al. [5] give an overview of research and demonstration projects regarding renewable energy systems on islands.

The work of Blechinger et al. [6] defines the potentials of renewable energies on islands. It determines the potential of among others wind and solar power around the world and concludes that the potential is not yet fully utilised. The work of Meschede et al. [7] shows a cluster analysis using climatic, physical, and socio-economic parameters to highlight similarities of global islands to allow the fast transfer of well-designed solutions to similar islands.

The International Renewable Energy Agency (IRENA) analyses the importance of tourism for islands. Tourism is very energy intensive and one of the largest economic sectors on islands. High energy costs lead to disadvantages in economic competition. Different barriers like access to finance and a lack of investment are identified by the IRENA[8].

The project HOTRES [9] elaborates on possibilities to increase the utilisation of renewable energies in European hotels. Wang and Huang [10] investigate the influence of guests from different regions on the energy demand of hotels in Taiwan. Also, the authors give a good literature review of energy consumption in hotels. Dalton et al. [11] simulate a renewable energy system for a large off-grid hotel in Australia using load data for one year as a reference. The research of Fortuny et al. [12] analyses how investments in sustainable solutions for energy and water supply as well as waste treatment will lead to increasing profitability for hotels on the Balearics. Some economic solutions include the use of photovoltaics to generate electricity as well as using a biomass burner and solar thermal system to provide domestic hot water. However, special arrangements should be taken to handle the high fluctuation of renewable energy sources like wind and solar. The works of Notton [13] and Yue et al. [14] identify that the volatility of energy generation is a critical factor for two different islands – La Réunion and Taiwan. This volatility can be managed by forecasts, energy storage and energy management systems as well as the use of biomass.

The economics of renewable energy systems depends on several inputs. Besides deterministic economic values like investment costs, operation costs and rate of interest, probabilistic inputs like weather or occupancy determine the economic feasibility. These inputs cause fluctuating energy supply as well as fluctuating energy demand. Most of the parameters are interdependent, which makes analytical design approach almost impossible. To quantify the technical and economic risk of these probabilistic inputs, researchers therefore use Monte Carlo methods to simulate complex energy systems.

Particle swarm optimisation is commonly used to optimise the size of power plants in renewable energy systems [15–17]. However, these optimisations do not consider the system's sensitivity on varying inputs. Sharafi & ElMekkawy use particle swarm optimisation and stochastic inputs to optimise the energy system of a Canadian apartment with regards to costs [18]. The study also considers the volatility of weather and load data using Monte Carlo methods. In the work of Arriagada et al. [19], Monte Carlo methods are used for analysing the influence of probabilistic wind, solar and energy demand on an energy system in Northern Chile containing diesel power plants, photovoltaics, and wind turbines. Dufo-López et al. show two approaches to optimise off-grid energy systems. The first work analyses the energy supply for a hospital in Congo [20], the second paper deals with a stochastic-heuristic methodology to optimise the size of components and the system control [21]. In both cases, the system consists of a diesel generator, photovoltaics, and a battery. In the second work a wind turbine is added to the system. Monte Carlo methods are used to represent fluctuation of solar radiation and electrical load. The work of Arun et al. [22] uses normally distributed solar radiation values and load profiles for optimised design of electrical storages while Roy et al. [23] present a methodology for optimised sizing of wind-battery systems with regard to uncertainty of wind resources. Nijhuis et al. present an approach for probabilistic load profiles of households [24]. Probability density functions (PDF) of the user's occupancy and activity level are developed, using publicly available data.

Regarding the scientific literature, there is a lack of information about the generation of synthetic energy demand series in hourly resolution for hotels and the influence of probabilistic distributed inputs on the energy system configuration. With respect to the presented research, the energy system's dependence on probabilistic inputs is only analysed for households [18,24] and off-grid hospitals [20]. Detailed information on the synthetic load profile generation is hereby missing. Hotels have been the issue of several research works and projects [8–14], but detailed and high temporal dissolved information on their energy and water demand is not given in the literature yet. However the time series of both weather and energy demand are needed for renewable energy system simulations and smart grid applications.

Due to the role of hotels in island energy systems, this paper analyses the sensitivity of hotels' energy systems and determines the system's cost dependence on varying inputs. Instead of using one reference year, the assessment is based on stochastically distributed inputs like weather and loads using Monte Carlo methods. For this purpose, a novel methodology for generating synthetic energy demand series for hotels is developed and presented in this work. The algorithms are based on measured weather data and energy needs of a real hotel on the Canary Islands. The influence of deterministic inputs is statically analysed and compared to the influence of weather and load changes.

The work is organised as follows: Section 2 gives an overview about the methodology to generate synthetic weather data. Previous work in this field is presented and the algorithms used are explained. Furthermore, the generated data is compared to measured data. Section 3 describes the methodology to generate synthetic time series for the energy needs of a hotel. Based on an existing hotel, algorithms are developed and presented. Section 4 describes the simulation model and section 5 highlights the design of the energy system configuration. In section 6, the results of a case study for a hotel on the Canary Islands is shown. The influence of deterministic and probabilistic inputs on the economy of the system are discussed and compared with previous works in this field. Section 7 concludes the work and gives an outlook on further investigations.

2 Methodology of probabilistic distributed weather data

In this section, the approaches to generate synthetic weather data for wind speed, solar radiation, and ambient temperature are explained in detail giving also a literature review for the single parameters. In the approach shown, the wind speed and solar radiation do not depend on any other input except the hour of year and historical weather data. The ambient temperature depends on historical data, the hour of year and the global solar radiation. The results are compared to measured weather data for a location on the Canary Islands.

2.1 Solar radiation

Duffie & Beckman [25] show a probabilistic approach to determine the solar radiation. They represent the frequency distribution of the mean value by the daily clearness index K_t. It is depicted as a function of the monthly average clarity index. For locations with the same $\overline{K}_t$, very similar PDF profiles are obtained. The distribution of the hourly clearness index k_t is described by a similar approach. The PDF can be used in Monte Carlo methods to determine concrete clearness index values for a time series of hourly values. The global irradiance on a surface results from the multiplication with the extra-terrestrial radiation.

This research modifies the approach as follows: For each month, a PDF (k_t) of the hourly clearness index is determined. Furthermore, additional factors for the daily and monthly variability are calculated. describes the relation of the daily irradiance to the average daily irradiance of the selected month $\overline{H}_{(d)}$, whereas F_m is defined as the ratio of the monthly irradiance $H_{(m)}$ to the long-time average monthly irradiance .

$$—— \quad (1)$$

(2)

For the Canary Island, F_m is approximated to be normally distributed with the mean value μ=1 and the standard derivation SD=0.15. To bind the values, the 2σ-interval is chosen. is described with a PDF for each month.

To generate probabilistic time series of the global irradiance, the clearness index of the hour as well as the additional factor are probabilistically determined by using the corresponding PDFs, whereas F is a normally distributed random number in that specific case. The hourly global irradiance is the product of the chosen values, the clearness index and the extra-terrestrial irradiance of the selected hour of the year.

(3)

To reduce the variability, a moving average over three time steps is used.

The daily profile of solar irradiance is shown in **Figure 1**. The figure underlines that the overall quality of the generated profile is high. In both cases (i.e. the measured and generated time-series), the irradiance at night is zero and sunrise as well as sunset are at the same time. The comparison also shows the fluctuation of solar irradiance due to clouds.

The comparison of seven measured years and seven probabilistically generated years is shown in **Figure 2**. The seasonality of the generated data matches the measured figures. The difference between measured and generated annual average irradiance is 1 %. The maximum of the measured data is 1,126 W/m² and the maximum of the generated values is 1,155 W/m² meaning a minor deviation of 2.6 %.

2.2 Ambient temperature

Several publications deal with different approaches for synthetic generation of ambient temperature time-series. The work of Erbs et al. [26] generates time-series based on a deterministic approach using a sine profile, whereas the work of Almonacid et al. [27] shows an approach based on neuronal networks. For the latter, inputs are the daily mean, maximum and minimum temperature as well as the geographical locations. The approach of Krenzinger & Scain Farenzena [28] is based on correlations among daily solar irradiance and daily ambient temperature. The minimum of ambient temperature is set to sunrise and the maximum is set to 3 pm. Variations are realised through an added random term. A further approach based on first order Markov-chains is used by Yang et al. [29]. Hereby, the temperature of each time step depends on the last time step. For this approach, a sufficient large volume of measured data is needed. Finally, the approach introduced by Dunkelberg et al. [30] combines the first order Markov-chain and the dependence on global solar irradiance. The same approach is used for this research and is shown in **Figure 3**.

Based on 13 years of historical measurements, transition probability matrices (TPM) are generated to respect the dependence on the last time step's value. Hereby, the data is categorised into month, hourly sum of global irradiance (divided into classes of 100 Wh/m²) and trend of global irradiance (equal, positive, or negative). Irradiance of 0 Wh/m² forms its own class. For the maximum global irradiance of 1,200 Wh/m², this results in 468 different TPM.

For the generation of synthetic ambient temperature data, the start temperature is set to a random number. The month as well as sum and trend of global irradiance determine the corresponding TPM to generate the probabilistic temperature of the time step. Finally, a moving average over five time steps is used for reducing variability.

In **Figure 4**, the daily profile of the synthetic data is compared to the measured ambient temperatures. The figure shows the typical daily temperature curve and stochastic variations.

Regarding the annual profile, which is shown in **Figure 5** as the average of seven years, it is obvious that the generated data represents the seasonality of the measured data. For this location, the annual average of the measured data is 21.5 °C, whereas the simulated annual average is 21 °C. Because of the moving average over five time steps, the range of the synthetic data is less than the range of the measured data. The minimum measured temperature is 10.9 °C and the simulated minimum is 11.7 °C. The maximum measured temperature is 41.3 °C and the maximum of the synthetic data is 36.7 °C.

However, the comparison with the results of other approaches presented above underlines the high quality of the generated data and the usability of this method.

2.3 Wind speed

An overview of some of the common methods to generate synthetic wind speed data is given by Feijóo & Villanueva [31]. The approach presented by Sahin & Sen [32] is based on first order Markov-chains. In the work of Shamshad et al. [33], the results of first order and second order Markov-chain approaches are compared. It underlines, that the quality of approaches using first order Markov-chain is sufficient if the seasonal term is removed, for example by several TPM representing different periods of the year.

Considering this, first-order Markov-chains are used for this research approach. The seasonal term is removed by setting up individual TPM for each month. The wind speed data is categorised in classes with a resolution of 0.5 m/s.

Figure 6 compares the daily profiles of generated wind speed data to measured ones for a location on the Canary Islands. The figure illustrates the high fluctuation of wind speed in both time-series.

With regard to the annual time-series shown in **Figure 7**, both the generated and the measured values show higher wind speeds in winter than in summer. This underlines, that the chosen approach with one TPM for each month correctly considers the seasonal fluctuation of the wind speed.

The annual average is 2.48 m/s for the measured data and 2.44 m/s for the synthetic data. The frequency distribution of both time-series shows a comparable Weibull distribution.

3 Methodology of probabilistic distributed energy demand

Besides weather inputs, energy demands must also be considered for the simulation and design of energy systems. In contrast to the weather data, the approach for generating synthetic energy demands is highly dependent upon the individual datasets of the analysed system. In the case of hotels, room occupancy influences the overall demand for energy. Moreover, the cooling energy is determined through the ambient temperature.

In this paper, a destination on the Canary Islands is chosen. The presented algorithms are based on measured data in an existing hotel. The general approach can be transferred to destinations with similar conditions (i.e. no room heating but air conditioning and comparable climate). To improve transferability, the following equations are standardised to the average values. The given values in equation 4-12 are based on measured data and are valid for a four-star hotel on the Canary Islands without a Spa area. These values must be adjusted to the energy consumption of the analysed object.

3.1 Room occupancy

The algorithm for generation of probabilistic room occupancy consists of a seasonal and a stochastic component. This approach provides high quality synthetic room occupancy time-series.

The year is divided into three sections. However, for the middle section representing the summer months June to August, working days and weekend are considered separately, as the behaviour of the measured data dictated this approach. In total, four different sections for room occupancy are generated: season I (January to May), season IIa (working days June to August), season IIb (weekend June to August), and season III (September to December). For each section, algorithms to determine a seasonal/deterministic and a stochastic/probabilistic component are developed. The seasonal component can be described through a trend curve. In the observed case, the seasonal component has a periodic nature, hence Fourier series fit best. To determine the stochastic component, the seasonal component is subtracted from the observed data and the result is described through PDF. At least, upper, and lower bounds for the room occupancy are set.

3.2 Domestic hot water (DHW)

The approach to generate synthetic domestic hot water demand consists of two steps. First, the total demand per day is determined. In a second step, the daily profile is generated from the daily demand.

The daily DHW demand depends on the room occupancy. Measurements suggest that the daily demand of DHW for dormitories per VDI 6002-2 fits the demand of the hotel. Therefore, the daily DHW demand is set between 35 and 50 l per person and day. The average difference in temperature of the fresh water and DHW is 50 K, hence the energy demand is between 4.1 and 5.8 kWh per person per day. Based on these figures a uniformly distributed PDF is generated to set the daily DHW demand.

The daily profile of the DHW demand is described by the mean value and standard derivation of measurements.

3.3 Steam

To generate synthetic steam demand time-series, the week is divided into “no washing days” and “washing days”. For the latter, the steam demand is only weakly fluctuating. The number of “washing days" per week depends very weakly on the room occupancy of the last seven days. It can be estimated by the following equation using a normally distributed random number with }:

(4)

The daily steam consumption on "washing days" can be estimated by the following normal distribution:

(5)

It is suggested that the daily profile of steam consumption is uniformly distributed between 9:00 and 16:00 h.

3.4 Cooling demand

The private and common rooms need to be air-conditioned and therefore require additional cooling energy. The cooling energy is provided by a central compression chilling machine in combination with decentralised fan coil systems. The electricity demand of the compression chilling machine is measured and can be converted into cooling energy by applying the temperature-dependent energy efficiency ratio:

(6)

It can be suggested that the cooling demand depends on the ambient temperature. This weak linear correlation is visualised in Figure 8.

After subtraction of the deterministic temperature component, no further relations and dependences, e.g. to the number of occupied rooms, can be derived from the measured data. Hence, a normally distributed component is added to the deterministic part.

(7)

(8)

(9)

To consider the slight dependence on the room occupancy, the cooling demand is divided into one independent part representing the cooling demand of the common rooms (33 % of total cooling demand) and one dependent part representing the cooling demand of the private rooms (67 % of total cooling demand). The factor F_c describes this behaviour and is the ratio of the occupancy of the day to the average occupancy:

(10)

The following equation then determines the final daily cooling energy demand:

(11)

Finally, a moving average over three periods is performed to remove abnormal high variations between neighbouring periods.

For the generation of a daily profile, two studies are considered in addition to the measured data. In the study of Chung & Park [34], the energy demand of 16 Korean hotels is analysed and a normalised cooling profile is given. The study of Atikol [35] shows similar daily profiles for hotels in Northern Cyprus which is only slightly dependent on the time of day. This is also in accordance with the measured data. Thus, the flat daily profile is adopted.

3.5 Electricity

Furthermore, an algorithm to generate synthetic time-series of the electricity demand of the hotel (excluded electricity demand for the chilling machine) must be developed. The measurement of daily electricity consumption shown in **Figure 9** suggests, that there is no dependence on occupancy. This is due to the the electricity demand of occupancy-independent consumers like lighting, kitchen, or offices.

The daily electricity consumption can be determined by the following equation using a strong normally distributed additional term.

$$\frac{\quad}{\quad} \qquad (12)$$

The daily profile is derived from measured data and is normally distributed whereas the mean value depends on the hour of the day. Due to similarities of neighboured days, a moving average over three periods is applied.

4 Simulation model

The basic set up of the simulation model is shown in **Figure 10**. Besides the different inputs, technical modules are implemented which either describe a technical process or an energy balance.

Hereby the model represents a simplified system configuration of a fictional hotel. The energy need is divided in cooling, heating, steam, and electricity. An electric driven compression chiller with heat recorder delivers the necessary energy for room cooling. The chiller includes heat recovery to deliver also energy for the heating of DHW. Furthermore, solar thermal energy is used to satisfy DHW needs. The DHW is stored in thermal energy storage. If solar water heating and the heat recovery do not produce enough heat to reach the necessary water temperature, a diesel burner is used to supplement. Furthermore, a diesel-powered steam generator provides steam for the in-house laundry service. There is no need for room heating on the Canary Islands. Electricity demand is partly satisfied by photovoltaic systems and wind turbines in combination with a battery to bridge the gap between energy supply and demand with feed into the public grid not possible. If the renewables cannot satisfy the whole electricity demand, the hotel is connected to the public grid, which is fed by electricity from a diesel power plant.

4.1 Compression chiller

The general equation to determine the electricity demand of a compression chiller is described in equation 6. Schlüter [36] describes an approach to determine the temperature depending the energy efficiency ratio (EER) of a compression chiller as a product of a basis EER and different factors describing the dependence on the ambient temperature and a factor for the dependence on the cooling temperature. In the research of Dunkelberg et al. [30], this model is modified by the introduction of a third factor to involve part load performance dependence.

(13)

4.2 Solar collector

The solar thermal system based on the energy balance for collectors expressed in the following equation.

(14)

Hereby, the fluid temperature T_f is the arithmetic middle of the inlet temperature and the outlet temperature T_{out}.

4.3 Heat storage

The modeling of the heat storage follows the multinode approach described in Duffie & Beckman [25]. The multinode approach converts the partial differential equation of the energy balance into a system of ordinary differential equations representing the single nodes. For one node, the temperature does not depend on the location.

The model takes into account temperature layering, heat losses through the storage walls, and convection between neighboured nodes inside the storage. Firstly, the mass flows between neighboured nodes must be determined. On the one side, they depend on the receiving input flow of the heat source and the returning flow of the heat sink (both to a variable node depending on the temperature). On the other side, the output flows to the heat source (from the bottom node) and to the heat sink (from the top node) must be considered. These flows determine the inside heat convection. Free convection due to differences in density is negligible for water storages with high rates of forced convection. Regarding the mass flows, the energy balance of a node i can be expressed by the following equation [25].

(15)

Hereby, F_i^L and are equal to 1, if the receiving mass flow of the heat source or the returning mass flow of the heat sink enter the node i. If not, both are set to zero. represents the net flow inside the node i from the node $i-1$ and $\dot{m}_{m,i+1}$ is the net flow from node i to node $i+1$. The system of ordinary differential equations is solved using the iterative Gauß-Seidel procedure.

4.4 Diesel boiler and steam generator

Both plants are simulated with a constant efficiency. The fuel demand (in kWh) is calculated with the following equation.

(16)

4.5 Photovoltaics

The mathematical description of the photovoltaics system can be found in Duffie & Beckman [25]. The photovoltaic model considers the cell efficiency's dependence on the cell temperature, whereas the cell temperature is a function of the cell efficiency. The solution is found rapidly by iteration starting with $\eta_c = \eta_{cSTC}$.

(17)

(18)

Finally, the electricity generation of the PV generator is the multiplication of the cell efficiency, the PV plant efficiency (set to 85 %), the area and the solar irradiance on the tilted surface.

(19)

4.6 Wind turbine

The wind turbine is simulated using characteristic curves of several wind turbines of different nominal capacities. These characteristic curves show the electricity generation over the wind speed in the hub height. Based on the wind speed of the reference height, the wind speed of the hub height is calculated by the following equation using the Hellmann exponent g depending on the shape of the terrain.

(20)

4.7 Battery

For the storage of electric energy, a simple battery is modelled. This model is characterised by the maximal input and output power, the effective capacity and efficiency for charging and discharging. The capacity is the upper bound for the energy storage. The charging depends on the batteries efficiency; hence the effective power input to the battery is calculated as:

(21)

Furthermore, the following assumptions are made:

- The model does not consider ageing.
- The efficiency for charging considers also the efficiency for discharging, hence no further equation for discharging is needed.
- The storing efficiency of the battery is set to one, hence the model does not consider any self-discharge.

Due to the assumptions, especially not considering ageing, the life cycle costs of the battery can be underestimated, as it is shown in [21]. Nevertheless the battery model is considered to be sufficient for the scope of this research, since the focus is on the assessment of sensitivities of probabilistic inputs.

5 Energy system design

A renewable energy system has to be designed for the case study. The annuity is chosen to determine the economic performance of the configuration. Although previous studies focus on the integration of MCM into the optimisation process, in this work the design is examined by using time series of ten consecutive years. Particle swarm optimisation is used to find the best economic configuration for these ten years.

5.1 Economic performance indicator

The system is optimised to reach best economic performance indicators. In this paper, the economy of the energy system is described through the annuity which is an indicator for the average annual costs over the entire observation period. Thus, one-time costs like investment costs are converted to regular annual cash flows which can be compared to further annual cash flows relating to operation and maintenance, e.g. diesel and electricity costs. The choice of the annuity as the economic performance indicator allows the comparison of investment cost-intensive renewable energies to operation cost-intensive fossil powered systems. The annuity A is the product of the net present value (NPV) and the annuity factor a_i:

(22)

The NPV considers the investment costs C_i and the annual costs for operation and maintenance C :

(23)

The annuity factor is calculated using the inflation-adjusted interest rate , which is calculated using the nominal interest rate i_{nom} and the inflation rate j:

(24)

(25)

As shown in equation 23, the NPV includes the energy costs for operation. The costs for diesel are set to 0.10 €/kWh and the costs for electricity are set to 0.29 €/kWh. The last value represents the LCOE of a diesel power plant on the Canary island (i.e. the costs without any subsidy) [37,38]. The inflation rate is set to 2 % and the nominal interest rate is set to 3 %, both will be varied statically by a sensitivity analyses. The investment costs and the costs for maintenance depend on the installed capacity. In this research a linear correlation for the PV generator, the wind turbine (WT), and the battery is assumed following Blechinger et al. [6]. To determine the costs of the compression chiller (CCM), the thermal water storage (TWS), the DHW heater (H-DHW), and the steam generator (SG), empirical cost functions according to Gebhardt et al. [39] are used. The costs of the solar water heating system (SWH) are calculated using the function presented in Taibi et al. [3]. An overview of the used functions is listed in the following table.

5.2 Particle swarm optimisation

The energy system's configuration is calculated by a particle swarm optimisation (PSO) The PSO approach, introduced in 1995 by Kennedy & Eberhart [40], follows animal's swarm behaviour e.g. birds or fish. Basically, in each iteration step for each particle's position a fitness (in this case determined by the annuity) is calculated. This value is compared to the best fitness of previous particle positions p_i^t and the fitness of the global best position . If the present fitness is better, the positions will be adjusted. Using the unified random numbers r_1 and r_2 (∈]) as well as the cognitive and social parameters c_1 and c_2 and the present velocity the parameter's velocity for the next iteration step v_i^{t+1} is calculated as:

(26)

In addition to the basic equation, the constriction factor χ, introduced by Clerc in 1999 [41], is used. Hereby, the constriction factor is a function of the sum of the social and cognitive parameters:

(27)

The particle's position is then adjusted using the following equation:

(28)

The PSO approach is visualised in **Figure 11**. The PSO in this research uses 20 particles and 100 iterations. The cognitive and social parameters are set to 2.05 each, so the constriction factor is calculated to 0.729. In total, eleven parameters are varied. The step for changing surface areas of the PV plant and the solar collector is set to at least 1 m². The lower bound for both areas is 0 m², an upper limit is not set. The orientation of both plants is also optimised using the minimum step of 1° for both, azimuths and slops. The lower and upper bounds for the slopes are 0° and 90° while the bounds for the azimuths are -180° and 180°. Furthermore the nominal electric power of the chilling machine is varied in at least 1 kW steps from 370 kW on. An upper bound is not set. The size of the battery is optimised in at least 10 kWh steps. The ratio between loading power and capacity is set to 1. The lower bound is 0 kWh, an upper bound is not used. Regarding the wind turbines, none, one or two plants can be considered. The height and the characteristic curve of the wind turbine depend on the nominal size. For each plant, the nominal power can be 55, 80, 500, 800, 2,000 or 3,050 kW.

6 Discussion of the results

An example simulation is done for a hotel on a Canary Island. The Canary Islands are located off the coast of Morocco and Western Sahara. The Spanish archipelago with subtropical climate consists of seven main islands. The eastern islands are flat while a mountainous landscape characterises the western islands. The topography of the islands and the moist north east trade winds lead to several distinct microclimates on each island. In general, the north of each island is characterised by higher humidity while the south is dry. Average wind speeds in the south are lower than in the eastern and western parts of the islands. An assessment of the PV potential for the Canary Islands is given by Schallenberg-Rodríguez [42], and the on-shore wind potential is evaluated by Schallenberg-Rodríguez and Notario-del Pino [44]. A 100 % renewable energy supply for this archipelago is simulated and presented by Gils and Simon [43].

The location chosen for this case study is situated on the southern coast of an island. Hence, global irradiation is high over the entire year while wind speeds are low and very seasonal. The presented approach considers the climate characterisations of the chosen destination. Nevertheless, the overall approach is transferable to other locations.

To design the configuration and to size storages, the system is simulated with the data of ten different years. Hence, differences within weather and occupancy are considered. Apart from the average energy consumption, the annuity is calculated. An overview of the components and their optimised size can be found in **Table 2**.

To satisfy the electricity demand, a photovoltaic system of 1,525 kW and a wind turbine of 800 kW are installed. Furthermore, a battery of 2,575 kWh helps to compensate daily weather and demand fluctuations. The minimum power to satisfy the maximum cooling needs is 370 kW. Because of the higher efficiency of the chiller in partial load, the optimal dimensioning is 570 kW. In this case, the higher investment is overcompensated through the lower electricity consumption due to the longer operational time in the more efficient power ratio. Regarding heat recovery system (HRS), the size of the solar thermal system is 190 kW with a water storage of 13,400 litres. The size of the diesel boiler used as an auxiliary heater is 215 kW and the steam generator is 355 kW.

The energy demand and the annuity of the designed system are shown in **Figure 12**.

The main part of final energy consumption is the electricity demand for lighting, pumps, offices, kitchen, and entertainment. Together with the electricity used for cooling, 75 % of the hotel's final energy consumption is electricity. If the different primary energy factors for diesel and electricity are considered, the primary energy share of electricity is even higher. Using the chosen energy system configuration, 63 % of the electricity demand can be supplied by renewable energies. Due to the high solar radiation throughout the whole year, the average energy generation with photovoltaic is 1,769 MWh per year. This is 67 % of the total renewable electricity generated. The photovoltaic system achieves a LCOE of 0.115 €/kWh, which is comparable with previous findings [7,38,42]. The other 33 % (or 878 MWh per year) is generated by the wind turbine, which reaches LCOE of 0.160 €/kWh. This value is higher than the marginal costs for wind energy on the Canary Islands [44], because the location in the south of the island is not best suited for wind generation. This also impacts the share of PV and wind to the overall energy supply. The cost of the battery increases the price for a renewably generated kWh to 0.238 €/kWh. According to the total share of consumed renewable electricity of 63 %, this results into effective electricity costs of 0.259 €/kWh for the hotel. The diesel consumption is mainly a result of the steam demand. This means, 16 % of the final energy is used to supply steam to the laundry service. Solar water heating and the heat recovery of the compression chiller can supply 78 % of the DHW demand.

The annuity of the designed system is 934,063 € per year. The structure and the values of annuity underline the high investment costs of renewable energy systems. These costs accumulate to the highest share which can be split into 22 % for photovoltaic, 15 % for the wind turbine, 11 % for the battery and 3 % for the other investments. Furthermore, the distribution of the annuity reflects the higher electricity cost compared to the diesel price. In total, the electricity supplied from the grid amounts to 40 % of the costs. Other costs include solar water heating system, compression chiller and diesel burner. Regarding the battery and previous findings in the work of Dufo-López et al. [21], the costs can be underestimated since the battery model does not consider any ageing.

To analyse the sensitivity of the designed system 1,000 different years are simulated. Although some approaches use stopping criteria to determine the number of simulations, in this paper the Monte Carlo simulation was carried out with a fixed number of runs. To distinguish the different influences of weather and occupancy three cases are defined:

1. Only weather varies (Won)
2. Only occupancy varies (Oon)
3. Weather and occupancy varies (WaO)

The following figure shows the frequency distribution of the annuity.

All values of the 1,000 simulated years are normally distributed in a 3σ-interval. This underlines, that the chosen number of runs is sufficient to cover the whole range of possibilities. The 2σ-interval contains 95.5 % of all values with a tolerance of $\pm$ 2.4 %. The Monte Carlo simulation shows that the mean annuities of the system configuration are 940,790 €/a for the case Won, 944,430 €/a for the case Oon, and 940,510 €/a for the case WaO. The sensitivity caused by differences in the occupancy (case Oon; SD=3,821 €) is about one third of the sensitivity depending on the weather (case Won; SD=10,118 €). There is no significant difference in the results of varying weather and occupancy at the same time (case WaO) and only varying weather (Won). The analysis shows that probabilistic weather conditions have a higher impact on the economy of a renewable energy system for hotels than the hotel itself. On the other hand, the results also show that considering both varying weather and occupation conditions does not lead to uncertainties equal to the sum of the uncertainties of the single parameter sets.

Regarding the design of renewable energy systems, the Monte Carlo method has two advantages. On the one hand, the approach visualised the risk during the design of the configuration. If a system with a similar share of renewable energy is dimensioned using a reference year, the resulting annuity will be within the shown distribution. Based on the 2σ-interval and a probability of 95.5 %, the deviation between the result of a reference year and another year can be up to $\pm$ 4.8 %. Using ten consecutive years to design the configuration covers sufficiently probabilistic fluctuations and minimises the economic risk. In the simulated case, the design process leads to an underestimation of 0.7 % (Won, WaO) respectively 1.1 % (Oon) of the mean annuity. These findings are in accordance with findings of previous studies which integrate MCM in the optimisation process [18,20–23].

On the other hand, the results shown in **Figure 13** stress the cost effectiveness of such a system during its operation. The highest annual difference of the annuity caused by varying weather and occupancy conditions will lead to differences of -37,810 €/a or +35,490 €/a since fluctuating weather and occupancy conditions always cause an annual amount of uncertainty. Hereby, the advantage of the Monte Carlo method is to define the mean annuity and the stochastic fluctuation risk more accurate and thus enable a characterisation of the system's economic stability.

To get a better understanding of this uncertainty, the results are compared to a variation of different economic parameters by a margin of 20 %. It is worth to note, that as opposed to variations in weather and occupancy conditions differences of investment costs occur only once during the design process and not continuously during the operation. The analysis shown in **Figure 14** underlines the different effects on the annuity.

The biggest influence on the annuity is observed by varying the cost for electricity from the grid. Moreover, it is obvious that investment costs of photovoltaic and inflation rate have a big impact, too. The cost influence of the wind turbine and the battery as well as diesel price and interest rate on the annuity is approximately half the impact of the PV investment costs. In general, the weather fluctuations have roughly the same influence on the annuity as varying a relevant economic parameter by about 20 %. The influence of the weather data is higher than both, the influence of investment costs of the wind turbine and the price-increase rate of diesel fuel. This underlines the importance of investigations with correct prices as well as the influence of unpredictable weather conditions.

7 Conclusion and Outlook

In this paper, different MCM approaches are proposed to generate synthetic weather, occupancy, and load data for hotels. The algorithms are based on measured data. The validation compares simulated data with measured data and shows sufficient accuracy in the results. For the different influencing factors, the presented methodology considers seasonal as well as probabilistic components. A simulation model for the simulation of renewable energy systems and analysis of economic KPIs in different system configurations is introduced. The model includes the following components: photovoltaic, wind turbine, battery, solar water heating, compression chiller and diesel burner.

To evaluate the influence of probabilistic inputs to a renewable energy system of a hotel, a case study for the Canary Islands is examined. Based on a time series of ten consecutive years, particle swarm optimisation is used to design the energy system configuration. For this time series, an economic optimum for the hotel is found if renewable energies cover 63 % of the electricity demand. Furthermore, 78 % of DHW consumption is provided by the solar water heating system and the chiller heat recovery. In total, only 46 % of the final energy demand of the hotel is satisfied through fossil fuels. These results support former researches on the high potential of renewable energies in island regions. The composition of solar radiation and wind speeds determines the best technology mix. For the case study, an optimum is defined with 1,525 kW from photovoltaic and 800 kW from wind turbine. Photovoltaic achieves LCOE of 0.115 €/kWh and the wind turbine reaches LOCE of 0.160 €/kWh. Taking the implementation of a battery into account, electricity costs 0.238 €/kWh for each consumed kWh.

In general, the investment in renewable energies results in 17 % less total energy costs. Without renewable energies, the LCOE depends mainly on the electricity price which accounts for over 90 % of total energy costs. For the optimal solution including renewable energies, the share of electricity price decreases to about 40 %. For this scenario, the LCOE is dominated by the investment costs of

RES. These costs make up 51 % of the total costs. With regard to the fluctuating nature of weather and occupancy, the economic stability of the energy system is evaluated through Monte Carlo simulation.

The variation of an economic parameter of about 20 % results in the same sensitivity as differences caused by weather fluctuations with a 95.5 % probability. In opposite to annual changing weather and occupancy influences, most economic parameters influence the system only during the design process and not during its operation. Furthermore, the results show that the sensitivity to occupancy is about one third of the sensitivity to weather. This underlines, that the influence of varying weather conditions on the energy system of the hotel is higher than varying energy needs due to differences in occupancy. Regarding the design process, the MCM approach helps to determine the mean and the standard deviation precisely. Hence, the system design based on a reference year can cause variations of $\pm$ 4.8 % because of different weather conditions.

The presented approach enables the generation of synthetic load profiles with high temporal resolution. The methodology is transferable to other destinations and buildings if location-specific values are adjusted. Most notably, the approach to generate probabilistic distributed load data highly depends on the local building. In order to generate more accurate cooling load series, more detailed data is needed. Further work should test the approach for generating synthetic load data for hotels for further destination. Nevertheless, the results show that the economy of an energy system of a hotel depends more on weather data than on load or occupancy data.

8 References

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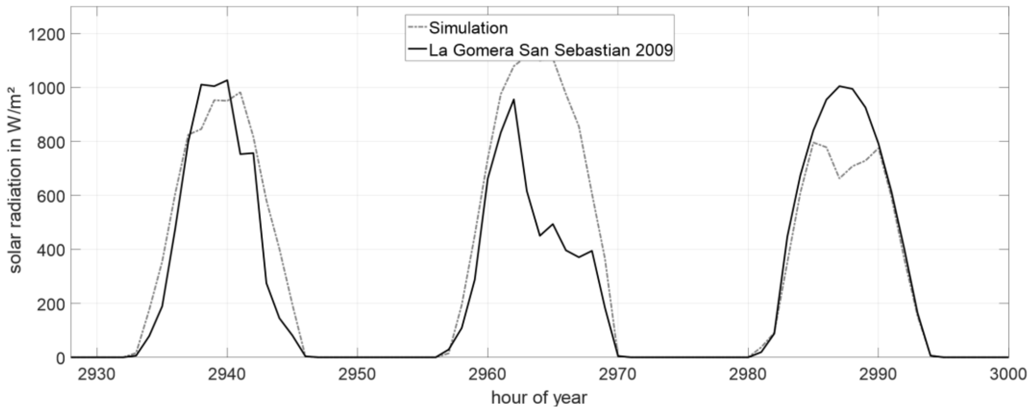


Figure 1: Comparison of the daily profiles of measured and generated solar irradiance of three days for Canary Islands

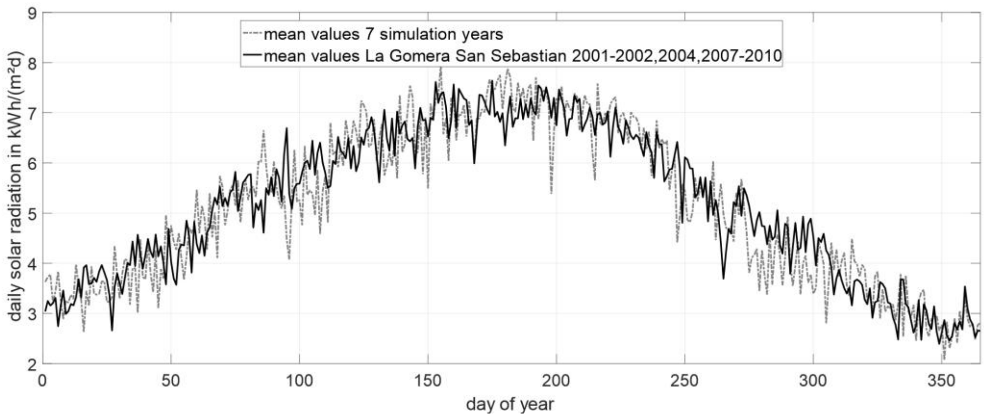


Figure 2: Comparison of the annual profiles of measured and generated solar irradiance for seven years for the Canary Islands

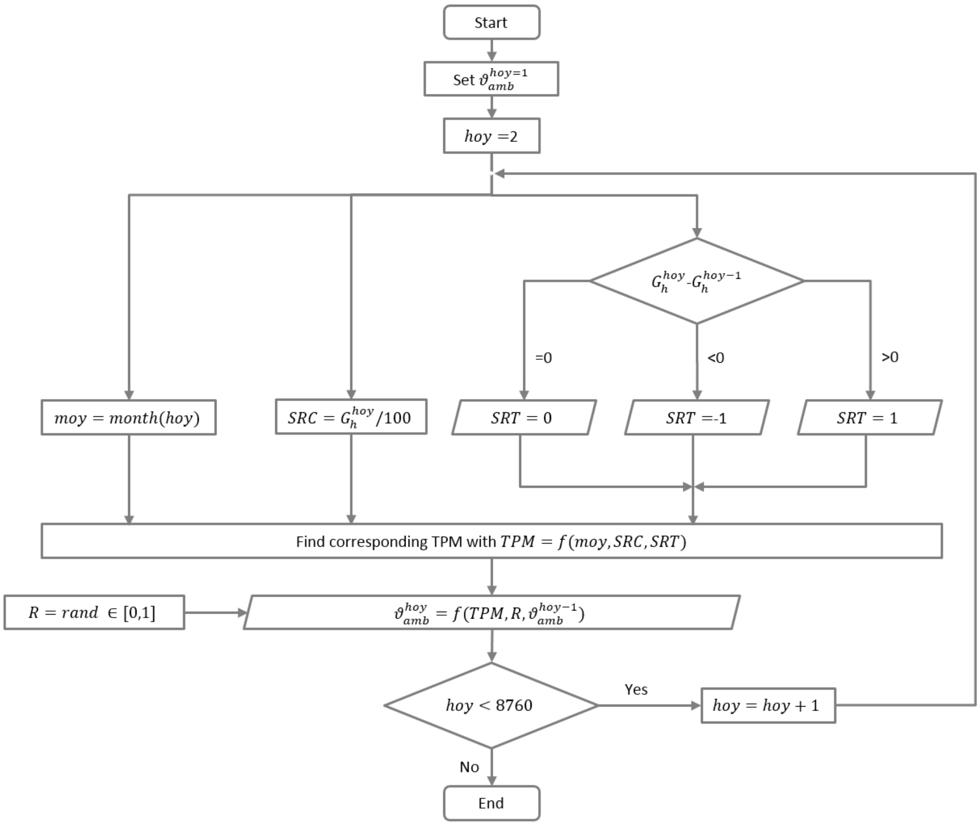


Figure 3: Flow chart for generating synthetic ambient temperature time series

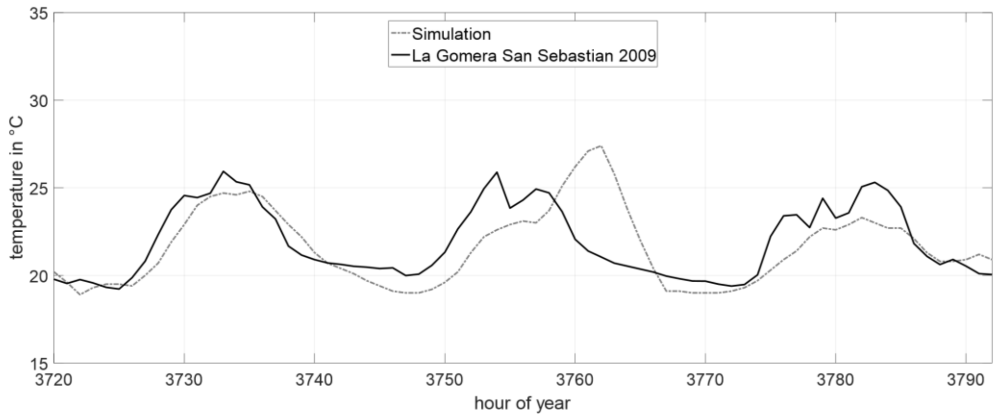


Figure 4: Comparison of the daily profiles of measured and generated ambient temperature of three days for Canary Islands

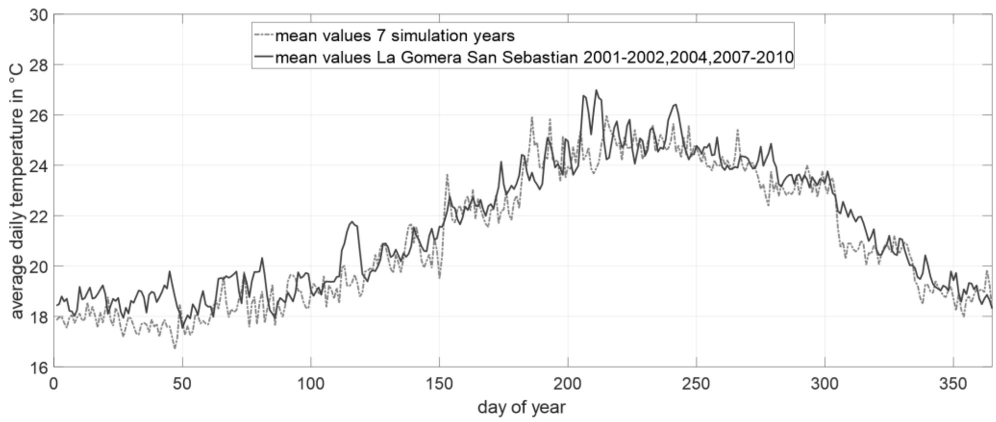


Figure 5: Comparison of the annual profiles of measured and generated ambient temperature for seven years for the Canary Islands

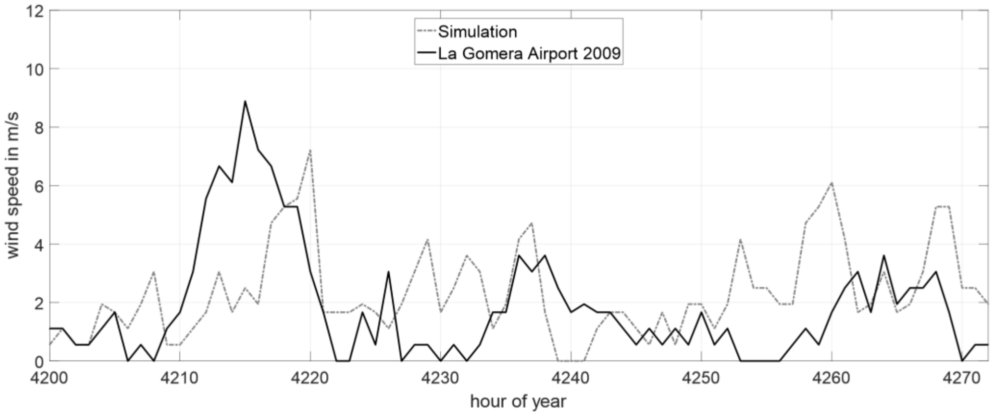


Figure 6: Comparison of the daily profiles of measured and generated wind speed of three days for the Canary Islands

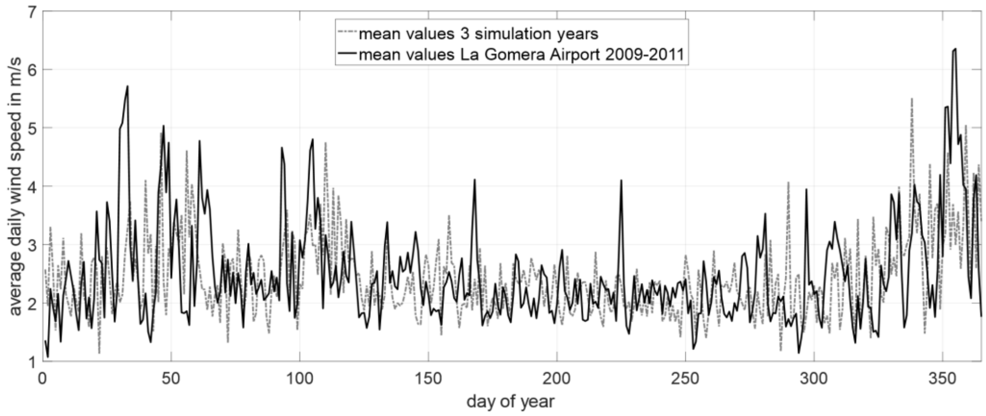


Figure 7: Comparison of the annual profiles of measured and generated wind speed for three years for the Canary Islands

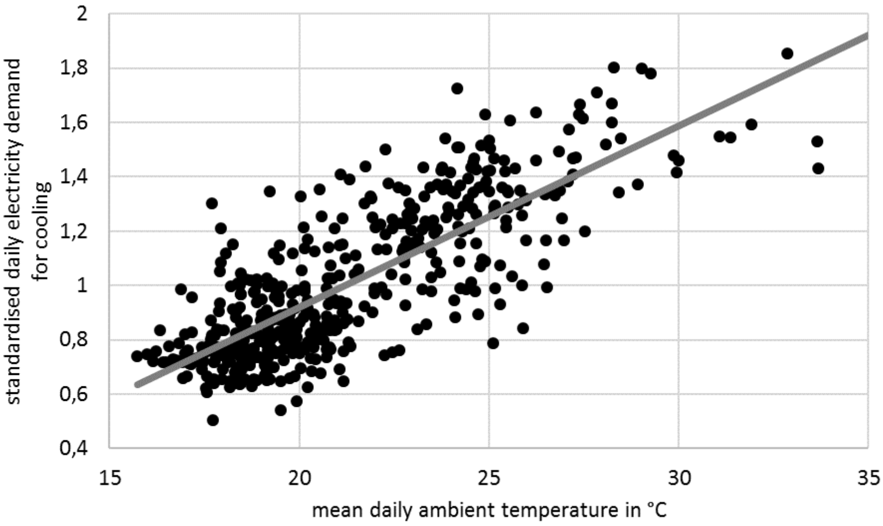
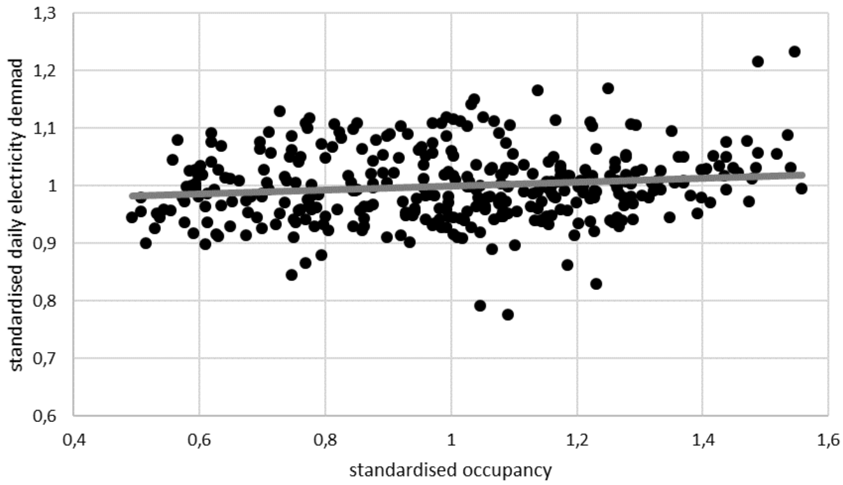


Figure 8: Relation among daily the standardised cooling demand and ambient temperature, measured data of 1.5 years



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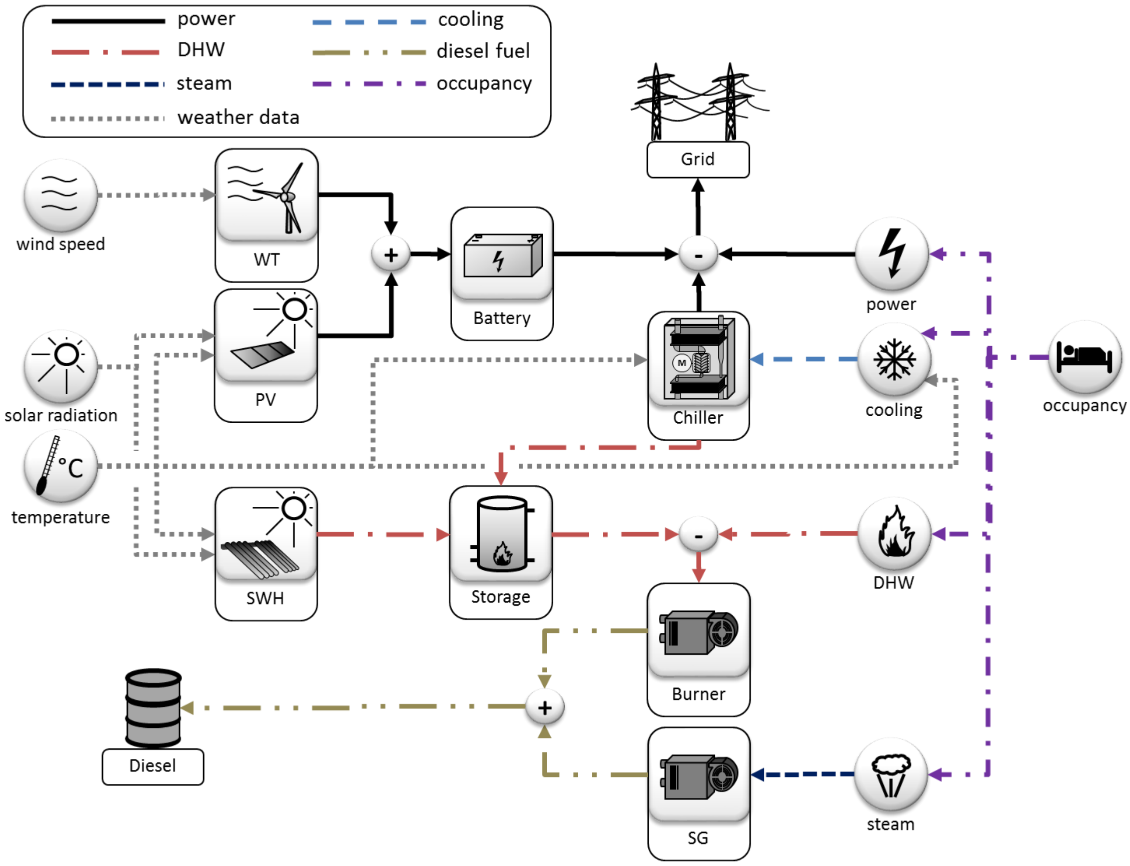

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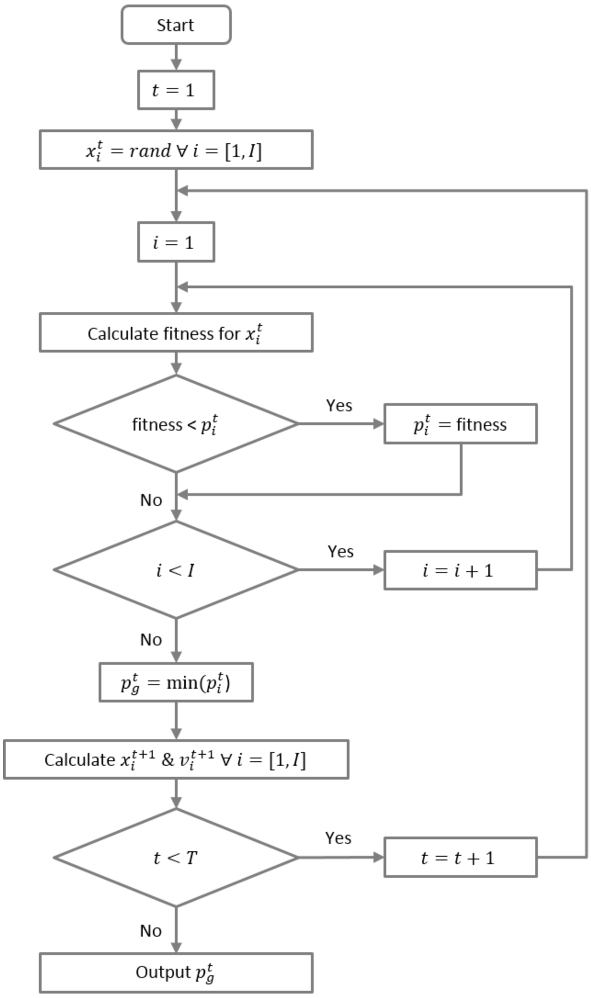

Figure 11: flow chart PSO approach

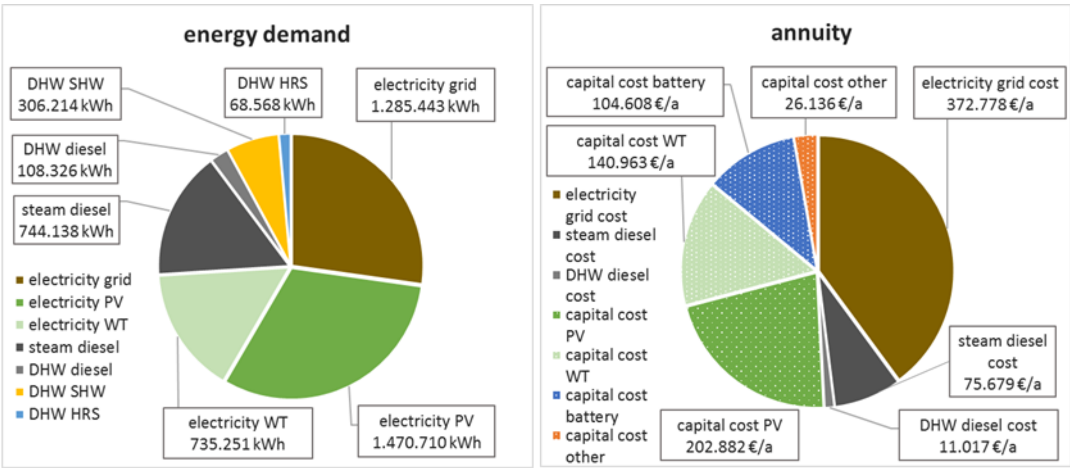

Figure 12: end energy demand (left) and annuity (right) of optimal solution

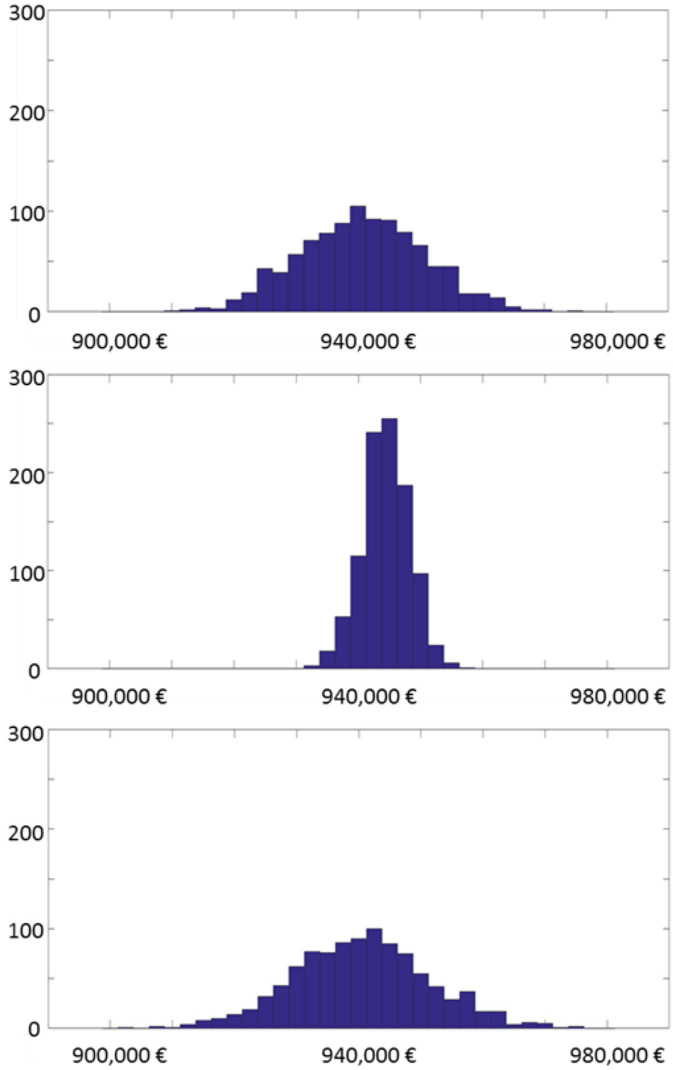

Figure 13: Frequency distribution of annuity; top Won, centre: Oon, bottom: WaO

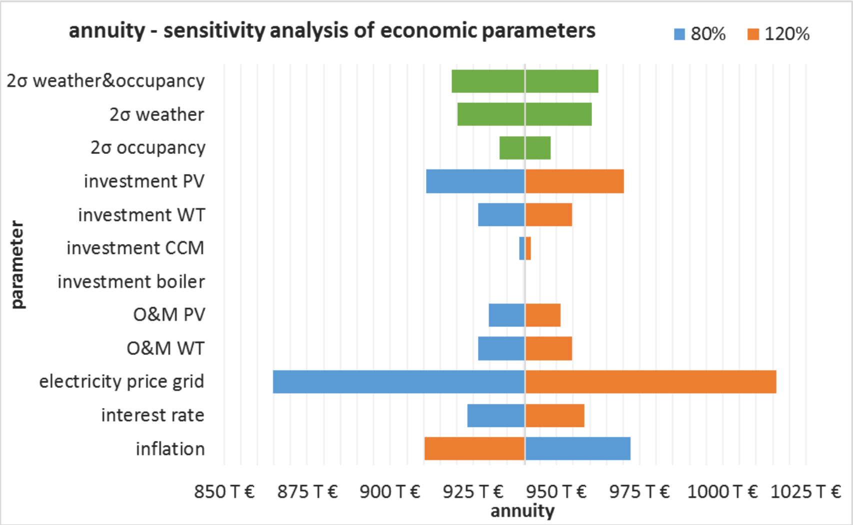

Figure 14: Analysis of sensitivity of different economic parameter (± 20 %)

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Table 1: Overview of investment costs C_i in € and annual maintanace costs in €/a; $\dot{Q}$ is the nominal heat flow in kW, P is the nominal electrical power in kW, A is the area in m², V is the volume in l

Plant	Investment costs	Maintenance costs
PV		
WT		
Battery		
CCM		
SWH		
TWS		-
H-DHW		
SG		

Table 2: Results of optimisation for ten consecutive years; design of energy system

Plant	Size
Photovoltaics	1,525 kW
Wind turbine	800 kW
Battery	2,575 kWh
Compression chiller	570 kW
Solar water heating	190 kW
Thermal storage	13,400 l
Burner domestic hot water	215 kW
Steam generator laundry	355 kW

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Abstract: This paper investigates the use of renewable energies to supply hotels in island regions. The aim is to evaluate the effect of weather and occupancy fluctuations on the sensitivity of investment criteria. The sensitivity of the chosen energy system is examined using a Monte Carlo simulation considering stochastic weather data, occupancy rates and energy needs. For this purpose, algorithms based on measured data are developed and applied to a case study on the Canary Islands.
The results underline that electricity use in hotels is by far the largest contributor to their overall energy cost. For the invested hotel on the Canary Islands, the optimal share of renewable electricity generation is found to be 63 %, split into 67 % photovoltaic and 33 % wind power. Furthermore, a battery is used to balance the differences between day and night. It is found, that the results are sensitive to weather fluctuations as well as economic parameters to about the same degree. The results underline the risk caused by using reference time series for designing energy systems. The Monte Carlo method helps to define the mean of the annuity more precisely and to rate the risk of fluctuating weather and occupancy better.