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On the impact of probabilistic weather data on the economically optimal design of renewable energy systems – a case study of La Gomera island

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ABSTRACT

Renewable energy and storage systems are widely discussed to minimise the impact of global warming. This study analyses the impact of probabilistic weather data on the design of renewable energy systems. The main objective is hereby the determination of the robustness of a recently state-of-the-art design process of a 100% renewable energy and storage system with varying probabilistic input data. The island of La Gomera, Canary Islands, is taken as a case study and simulated with EnergyPLAN for different probabilistic input time-series. Although all analysed systems show some variance in their annual economic and energetic results. The combination of vehicle-to-grid and power-to-hydrogen shows the best economic performance. Hereby, small island energy systems depending heavily on wind energy show higher variations than those with high shares of solar energy. This analysis illustrates clearly that the choice of one historical reference year is not suitable to determine the expected performance of an energy system. To learn about their sensitivity, synthetic probabilistic inputs as applied in this study are a good way to determine both the expected mean values and their variance.

Keywords:

100% renewable energy;
Small islands;
Smart energy system;
Canary Islands;
Probabilistic time-series

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1. Introduction

Renewable energy and storage systems are widely discussed to minimise the impact of global warming. In this context, special attention is put on islands (for further information see [1,2]). On the one hand, islands are particularly vulnerable regions that suffer from the effects of global warming and climate change. On the other hand, they are often analysed as blueprints and testbeds for technical solutions because of their isolation and the possibilities associated with this to evaluate the energetic and economic effects (for further information see [2–5]). To meet the fluctuating generation of renewable energy systems such as wind turbines and solar photovoltaics (PV), the utilisation of energy storage technologies is indispensable. In this context, Lund et al. [6] show that the utilisation of all kinds of energy storage technologies and the understanding of a smart energy system on the whole including sector coupling have several advantages compared to a single focus on electricity systems and electricity storage technologies.

Recently, especially energy storage systems have been implemented and tested on islands. Well known and widely discussed examples are the Canary Island of El Hierro (for further information see [7–9]), the Azores island of Graciosa (for further information see [10,11]), the German island of Pellworm (for further information see [12]) and the Danish island Samsø (for further information see [13–15]). Furthermore, many scientific studies analyse the energy systems of several islands and archipelagos. The impact of electric vehicles on the

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overall energy system is discussed for the Åland islands in [16]. The authors conclude that battery electric vehicles are a key pillar for a 100% renewable energy system on these islands. An economically optimal design of a carbon neutral energy systems for the whole archipelago of the Canary Islands is analysed in [17] with focus on the interconnection of the islands. The results underline that a carbon neutral energy system is possible through sector coupling and extension of the transmission grid. A more detailed analysis of one particular interconnection between Tenerife and La Gomera is analysed in [18]. Here, the authors only consider the electricity system and determined that the interconnection of these islands leads to the lowest levelized cost of electricity. In addition, some studies also focus on large islands and entire island states such as Ireland in [19]. Blechinger et al. [5] and Meschede et al. [20] conducted global assessments of renewable energy systems on islands while further overviews of island specific studies are summarised in [21] and [22].

Regarding the scientific literature on energy system simulation, a lot of research analyses the temporal resolution. Commonly, one-hour resolution is seen as a good compromise between computational efforts and accuracy [23–26]. Nevertheless, smaller time steps than one hour show more accurate results in the field of short but high load peaks, which affect mainly grid stability [25]. In addition to the temporal resolution, also the chosen input data might have a strong impact on the performance of renewable energy systems, and energy storage systems in particular. Especially for smaller grids, such as those found on islands, high fluctuations in both the energy demand and energy supply time-series can be observed. These result in more unbalanced systems and influence the utilisation of and requirements for energy storage. Furthermore, as for example addressed by Østergaard et al. [27] for the Danish electricity sector, energy demand depends on the day of the week while weather data does not. Furthermore, Meschede et al. [28] analysed the different occupancies of a touristic facility and determined that, especially in summer, weekends and weekdays are highly different for the case of La Gomera. Therefore, fixed time-series of both energy demand and weather do not reflect all possible combinations within one dataset. Thus, the representation of further, probabilistic variances is missing. The uncertainty of the performance might further influence the economic risk of renewable energy systems as shown for a small hydro-plant in [29].

Due to this, the utilisation of synthetic, probabilistic input data that can reflect a wide variance of possible situations in combination with principles of Monte Carlo simulations are discussed in a few scientific articles. Arriagada et al. [30] discuss Monte Carlo methods for analysing the influence of probabilistic wind, solar and energy demand on an energy system in Northern Chile. Also, Dufo-López et al. [31] use probabilistic time-series to optimise off-grid energy systems. In their first work the energy supply for a hospital in Congo is optimised [31], and the second paper deals with a stochastic-heuristic methodology to optimise the size of components and the system control [32]. Dunkelberg et al. [33] show an approach to generate probabilistic time-series of industrial processes and, based on this discussion, the design of decentralised energy systems in the plastic processing industry. Meschede et al. [28] present a methodology to generate synthetic time-series of the energy demand of a hotel and use this as inputs to evaluate the robustness of a decentralised energy system for a hotel. In another study, Meschede [34] reflects on the impact of probabilistic weather data on the electric demand shifting potential of a water system on a small island. In all cases, the energy systems show high shares of renewables with fossil fuel driven auxiliaries.

Regarding this review it is shown that many studies analyse the energy transition on islands. Moreover, the topic of the temporal resolution of energy system simulation is widely discussed. Although some studies reflect the impact of probabilistic time-series on renewable energy systems for various applications, there is still a gap of knowledge to analyse the impact of these stochastic energy demand and weather data on the energy transition of medium sized islands. With regard to this, the presented paper analyses the impact of probabilistic weather data on the design of renewable energy systems. The main objective is hereby the determination of the robustness of a recently state-of-the-art design process of a 100% renewable energy and storage system with varying probabilistic input data. The island of La Gomera is taken as a case study. An earlier published study on hypothetical future energy system designs for La Gomera presented in [35] is the baseline. From this, the most promising three scenarios are analysed: vehicle-to-grid, hydrogen-based transport and a combination of both. While in the baseline study only one set of input time-series of one reference year was used, the current paper goes further by analysing the impact of probabilistic inputs on the result. Furthermore, the research compares the designs of a reference and a standard year to the results gained by using probabilistic years. In this context, a reference year is based on one specific historical year while a standard year is an average year built on observations of several historical years. The widely used tool EnergyPLAN is used to simulate the system.

2. Methodology

In this section both, the simulation tool EnergyPLAN as well as the chosen case study and the simulated scenarios are presented.

2.1. Simulation tool EnergyPLAN

To evaluate energy systems and 100% renewable energy systems in particular, simulation tools are indispensable to consider the different inputs and plants. Lund et al. [36] discuss various tools and classify them either as optimisation or simulation tools. Hereby, optimisation tools such as Homer have internal algorithms that minimise or maximise an objective function and hence the energy system design (i.e. plant size and capacities). In contrast, simulation tools such as EnergyPLAN allow the user to define the energy system design and thus these tools allow the mapping of different energy transition paths and scenarios [36]. Overviews of different tools, their advantages and case studies can be found in [36,37].

For this study EnergyPLAN is used for annual simulation of the energy system since this work is based on the previous energy systems presented in [35]. EnergyPLAN has been developing since 1999 at Aalborg University in Denmark and is widely used in scientific projects to simulate energy systems on national and regional scales. In this work version 12.5 of the tool and the MATLAB toolbox for EnergyPLAN version 1 are used.

In a nutshell, in EnergyPLAN different technologies can be considered to satisfy all thermal and electric energy demands (electricity, heat and transport sectors). Energy demand and weather are determined by hourly time-series for one year. Moreover, different energy storage options can be used to balance the energy system. Furthermore, EnergyPLAN offers the possibility to define energy imports and exports to and from the system. Detailed information on EnergyPLAN can be found in [38].

2.2. Case study and simulated scenarios

To analyse the impact of probabilistic input data on the energy system design, the island of La Gomera is chosen as a case study. La Gomera belongs to the Spanish Canary Islands located in the Atlantic Ocean approx. 100 km west of the Moroccan coast. The archipelago consists of seven main islands, of which La Gomera is the second smallest. The population of this island is approx. 22,000 inhabitants while its annual electricity demand in 2016 was 71.63 GWh [39]. The demanded electricity is generated in a central diesel power plant of 22.9 MW installed capacity. Furthermore, 9.4 GWh of fossil gas and 14.41 GWh fossil oil are used for cooking and heating. For the latter, decentral heating with small units is realised. District heating is not installed. For mobility 3,817 tons of diesel and 3,311 tons of petrol were used in 2014 [40].

Regarding possible future energy systems three different designs are analysed within this study:

1. Scenario 2030-H2
2. Scenario 2030-V2G
3. Scenario 2030-Combi

The scenario 2030-H2 analyses power-to-hydrogen technology to store surplus renewable energy. Hydrogen is used in both combined heat and power plants and in the mobility sector. Within this scenario, wind is the main renewable energy source to cover electricity demand. In addition to that, the scenario 2030-V2G focusses on the utilisation of battery electric vehicles (BEV) as the main storage solution for variable renewable energy supply. In contrast to the scenario 2030-H2, solar PV is the main source for electricity. Finally, the scenario 2030-Combi combines both aspects, i.e. power-to-hydrogen as well as vehicle-to-grid (V2G) participation. In this scenario, solar PV is the main source. Moreover, the installed capacities of all renewable energy sources are the highest for all three scenarios.

Summarised, all scenarios reduce the utilisation of fossil fuels to zero, hence only 100% renewable energy scenarios are simulated. In all three scenarios demand shifting is allowed. Regarding the consideration of demand side management, the assessment of the demand shifting potential in [34] visualises the limitations of the utilisation of fixed rates as the rate depends on the demand and weather data. In this study a mean value is therefore used. The scenarios and the determination of the plant's nominal capacities were based on the work done in [35]. Moreover, the same cost assumptions as presented there are applied in this study. They are summarised in Table *1*.

Table 1: Cost assumptions for 2030 (taken from [35])

	Capex	Opex	Lifetime
Wind turbines	1300 €/kW$_{el}$	2.5 of Capex/a	25 years
Photovoltaics	700 €/kW$_p$	1% of Capex/a	30 years
Combustion power plants	900 €/kW$_{el}$	1% of Capex/a	25 years
Electricity storage	150 €/kWh$_{Cap}$	5% of Capex/a	10 years
Hydrogen storage	200 €/kWh$_{Cap}$	0.5% of Capex/a	50 years

Table 2: Installed capacities in all scenarios

	2030-V2G	2030-H2	2030-Combi
PV capacity in MW	52.5	37.5	62.5
Wind capacity in MW	12	20	12
Combustion engine (biofuel) capacity in MW	22.9	22.9	22.9
Stationary battery capacity in MWh	–	13	-
V2G storage capacity in MWh	197.1	–	197.1
Electrolyser capacity in MW	–	11.5	3.86
hydrogen storage capacity in MWh	–	35	5

An overview of the technical aspects of all scenarios can be found in Table *2*. Hereby, the installed capacities represent the values observed for the minimum annualised energy cost in each scenario according to the analysis done in [35].

3. Data

Tools such as EnergyPLAN simulate energy systems for one specific year. Thereby, input time-series of various data characterise these systems. These inputs include time-series of, for example, power consumption, weather data or consumer behaviour. In the case of EnergyPLAN, the conversion of weather data to generated power is not possible within the tool. Indeed, EnergyPLAN needs time-series of generated power instead of weather data. Due to this, for PV and wind turbines weather time-series like wind speed have to be converted into generated power in a pre-processing step using suitable simulation tools.

For this paper, the pre-processing is realised with simulation models in MATLAB/Simulink presented in [28]. The generated power of a PV plant is the product of the cell efficiency, the plant efficiency, the area and the irradiance.

$$PPV = \eta_{cell} * \eta_{plant} * A * I \tag{1}$$

The generated power of a wind turbine is simulated using a characteristic curve of the Enercon E-70 wind turbine with a nominal power of 2 MW [41]. Therefore, the wind speed at hub height is needed which is calculated using the Hellmann exponent g and an exponential extrapolation.

$$v_H = v_{ref} * \left(\frac{H}{H_{ref}}\right)^g \tag{2}$$

Often historical data of one specific year is used. Nevertheless, this year cannot reflect all aspects and characteristics of the system. In this study three different reference years regarding input time-series for electricity demand and solar radiation as well as temperature are analysed, and the results are compared. In total, the years 2013, 2015, and 2016 are used. The load data is provided by [39], its temporal resolution is 10 minutes. Half-hourly solar irradiance and temperature time-series are provided by [42]. All other inputs (i.e. heat demand, wind power, traffic and water demand) are based on synthetic approaches and hence are not varied. This is especially true for the used wind data. Since the generated wind power is simulated with synthetic data, the identical time-series is used in all reference year scenarios. Some characteristics of the chosen years are summarised in Table 3.

Table 3: Characteristics of reference years

	2013	2015	2016
Annual electricity demand in GWh	67.57	68.31	71.63
Peak electrical load in MW	12.1	12.4	12.2
Annual solar irradiation in kWh/m²	1954.6	1982.0	1988.8
Average wind speed at 60 m in m/s	6.66	6.66	6.66
Mean ambient temperature in °C	21.3	21.3	21.4

EnergyPLAN uses hourly time-series, hence the simulated power data have to be compressed. To do so, three different methods to reduce the data resolutions are applied. These methods are:

- Mean: The mean value of all observations within a certain hour is used.
- Max: The maximum value of all observations within a certain hour is used.
- Min: The minimum value of all observations within a certain hour is used.

In addition to different historical reference years, an infinite number of further probabilistic reference years exists. Hereby, "standard" years occur more often than extreme years. One aim of this paper is a sensitivity analysis of the design based on one historical reference year and its comparison to probabilistic years. Regarding this objective the generation of synthetic input data based on probability is crucial for the analysis. Based on previous studies with similar intentions the following time-series are seen as most critical:

- Wind speed
- Solar irradiance
- Traffic volume

The approaches to generate probabilistic solar irradiance and wind speed profiles are presented in [28] and are applied in this study. Synthetic solar irradiance time-series $I\,(hoy)$ are generated using the hourly clearness index $k_t\,(hoy)$, the relation of the daily irradiation to the average daily irradiation of the selected month F_d, and the ratio of the monthly irradiation to the long-time average monthly irradiance of the hour F_m.

$$I\,(hoy) = F_d * F_m * k_t\,(hoy) * G_0\,(hoy) \tag{3}$$

The first two factors, i.e. the hourly clearness index and the relation of the daily irradiation to the average daily irradiation, are based on the case-specific probabilistic density function (PDF). In addition, the third determining factor, i.e. the ratio of the monthly irradiation to the long-time average monthly irradiation, is represented by a normal distribution for the case of La Gomera [28].

In contrast to this, wind speed time-series $v_{wind}\,(hoy)$ are generated through first-order Markov-chains, i.e. they depend on the wind speed of the last time step $v_{wind}\,(hoy\text{-}1)$. Thereby, the seasonal term is removed by setting up individual transition probability matrices *TMP* for each month *month* (*hoy*). A random number *r* is used to finally determine the current wind speed depending on the TPM and the previous value.

$$v_{wind}\,(hoy) = f\,(TPM, month\,(hoy), v_{wind}\,(hoy\text{-}1), r) \tag{4}$$

For the generation of probabilistic traffic volumes the daily profile given in [43] for the case of Tenerife island is used as a basis and varied by a normally distributed random number with standard deviation of $\sigma^{\circ=\circ}$= 0.1. The resulting range of the traffic volume and its daily distribution is shown in Figure 1. Hereby, the box represents 50% of the observations from the first quartile q1 to the third quartile q3 (i.e. from 25th to 75th percentile). The red line shows the median. Outliers are represented by red cross and defined as values below q1−1.5(q3−q1) and above q3+1.5(q3−q1). The profile shows a morning peak from 7 to 8 am and second, less sharp peak from 2 to 6 pm. The same probabilistic profile is used for every day, thus there is no differentiation of weekday, weekend or holiday. Nevertheless, the distribution shown in Figure 1 implicates strong variations of the peak values and thus might be acceptable for a first estimation of the influence of the traffic volume on the energy system's performance.

Thus, in total 12 combinations (3 scenarios à 4 modifications each) are analysed. For the reference year there were 9 runs (3 years x 3 methods) and for each probabilistic input 100 runs are performed. In this study, neither additional runs nor any termination criteria are

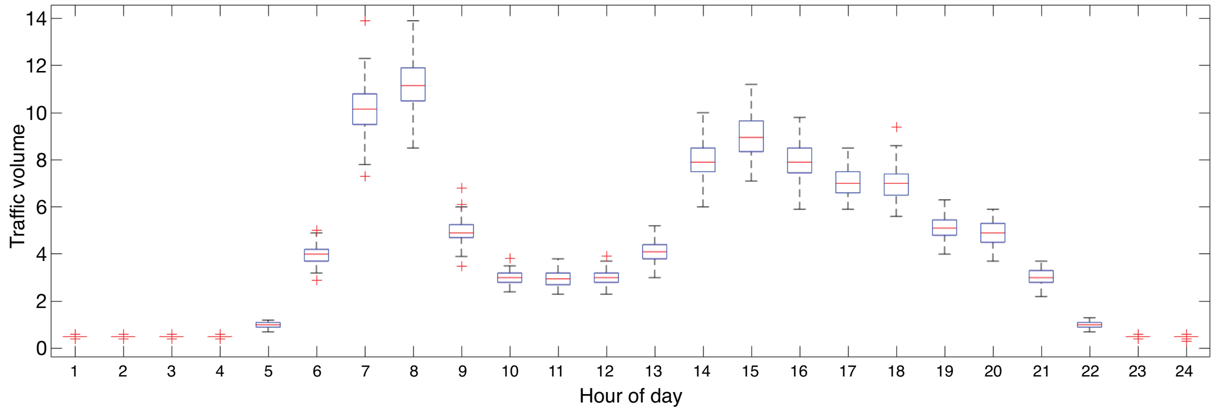

Figure 1: Range of varied traffic volume for one day

Table 4: Short description of varied input data

Number of runs		Methodology
reference year	9 *(3 × 3)*	3 different reference years (2013, 2015 and 2016) based on 10-minute load data [39] and half-hourly irradiation data [42]; 3 different methods to compromise load data to hourly data (i.e. mean, max, min)
probabilistic wind	100	Probabilistic wind profiles based on [28]
probabilistic solar	100	Probabilistic irradiation profiles based on [28]
probabilistic traffic	100	Traffic profile based on [43] with normally distributed hourly deviation ($\sigma = 0.1$)

implemented. Table 4 summarises the varied input data analysed within this work.

4. Results and discussion

The choice of the reference year leads to significantly different economic and energetic results. The annual costs of the energy system vary between 10.87 and 11.28 M€ if a combination of different technologies is chosen. This indicates that an under- and overestimation of up to 3.6% is possible due to the choice of reference year. Similar results and sensitivities for the choice of the reference year can be found in [28] for the case of a hotel where the uncertainty due to the choice of reference year is up to ±4.8%. Furthermore, also [31] shows for the case of a hospital a relative standard deviation of ±2.7% of the total costs of the optimised systems. Hence, both studies underline that the variance of the results of this study due to probabilistic input data is reasonable.

Nevertheless, the results in this study underline also that the technology mix represented by Scenario 2030-Combi shows the lowest annual costs of all analysed scenarios as evaluated in [35]. This finding is also in-line with results of previous studies (e.g. [16] and [34]). The annual costs of Scenario 2030-H2 are always higher than those of both other scenarios. Regarding Scenario 2030-V2G, the annual costs of the best case (i.e. the minimum value shown in Table 5) can reach the maximum costs in Scenario 2030-Combi. The results of the annual costs are summarised in Table 5.

In the following all three scenarios will be more deeply analysed. The marking of all different reference years in Figure *2*, Figure 3 and Figure 4 underline that these (three respectively) nine different reference years show a wide variance of possible energy demand and supply characteristics. The analysis of the probabilistic weather data shows that both wind and solar data have even higher uncertainties resulting in a range of about 6% of the baseline value. Furthermore, the results reflect that the combination of different technologies has nearly the same uncertainties of annual costs (standard deviation of 199.74) as vehicle-to-grid only (standard deviation of 179.98). Thereby, the variances due to probabilistic wind profiles and probabilistic solar profiles are almost equal. In contrast, in the hydrogen-based transport scenario where wind turbines and electrolysers are key components, the choice of wind data is much more

Table 5: Annual costs in k€ for different energy system designs with varying input data

	Reference*	Minimum	Maximum	Mean
Combi	10,892	10,796	11,553	11,091
reference year		10,873	11,284	11,104
probabilistic wind		10,796	11,490	11,119
probabilistic solar		10,969	11,553	11,279
probabilistic traffic		10,858	10,869	10,863
V2G	11,552	11,437	12,165	11,738
reference year		11,535	11,882	11,734
probabilistic wind		11,437	12,111	11,760
probabilistic solar		11,622	12,165	11,913
probabilistic traffic		11,541	11,547	11,544
H2	13,299	12,964	14,224	13,538
reference year		13,307	13,564	13,428
probabilistic wind		12,964	14,224	13,688
probabilistic solar		13,511	13,921	13,737
probabilistic traffic		13,299	13,299	13,299

[*] reference values for historical year 2016 based on [35]

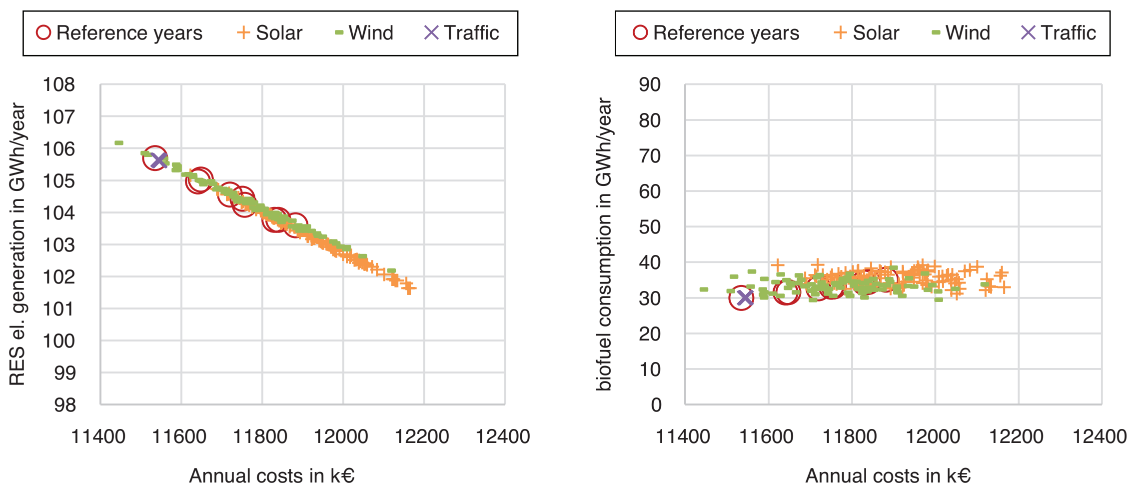

Figure 2: Annual results of Scenario 2030-V2G: annual electric generation of renewable energy systems over annual costs (left) and annual biofuel consumption over annual costs (right)

sensitive to the annual costs (total standard deviation of 249.77, only regarding observations with probabilistic wind inputs results in standard deviation of 268.78). Regarding previous work a high sensitivity of renewable energy systems towards probabilistic wind speeds is also stated in [32], [34], and [44].

All scenarios show linear correlation of renewable energy systems electricity generation and annual costs. Higher electrical generation through variable renewable energy systems (i.e. wind and solar power) results in lower annual costs of the energy system due to the lower variable costs of biofuel. Nevertheless, the consumption of biofuel does not show the same intensity of correlation as is obvious in the right graphic of Figure *2*, Figure *3* and Figure *4*. In both scenarios using power-to-hydrogen (i.e. Scenario 2030-H2 and Scenario 2030-Combi), the

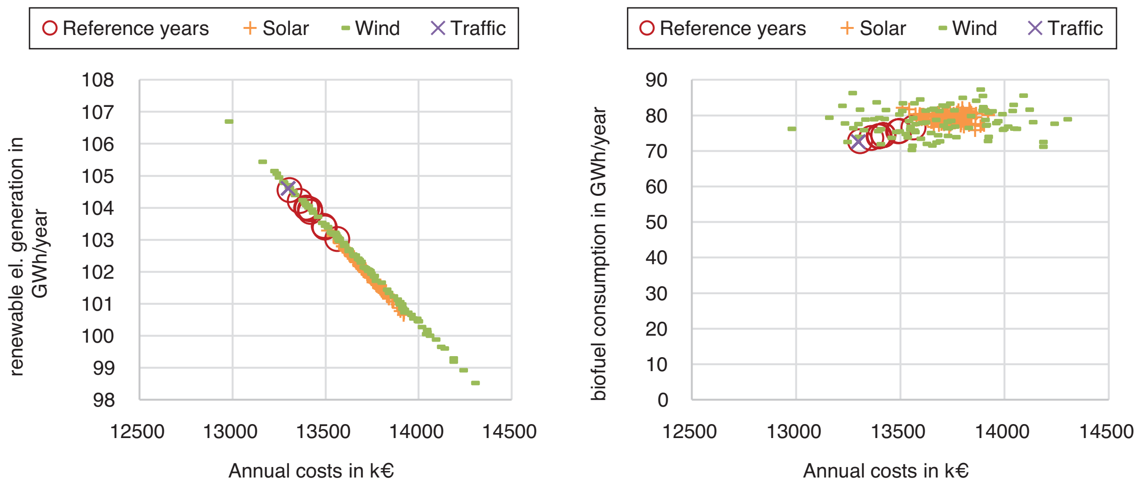

Figure 3: Annual results of Scenario 2030-H2: annual electric generation of renewable energy systems over annual costs (left) and annual biofuel consumption over annual costs (right)

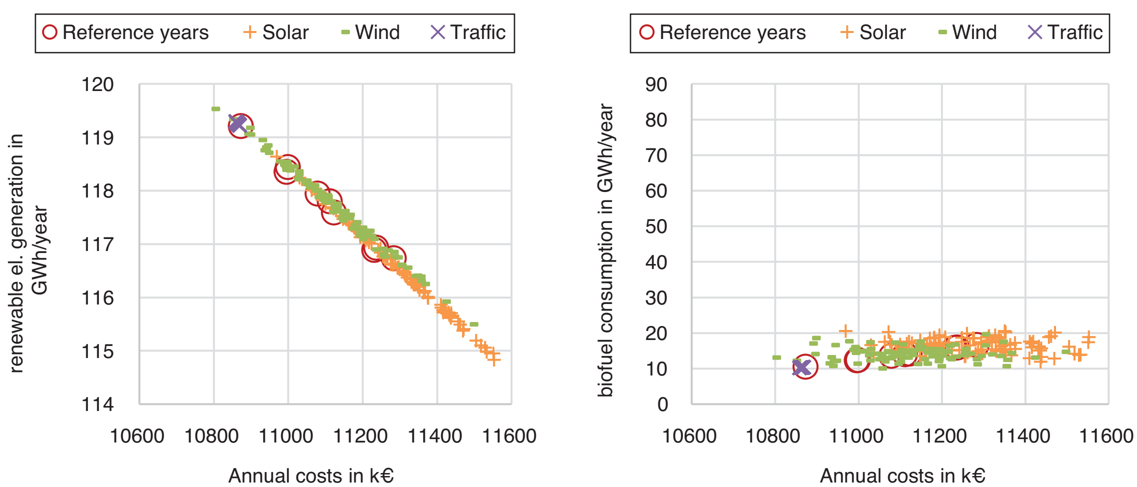

Figure 4: Annual results of Scenario 2030-Combi: annual electric generation of renewable energy systems over annual costs (left) and annual biofuel consumption over annual costs (right)

electrolyser operates independently of any varying inputs (see Figure 5). Hence, further balancing technologies like stationary batteries (Scenario 2030-H2) or V2G (Scenario 2030-Combi) have to balance the annual generated electricity depending on the temporal distribution of supply and demand.

In Figure 6, the sums of V2G charge are shown over the annual biofuel consumption for the scenarios 2030-V2G (left) and 2030-Combi (right). In both graphics a clear linear correlation between the sum of charging and the consumption of biofuel for probabilistic solar inputs as well as for the reference years can be seen. In contrast, the observations show no clear correlation for probabilistic wind inputs. Nevertheless, the sensitivity of consumed biofuel is almost the same for both probabilistic weather inputs as well as for the reference years in both scenarios. In Scenario 2030-V2G the observations of the annual consumed biofuel result in standard deviations of 1.82 for using probabilistic solar data, 1.85 for using probabilistic wind data and 1.66 for the reference years. Similar results can be found in Scenario 2030-Combi (standard deviations of 1.95,

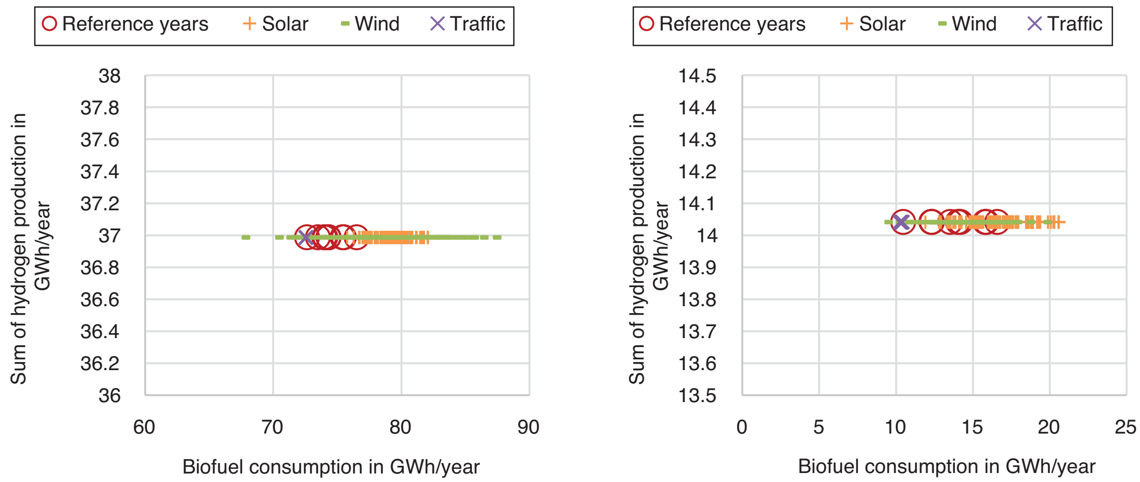

Figure 5: Sum of hydrogen production over biofuel consumption in Scenario 2030-H2 (left) and in Scenario 2030-Combi (right)

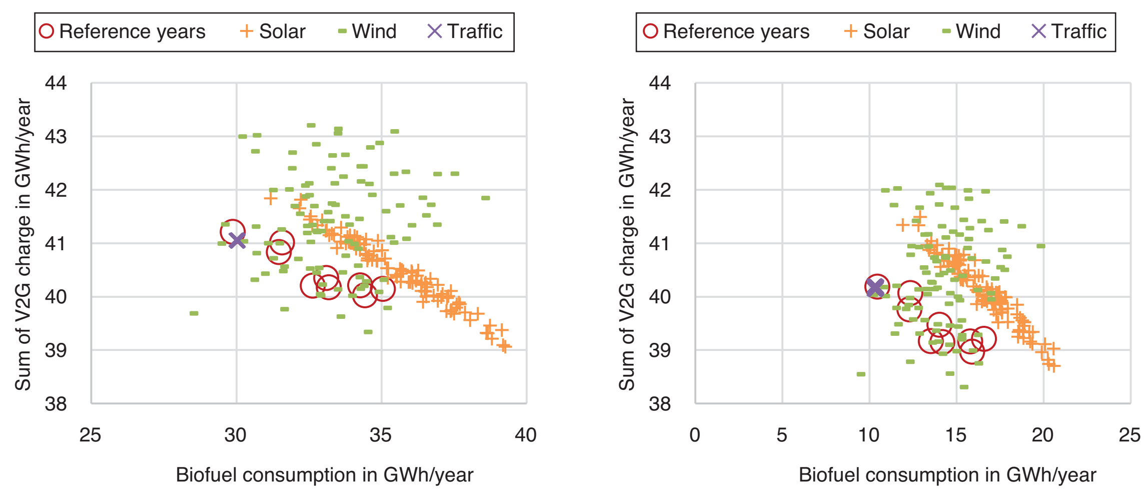

Figure 6: Sum of V2G charge over biofuel consumption in Scenario 2030-V2G (left) and in Scenario 2030-Combi (right)

1.92, and 1.99, respectively). Moreover, varying traffic inputs as assumed in this work seem to have no influence on the annual performance of an energy system although V2G and thus the temporal distribution of traffic volume are determining inputs for the hourly balancing of the system. This supports the positive assessments of this technology determined in different case studies, such as [16], [43], and [45].

5. *Conclusion and outlook*

The objective of this study is the assessment of the robustness of different 100% renewable energy system designs for the island of La Gomera. Therefore, the systems – optimised for one reference scenario – are stressed with various historical and probabilistic input time-series to analyse their sensitivities. To generate probabilistic time-series of different influencing variables, historical observations of several years are used in the cases of wind speed and solar irradiation. Furthermore, three historical reference years are used to reflect the electricity demand. The probabilistic traffic volume is generated based on an analysis of the traffic volume for the neighbouring island of Tenerife and the assumption of normal distributed traffic volume for each hour of the day.

The results underline the economic and energetic advantage of energy systems based on diversified supply and storage solutions. Although all analysed systems show some variance in their results, the combination of V2G and power-to-hydrogen as is realised in Scenario 2030-Combi shows the best economic performance. The total installed generation capacity in this scenario is higher than in both other scenarios. Nevertheless, the high electricity generation through renewable energy systems annualises the capital costs of these systems. Furthermore, it is shown that a system depending heavily on wind energy shows less robustness to probabilistic changes. In this analysis, especially the combination of wind dependent and less flexible electrolysers as are used in Scenario 2030-H2 shows higher variance on the energetic and economic performance of the system. Due to this, further research might focus on the analysis of flexible electrolysers and their performance with varying weather inputs.

Finally, this analysis illustrates clearly that the choice of one historical reference year is not suitable to determine the expected performance of an energy system. This might be even more relevant for small systems like islands. Larger systems like nationals and continental energy systems might show less fluctuations. The utilisation of standard reference years should be addressed to gain the expected mean values. Nevertheless, these standard reference years do not show the robustness of the system. To learn about their sensitivity, synthetic probabilistic inputs as applied in this study are a good way to determine both the expected mean values and their variance.

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