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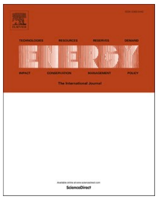

Best estimate plus uncertainty methodology for forecasting electrical balances in isolated grids: The decarbonized Canary Islands by 2040

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ABSTRACT

This paper investigates the challenges isolated islands face in transitioning from fossil fuel-based electricity generation to renewable energy sources. The Canary Islands serve as a case study, where photovoltaic and wind power are the primary renewables, but their variability requires a deep techno-economic analysis. The island's energy demand is predicted to rise by 100% due to economic growth, electrification and electric vehicles. However, implementing renewable systems encounters obstacles, such as limited suitable sites and protected areas. The study uses Wilks' methodology and Monte Carlo sampling to explore 59 combinations of randomly selected inputs of the uncertain variables, aiming for a 95/95% coverage and confidence level in the results. In most cases, they experience energy shortages, failing to meet electric demand. Even though a new generation mix appears to cover demand under all circumstances, the uncertainty unveils a different reality, leading to an approximate 25% increase in system costs. Surpluses in energy generation, while seemingly positive, can pose challenges. The new system's Levelized Cost of Energy increases from around 14 to 17c€/kWh. These cost increases are contingent upon future performance and the variability of uncertain parameters, leading to excesses ranging from slightly below 25% to over 40%.

1. Introduction

Energy in general, and electricity in particular, is now an essential service for all economic and social activities of the citizens of almost any country in the world. Thus, the power generation sector is considered within the main block of any country's economy. Global energy demand has been growing steadily over the last few centuries, which has accelerated in recent decades [1], although there has been a slight decline in 2020 due to the Covid-19 pandemic. However, this trend has returned to growth in 2021, even though the pandemic has not ended [2]. Most of this energy production comes from fossil fuels; in the case of electricity generation, approximately two-thirds of the energy production comes from fossil fuels [3].

Since there are two problems, energy generation based on fossil fuels is entirely unsustainable. On the one hand, there is more than specific depletion of these fuels in the medium term if the current extraction rate of raw materials is maintained [4]. On the other hand, there are unacceptable levels of polluting emissions, especially greenhouse gas emissions, vast quantities of which are emitted into the atmosphere when energy uses are based on fossil fuels as raw materials [5].

Therefore, renewable energies must be present in any generation mix or the only generation source used in the not-too-distant future, thus achieving the central objective of reducing or eliminating fossil fuels and significantly minimizing greenhouse gas emissions [6]. Focusing on electricity generation and implementing renewable energies is necessary; otherwise, achieving the ambitious CO2 emission reduction targets will be impossible. The use of electricity in final energy consumption is expected to increase sharply in practically all countries [7]. Electricity demand is expected to exceed 30% of total energy consumption in many countries in the short term [8].

1.1. Research status on renewable systems in islands and isolated locations

Islands face a pronounced reliance on fossil fuel-based electricity generation due to their isolation, resulting in challenges to meet energy demand sustainably and economically [9]. This heavy dependence poses environmental concerns and raises fuel costs due to transportation expenses [5]. Islands have implemented policies aligning with European Union (EU) objectives for sustainable energy supplies by 2050 to address

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these issues and reduce greenhouse gas emissions [10].

Renewable energies, such as solar photovoltaic and wind power, are gaining significance globally due to their environmental benefits and strategic importance in achieving energy autonomy and competitiveness [11]. However, these sources' inherent variability and unpredictability pose challenges, necessitating system oversizing or significant energy storage capacity to manage excess energy effectively. The ideal solution involves finding an economical balance between generation and storage to meet energy needs efficiently. This approach becomes more complex for islands due to limited suitable sites and protected areas for large-scale solar and wind power generation combined with storage systems, such as pumping stations and mega-batteries [12].

Despite all these problems, many research studies analyze the implementation of these systems in different islands or isolated regions worldwide. Curto et al. [13] evaluate a renewable electricity mix for Lampedusa Island (Italy), covering around 40% of the energy demand through these kinds of energy sources. Lorenzi et al. [14] studied a system on the Terceira Island of the Azores Archipelago, almost 50% based on renewable sources. Arevalo et al. [15] have developed a renewable system using different renewable energy technologies for two islands of the Galapagos Archipelago (Ecuador). All these systems, among others available in the literature, are relatively small. Some of them are only partially renewable and/or cover current demand. Probably the biggest fully renewable systems implementing future calculations are Berna-Escriche et al. [16], who studied the Canary Islands' promotion to a carbon-free energy mix, taking profit of the electric surpluses for hydrogen production; Vargas-Salgado et al. [17] analyzed scenarios for total electrification of Grand Canary Island which optimal solution includes PV, off-shore wind, pump storage, and ion-lithium batteries and Rivera et al. [18] analyzed a fully renewable generation system for Canary Islands by 2040 highlighting a system which includes solar PV, wind, pumped storage, and vanadium redox flow batteries with an interconnection between islands for optimization.

Other exciting studies in the literature focus on a renewable trigeneration system by achieving local energy independence, emphasizing the crucial role of battery storage and dynamic load interactions [19]. In the study of Mazzeo et al. [20], a hybrid system composed of PV and wind energy sources, energy storage systems and electric vehicle charging stations, to meet the building district energy demand is sized and assessed using artificial intelligence. While the assessment of the optimal locations to implement a renewable system is made in Eltamaly et al. research [21]. Mohamed et al. [22] analyses multi-agent energy management of "smart islands", which uses a primal-dual multipliers method, is examined. The commented works and others available in the literature analyze different aspects of implementing hybrid microgrids, such as artificial intelligence, system optimization, integration of electric vehicles and their economic analysis.

1.2. Best estimate plus uncertainty approach using non-parametric methods: the wilks' formula

Best Estimate Plus Uncertainty (BEPU) constitutes an approach capable of providing a value or its evolution over time for each of the different output variables in any analysis and estimating their uncertainty. Specifically, these methodologies have traditionally been aimed at making the application of thermal hydraulics in the nuclear field feasible, notably in the licensing processes and safety assessment of nuclear power plants [23]. In other words, it has traditionally been applied in the field of nuclear safety, where no aspect of safe plant operation can be left to chance so that the performance of these methodologies is thoroughly tested. The characteristics of BEPU make it attractive for addressing design and operational issues of different technologies in the different industrial and research fields. The development of BEPU involves interactions between deterministic and probabilistic analyses, also recognized as Deterministic Safety Assessment (DSA) and Probabilistic Safety Assessment (PSA) [24]. In other words, in the first step, a deterministic model produces a mathematical model where the same inputs or initial conditions will invariably yield the same outputs or results without considering the existence of randomness or uncertainty in the process modelled by that model. Then, in a second step, using a stochastic or non-deterministic model, an attempt is made to determine the uncertainty associated with the variable(s) under study. This variability arises from the nature of the system itself, which generates random effects, causing the evolution of the output variable to exhibit some variability around the previously estimated deterministic value.

Many classical statistical analyses require knowledge of the type of probability distribution function followed by the population. These methods, known as parametric, are accurate and precise, but they suffer from the drawback that in many applications, the probability density is rarely known a priori [25]. Therefore, to apply parametric methods, one must assume that the variables under study follow a probability density (normal, exponential, log-normal, etc.), which may rely on estimations. To avoid these assumptions, non-parametric statistical methods can be employed, applicable regardless of the underlying probability distribution. Hence, these non-parametric methods prove highly useful in manufacturing and computational applications when the distribution of the quantity of interest is unknown or difficult to predict before analysis.

One widely used method is Monte Carlo sampling, which involves conducting many simulations by randomly varying uncertain input parameters [26]. From the results, it is possible to determine the probability distribution of the output parameters of interest, particularly their mean and variance. This method has the advantage that the number of uncertain input parameters it can consider is unlimited. However, it has the significant drawback of requiring many simulations (~1000), resulting in excessively high computational costs for many applications. An alternative with lower requirements was proposed in the 1940s by Wilks.

Wilks proposed a method to determine the required sample size for two-sided tolerance limits of the output (variables that must lie between two values), with a specified confidence level [27]. Subsequently, also Wilks [28] extended this analysis to one-sided tolerance limits for variables that either must not reach a value or must exceed it and then Wald [29] extended it to multivariate distributions which are those with more than one output variable. Wilks' method quantifies uncertainty in tolerance intervals: a region expected to contain a certain fraction γ of the possible actual values with a certain probability β. γ is referred to as coverage, and β is the confidence level. One-sided intervals take the form (-∞, U] or [L, ∞), where U and L represent the interval limits. On the other hand, two-sided intervals are of the form [L, U]. The Wilks' method allows for the computation of the tolerance interval for a result by conducting n simulations, randomly varying uncertain input parameters, and using the smallest and largest outcomes as the bounds of the interval. The number of simulations depends on the desired coverage and confidence levels; the higher they are, the more simulations will be needed.

For one-sided intervals, the number of simulations is given by Ref. [28]:

$$n = \min\{n \in \mathbb{N} \,|\, 1-\gamma^{n} \geq \beta\} \tag{1}$$

For two-sided intervals, the following expression applies [27]:

$$n = \min\left\{n \in \mathbb{N} \,\middle|\, (n-1)\gamma^{n} - n\gamma^{n-1} + 1 \geq \beta\right\} \tag{2}$$

For the usual coverage and confidence values in most fields, 95% and 95%, the number of simulations for one-sided and two-sided intervals are n = 59 and n = 93, respectively.

The Wilks method, widely employed in nuclear engineering and statistical analysis, is a versatile tool based in probability and statistics theory. It enables the analysis of numerous uncertain parameters through its flexibility, allowing a theoretically unlimited number of parameters to be examined. However, the method relies on sampled parameter distributions, which introduces limitations when the probability needs to be estimated, based on other studies or assessed through experts' opinions. In cases where safety might be compromised due to these assumptions, it is a beneficial practice to employ conservative ranges for the uncertain variables of the system.

The Wilks approach is methodologically reliable for assessing prediction uncertainty at specified confidence levels. For instance, a modest number of simulations is sufficient at a 95% confidence level for one side (59 simulations). Yet, increasing confidence levels substantially raises the required simulations (459 simulations for 99% confidence level for one side output variables), posing a potential limitation for computational solvers and increasing the size of the new system. In practical applications, achieving absolute certainty, particularly considering confidence levels and the estimated range of uncertain variables, remains a considerable challenge. The Wilks method might still need contingency plans and backup systems in real-world applications. Rather than expecting perfect predictability, these backup plans offer resilience against unexpected events, providing a safety net for system operations. In any case, by taking into account the uncertainty of the different variables, a much higher degree of knowledge of the behavior of the system is achieved, which, in this study, facilitates a final estimation of the energy mix to be implemented in a more adequate way than simply simulating only one foreseen scenario (deterministic method).

1.3. The current research: objectives and scope

The Canary Islands, as part of Spain, are actively working on reducing Green-House Gas (GHG) emissions and decreasing their reliance on fossil fuels to align with the EU's decarbonization goals by 2050. The Spanish government aims to expedite the decarbonization process in the Canary Islands, advancing the transition to renewables within a decade [30], added to the own Canary Island Government [31]. The Canary Archipelago comprises seven islands 100 and 300 km from the Moroccan coast and about 1500 km from the European mainland. Its seven islands are inhabited with a total population of more than 2 million people, with a forecast of around 2.5 million by 2040 [32]. The total final energy demand was approximately 9.4 TWh for the whole archipelago in 2019 [33] and predictions for 2040 of 16–18.5 TWh depending on whether hydrogen production is considered (final demand percentage to cover "non-electrifiable" energy uses) [30].

In recent years, several calculation models have been defined and used throughout different research articles to estimate electricity demand and generation in a GHG emission-free scenario while maintaining high reliability. For instance, as particular applications of different code simulation tools, Berna et al. [9] presented a forecast for the Grand Canary Island by 2040 in a scenario of total decarbonization of the economy using HOMER software. Prina et al. [34] performed several forecast simulations for the South Tyrol region using the EnergyPLAN software, Segurado et al. [35] simulated different scenarios varying the renewable penetration in the S. Vicente Island in Cape Verde using the H2RES tool, and Mirjat et al. [36] carried out a research study focusing on long term analysis of Pakistan using the LEAP tool. Other research works collect reviews of many different energy simulation tools. Hall and Buckley [37] reviewed many energy simulation tools for the UK. In the same line, Ringkjob et al. [38] reviewed the most used tools for energy and electricity systems in which highly renewable resources are used, and Prina et al. present a review of the existing simulation tools for energy system scenarios applied at island level [39].

In the aforementioned cited documents and in the numerous existing literatures, the diversity of codes that can be used for simulating scenarios for energy planning at different levels is evident, being proved over the years to be capable of carrying out these analyses. The analyses range from a small isolated system through a micro-grid, or an isolated system, to a country or even continental level, with various tools used for each level. Among the different tools used for energy planning at various levels, notable examples include the use of HOMER code, EnergyPLAN, H2RES, MARKAL or LEAP, as displayed in the research work of Hall and Buckley [37]. Prina et al. [39] reviewed the energy models applied at the island level and found EnergyPLAN and HOMER to be the most used. As mentioned above, all of them are suitable for simulating current scenarios or estimating future scenarios with high levels of variable renewable energy (VRE) sources. Generally, they simulate one year with time steps, usually hourly. Based on the previous comments, it has been considered that several tools are helpful for the objective pursued in the current work since the calculations are employed as a baseline model on which to develop the significant novelty presented within the framework of this work, i.e. the implementation of the BEPU methodology using the Wilks formula to estimate the required number of simulations to achieve the desired levels of coverage and confidence within the uncertainty bands of the output variable/s under study.

In this context, the widely used tool Hybrid Optimization Model for Multiple Energy Resources (HOMER), which was developed by the National Renewable Energy Laboratory (NREL) has been used [40]. The software estimates the best system size, the required investment, the Levelized Cost Of Electricity (LCOE) and the payback time based on different simulated energy sources. The scientific community widely uses this software for different applications, such as predicting energy production and consequently choosing the best option for both stand-alone and grid-connected systems, planning the installation of hybrid energy systems, for estimating their feasibility, among others.

As advanced previously, the most significant contribution of this paper focuses on modeling and analyzing uncertainties in the main variables influencing electric generation mix proposals for meeting the Canary Islands' electricity demands in 2040. The study builds the uncertainty analysis upon another study for an interconnected renewable system in the Canary Islands [18]. The work presents an isolated grid system covering the total electric energy demand, taking the hourly values of the solar and wind resources for a year (several years have been reviewed and analyzed, taking 2019 as a characteristic). Based mainly on the Monitor's Deloitte report [30] which states the demand for a total electrification of the Canary Islands and in one of the Instituto Tecnológico de Canarias Reports [32] which highlights the effect of a strong penetration of EVs as the most important reason for the increase in demand, the resources and the estimated demand for 2040 are determined, and then the installations required to meet the demand always were determined. The technologies considered were solar PV, wind, and biomass (mainly used as backup systems) as generation sources, while pumped storage and mega-batteries were used as storage systems. With all this information, the software has estimated the powers of the generation sources needed and the powers and capacities of the storage systems. As mentioned above, these base case estimates have been made using data from a year considered characteristic. Still, in this research, taking it one step further, simulations based on a Monte Carlo method have been carried out [6]. Thus, the present work shifts from a deterministic estimation of the energy balances to reach the generation mix to a stochastic approach, where the uncertainties associated with the different input variables are considered. The development and application of this probabilistic analysis are the main novelty of the document since this type of analysis is not usually carried out in these energy balance studies. In these simulations, more than twenty years of historical data on solar and wind resources and electricity demand are used to determine probability distributions functions (PDFs) for the consideration of their variability. The technique considers the hourly variations in electricity demand profiles and the daily and between-day fluctuations in renewable generation sources, incorporating the information from the PDFs for both generation sources and demand profiles. All these code calculations of the energy balances are carried out hourly. Then, this sampling methodology allows for determining the nominal power of renewable sources required at different reliability levels.

In accordance with the above-mentioned objectives, Section 2 describes the base scenario of the total economy electrification for the Canary Archipelago to achieve the abovementioned objectives. Section 3 focuses on the description of the developed methodology. The following section describes the simulations' principal results, the uncertainty study, and the corresponding analysis and discussion. Finally, section 5 is dedicated to summarizing the conclusions of the present study according to the needs of the generation system in the scenarios under consideration.

2. The base scenario of economy electrification in the archipelago

The Monitor Deloitte report [30] develops a scenario of total decarbonization of the economy for all the Spanish non-mainland territories by 2040. It estimates that 10–11 GW of installed renewable generation capacity would be needed to cover the approximately 16 TWh of estimated demand (Fig. 1). Of this total power to be installed, the authors estimate in the report that at least 80% should correspond to solar PV, while the remaining percentage should come from wind energy. A large storage capacity should also be installed to provide the required flexibility to the system. The authors estimate a capacity of around 25 GWh (reversible pumped storage plus mega-batteries).

This scenario has been analyzed in detail in the work of Rivera et al. [18], proposing some improvements. In particular, the research develops a study that considers the total electrification of the island economy, favouring the implementation of efficiency measures and self-consumption. In its implementation, the authors have used, in addition to the Monitor Deloitte document, several documents of the Canary Islands Technological Institute, which is an entity attached to the islands' government. Such as the one focused on the self-consumption strategies with PV [41], studying the installation and energy production potential; or the report analyzing the storage technologies that can be installed in the islands [42]; and the one that highlights the electrification and depletion of the vehicle fleet in the islands [32]. In addition to the documents, necessary to introduce the technical characteristics of the technologies are used.

Concerning demand, the estimates carried out lead to an approximate increase of 100% regarding current electricity demand values. Fig. 2 shows the expected aggregate value for all of the Canary Islands. The profile of the current average hourly demand is taken, considering that only the recharging of electric vehicles (EVs) will modify it appreciably. Then, EV contributions were estimated by weighting the six EV recharging profiles (homes and public roads, workplaces, hotel parking lots, shopping centers and regular recharging points) [32]. So that, for the rest of the demand, the current hourly demand profiles were disaggregated by sector (residential, commercial, industrial, public administration, accommodation and other uses) [42] and multiplied by the factor that contemplates the estimated increase between now and 2040. So, the demand results in conserving each island's current consumption profiles and proportions and applying a multiplying factor to include economic growth up to 2040.

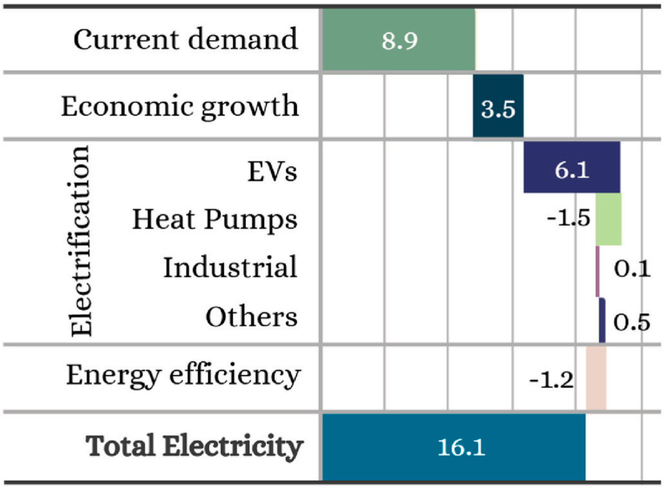

Fig. 1. *Forecast of the energy demand (TWh) in the Canary Archipelago from 2019 to 2040 (Adapted from* Ref. [30]).

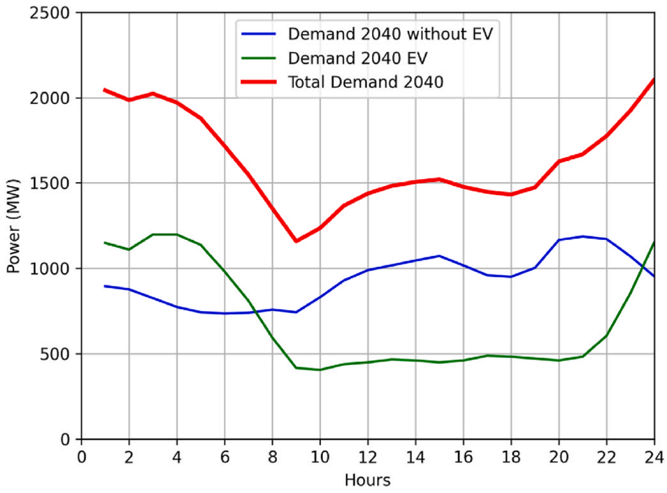

Fig. 2. Forecasted profiles of electric demand for the Canary Archipelago.

The hourly profiles of the Canary Islands radiation and wind resources have been taken regarding generation. The archipelago has the highest insolation in Spain and very stable and fort winds. These resources can be estimated through NASA's POWER Data Access Viewer [43]. Thus, based on them and on the system's technical characteristics, the dimensioning of the proposed system has been determined. Remark that for the solar PV generation, estimates have been made of the areas available for installing solar panels using the report of the Canary Islands Technological Institute [41]. This report assumes a maximum occupancy for self-consumption of 70% of the total available roofs. This value was taken as the limit for the installation of this technology (around 15 GW of maximum installable solar PV power), the installed power being below this value. As for wind power technology, the choice of off-shore generation has been motivated mainly by the disadvantages of on-shore technology in terms of land occupation, aggravated by the environmental and tourist issues of the installation of large wind farms on all the islands. For reverse pumping, the adequacy of the possible sites has also been considered [42].

The optimal scenario reached from the technical-economic point of view has been selected for Rivera et al. research ("Optimized Scenario" in Ref. [24]). The development of uncertainty studies of this scenario, which is the main contribution of this document, has been carried out. Considering the inherent variability of the solar and wind generation systems and the existing demand can make a system that a priori is viable but may not be viable. The technical aspects of this model are presented in detail below to have a clear picture of the characteristics of the energy mix proposed in this document.

The proposed generation mix mainly comprises solar PV, accounting for over 95% of the installed capacity. Wind generation constitutes less than 4% due to high off-shore technology costs. However, with an appropriate storage system, PV and wind can be effectively managed. Biomass plays a minimal role in the system, but increasing its installed capacity to 500 MW could provide a reliable backup system, utilizing the islands' resources. This additional capacity allows for an estimated generation of around 50–100 GWh per year using the existing biomass resources (around $1.63 \cdot 10^5$ tons per year). The scenario considers the interconnection between islands, accounting for associated costs and losses.

The general characteristics of the previously commented system are presented in the following tables. Table 1 shows the rated powers of the system, while Table 2 shows the data analogous to the previous table but for the electricity generated and refilled to the grid. The system's total cost is around 40,000 M€, while its LCOE is 101 €/MWh, with an energy surplus of 19.1%, all of which are very competitive figures for this type of system.

3. Methodology

The HOMER software can be used to perform many simulations of the scenario's operation. The scientific community has used this code over the last few years to compare and analyze different energy systems. In particular, as advanced in the introduction section, among many other research works using the HOMER software, the document of Vargas et al. focuses on the study of the Grand Canary Island using renewable and Small Modular Reactors (SMRs) [9], Berna-Escriche et al. performed estimations for the same island but considering three different scenarios [44] and Qiblawey et al. carried out analysis of Tenerife and Grand Canary Islands with and without interconnections [45]. This program performs energy balances in each defined time step (hourly balances) with the combinations of the generation/demand/storage systems considered. Fig. 3 displays a summary of the procedure followed by the code. After simulating all the scenario configurations, HOMER lists energy systems that meet the imposed conditions. The software allows leaving a part uncovered, called shortage, or even being connected to a grid and sorting them by Net Present Cost (NPC). The first solution shown is the optimal one (the global minimum optimum), but other options can also be explored. For example, additional criteria can be considered, such as the need for less installed power, minimization of energy wastage, the weighted combination of several factors, etc.

Next, the authors had to establish the characteristics of the base case for the uncertainty analysis; those were the ones in the optimized scenario with a generation mix, considering economic, technical, and social aspects provided by Rivera et al. [18]. Hourly data on wind and solar resources from the last decade were analyzed. As the values were consistently similar across the years, the data for a typical year, specifically 2019, were used. For demand, a prediction was made based on current hourly curves, considering the impact of EV implementation and a multiplier coefficient for future growth. The program ensures a positive or zero hourly balance between generation and demand in the isolated system using solar PV, wind generation powers, and non-variable systems like biomass, reversible pumping, and batteries. Excess generation is stored, while deficits are compensated using storage systems. The program performs these calculations throughout the year, estimating the required permanent installation of generation and storage system powers and capacities to meet the balance. Various scenarios are presented based on increasing costs.

Table 1
Summary of installed generation power and storage power and capacity.

Renewable sources	
Solar PV (MW.)	11,000
Wind (MW.)	390
Biomass (MW.)	150
Total power (MW.)	11,540
Storage systems	
Hydro pump (MW.)	2065
Battery system power (MW.)	3500
Total power (MW.)	5565
Pumped storage capacity (GWh)	16,636
Battery system capacity (GWh)	34,672
Total storage capacity (GWh)	51,308

Table 2
Summary of the energy annual generation and the energy re-fed to the grid by the storage sub-system.

Renewable sources	
Solar PV (GWh)	26,138
Wind (GWh)	1753
Biomass (GWh)	2
Total (GWh)	27,893
Storage systems[a]	
Hydro pump (GWh)	4801
Battery (GWh)	4551
Total (GWh)	9352
System excesses	
Surpluses (%)	19.1

[a] Energy re-fed to the grid by the storage systems; this energy comes from renewable generation.

This usual method of calculating energy supply balances for the estimation of the optimal scenario has some drawbacks. It usually assumes a standard year for calculations which means it may not account for adverse periods in other years with lower generation and/or higher demand. As a result, the system may fail to meet demand during specific periods. Since this method only considers the capacity to cover demand in a typical year, it does not take into account statistical approaches to address the unpredictable differences between electricity demand and renewable generation under different scenarios due to their intrinsic variabilities. These uncertainties pose a risk to the supply reliability of the proposed energy mix. Therefore, the BEPU analysis explores a variety of possible uncertainties in the input variables within specific confidence and coverage levels. These statements lead to a stochastic approach, which can be addressed using Wilks's methodology (section 1.2).

In order to describe the process followed in this statistical approach, Fig. 4 serves as a visual representation or diagram outlining the sequential process of the BEPU analysis. The figure illustrates the stepwise methodology starting from the exploration of uncertainties in input variables within specified confidence and coverage levels. It could also demonstrate the stochastic approach applied using Wilks's methodology, as referenced in the text. The diagram visually details the distinction between deterministic and stochastic approaches. Then, the proposed methodology carries out its calculations from the base case (optimal scenario obtained using a deterministic approach), along with the estimation of the Probability Distribution Function (PDF) followed by the input variables that present notable variability, such as electricity demand, solar irradiance, and wind speed, The estimation of PDFs for the parameters are presented in the next sections. However, the diagram highlights the factors influencing electricity demand forecasting, including economic growth (f_EG), energy efficiency (f_EFFI), electrification (f_ELE), electric vehicle fleet (f_EV), and energy demand management strategies (f_DM).

Moreover, Fig. 4 showcases the utilization of Wilks' formula involving 59 random combinations of values for multiple variables at a specified confidence and coverage level [28]. In our case, 59 random combinations of values will be used for all variables for confidence and coverage levels of 95 × 95%. This choice is justified because there is only one output variable, the electricity generation-demand balance, and this only must meet a one-sided interval constraint (the final electricity balance must be zero or positive).

Within the 59 simulated cases, some will have a capacity shortage as it will be impossible to meet, at each of the hourly calculations, the estimated electricity demand with the forecasted wind speed, solar irradiance and the rest of the uncertain sampled values. The reasons can range from high punctual electric energy demand to a lack of wind speed or solar irradiance during for some time periods. Therefore, the generation power of some generation sources and/or storage systems should be increased so that when repeating the calculations of the 59 cases sampled, the demand will always be covered, assuming no capacity

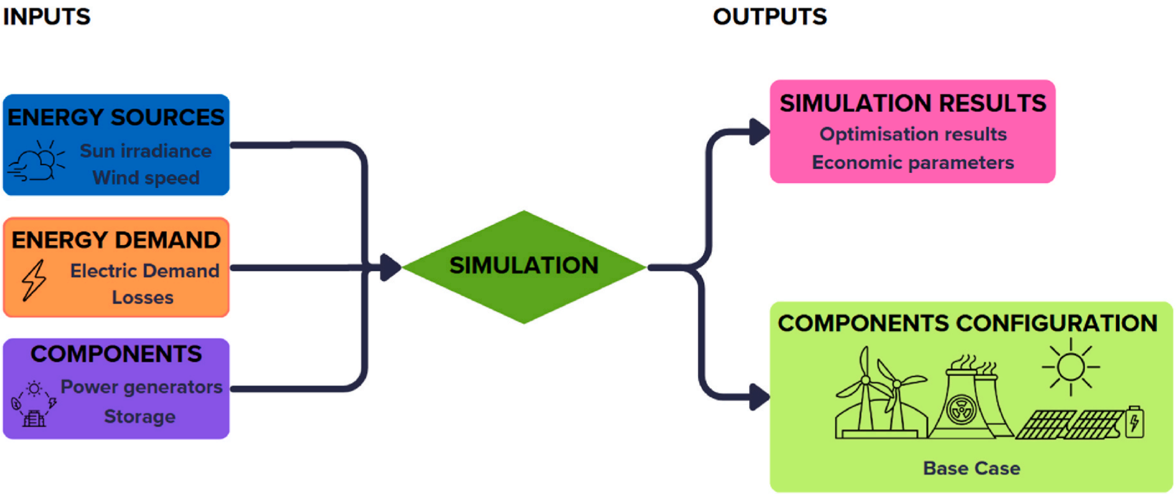

Fig. 3. Schematic view of the estimating process for the best-case scenario to meet the electric demand using HOMER pro.

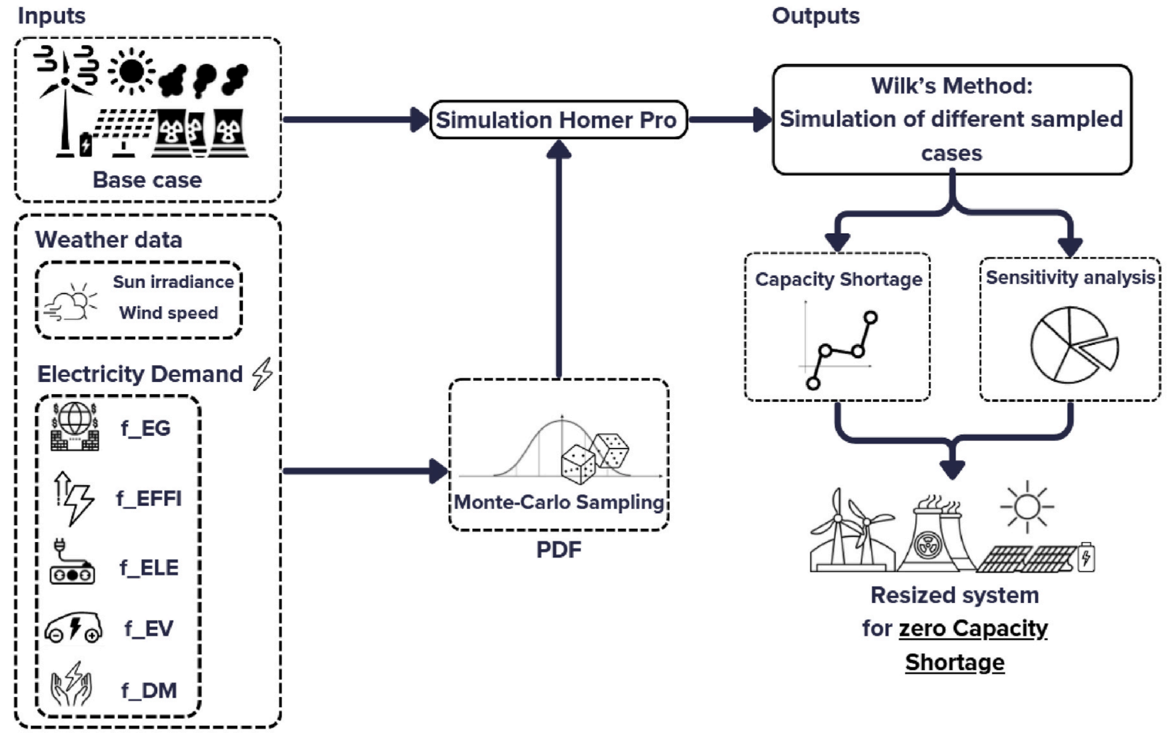

Fig. 4. A visual roadmap process of BEPU analysis.

shortage. High-capacity shortages identify the worst cases, and a new power capacity is proposed until the electricity demand is met. The surpluses are considered an interesting output to measure oversized installed capacity and for this reason have also been analyzed.

Lastly, sensitivity analysis offers valuable insights by highlighting the impact of specific inputs on the model's outputs. Understanding how changes in specific inputs influence the model's outcomes allows to make more informed decisions in the future, aiding in risk assessment and decision-making processes. Incorporating these influential factors into future planning strategies empowers better anticipation and readiness for potential changes or developments. In this sensitivity analysis, Spearman coefficients or partial correlation coefficients (PCC) have been calculated. The Spearman rank correlation coefficient measures the strength and direction of the relationship between two variables. Unlike other statistical analyses, such as Pearson correlation, which assesses only linear relationships, Spearman correlation evaluates the monotonic association, which could be linear or nonlinear. On the other hand, partial correlation is a coefficient used to describe the relationship between two variables while removing the effects of another variable, or several other variables, on this relationship.

3.1. Uncertainty weather factors

Referring to the above-described methodology, it is necessary to consider the different PDFs followed by the different uncertain input parameters. As for weather uncertainty, historical wind speed and solar irradiation data are available in NASA's POWER Data Access Viewer [41] from 2001 to 2022. As 59 datasets are needed for the BEPU analysis, datasets are created based on these historical data. Weekly periods are chosen as the basis for characterizing wind and solar resources. An auxiliary parameter is calculated for each week by normalizing the hourly magnitudes of wind speed and solar irradiance against their respective maximum hourly values recorded over the 22 years for the given week. Histograms are created based on these auxiliary parameters for each week. The beta distribution is the best fit for solar irradiance, while the Weibull distribution fits wind speed. Using the fitted distributions, datasets are generated to model the probability of wind speed and solar irradiance at weekly intervals for a whole year. Fig. 5 depicts the histogram of the auxiliary parameter for a particular week for solar irradiance and wind speed. For example, as shown in Fig. 5a, values near 1 are more probable for solar irradiance, and values between 0.5 and 0.6 are more probable for wind speed (Fig. 5b).

Therefore, by carrying out this procedure, the hourly availability of wind speed and solar irradiance can be built. Once the auxiliary parameter is randomly picked from the PDF, it is multiplied by the maximum hourly magnitude recorded during that week from the 22 years, obtaining a synthetic hourly availability of any of the two renewable resources. Thus, wind and solar resources are sampled each day of the year, considering their weekly PDF for shaping seven artificial days. This approach accounts for the variability within a day but may not explicitly consider the transition or relationship between hours within a day. This framework does not explicitly account for instances such as shifts from cloudy to sunny conditions or discernible fluctuations in wind speed. However, a smoothing technique was used to solve considerable jumps in the wind speed when changing from one day to the next, specifically a Gaussian-weighted moving average filter. It works by calculating the average value of a set of data points, giving more weight to points closer to the center point of the window and less weight to points further away. This smoothing process indirectly considers adjacent hours by applying a weighted average across neighboring data points.

This approach aims to generate artificial datasets that imitate the variability and probability distributions of wind speed and solar irradiance. The result provides an hourly representation of the availability of these renewable resources for the Canary Archipelago, considering historical data and their inherent uncertainties.

Table 3 summarizes the uncertainties and parameters of wind and solar distributions. The range of the parameters shows the Weibull and Beta distribution parameters derived from the historical datasets, for the 52 different distributions obtained (weekly estimates of wind and sun PDFs based on historical data). The Weibull distribution is commonly used for wind speed analysis, capturing the frequency and variability of wind speeds over time, making it ideal for modeling wind energy resources. While the Beta distribution has been used to model the variability of solar irradiance, representing the probability distribution of sunlight reaching an area over time.

Table 3
Summary of the energy parameters and the used PDF to perform the BEPU analysis.

Parameter	Distribution	PDF Parameters
Wind Speed	Weibull	$\alpha = [0.45,0.79]$ $\beta = [2.1165, 6.53]$
Solar Irradiance	Beta	$a = [2.98,8.88]$ $b = [0.75, 1.14]$

3.2. *Uncertain electricity demand factors*

Focusing on projecting the demand evolution in 2040, the foremost aspect considered is economic growth (f_EG), estimated to average around 2% per year. This estimation translates to an expected demand increase of approximately 3.1 TWh by 2040 (Fig. 1). The current base hourly curve has been scaled proportionally to accommodate this anticipated increment, incorporating the expected growth trajectory. A conservative approach involves considering a range of possibilities to address the inherent uncertainty in forecasting. As such, the uncertainty analysis considered a normal distribution with a mean of 2 % and a standard deviation of 0.5% of economic growth to include a spectrum of potential outcomes, thereby providing a more robust perspective on future energy demand.

Electrification constitutes a critical component of the forecasting process, requiring a careful distinction between EVs (f_EV) and other sources of electrification (f_ELE). The latter includes various areas, such as buildings and industries, with a notable contribution arising from the transition from conventional electric heaters to heat pumps. For 2040, an increase of 0.1 TWh is projected from industrial processes, while another 0.5 TWh is expected from other electrification sources. Simultaneously, a reduction in electricity consumption of 1.5 TWh is anticipated due to the implementation of heat pumps. To account for the uncertainty inherent in implementing these electrification measures that do not include the EVs, a variability factor ranging from 50% to 150% has been considered, resulting in a potential decrease in consumption between −0.75 and −2.25 TWh.

Among the various electrification components, the most significant impact stems from the rapid deployment of EVs (f_EV), which is expected to drive a substantial surge in demand amounting to 6.1 TWh by 2040. However, to accurately integrate this aspect into the forecast, the demand curve must be estimated beforehand, accounting for various EV charging profiles (Fig. 6). Based on previous estimations of the own Canary Islands government [32], this increase in demand is projected to result from the deployment of approximately 1.9 million EVs.

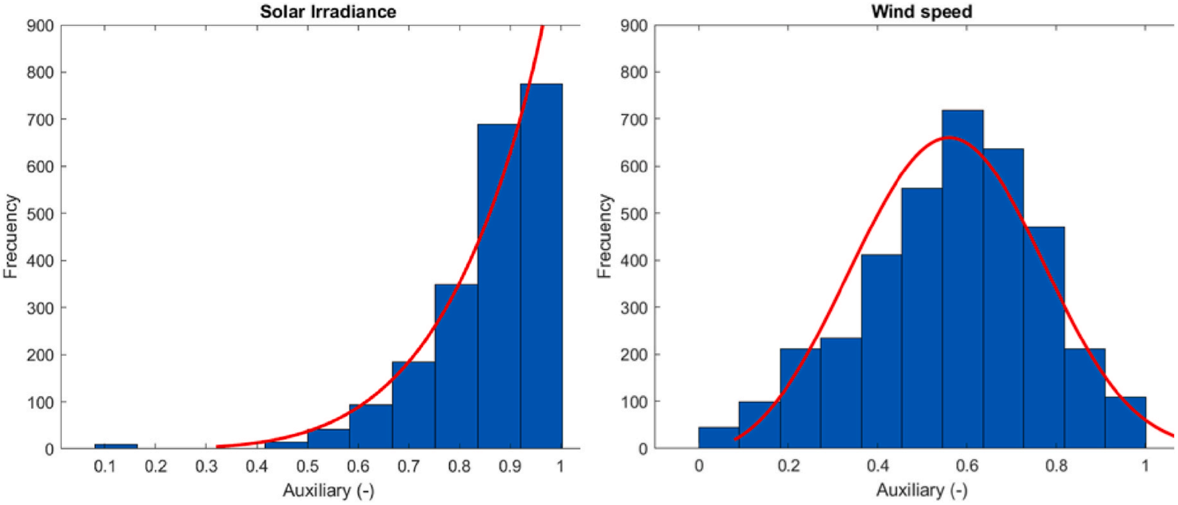

Fig. 5. Histograms of the solar (a) and wind (b) resources auxiliary parameters for a particular week.

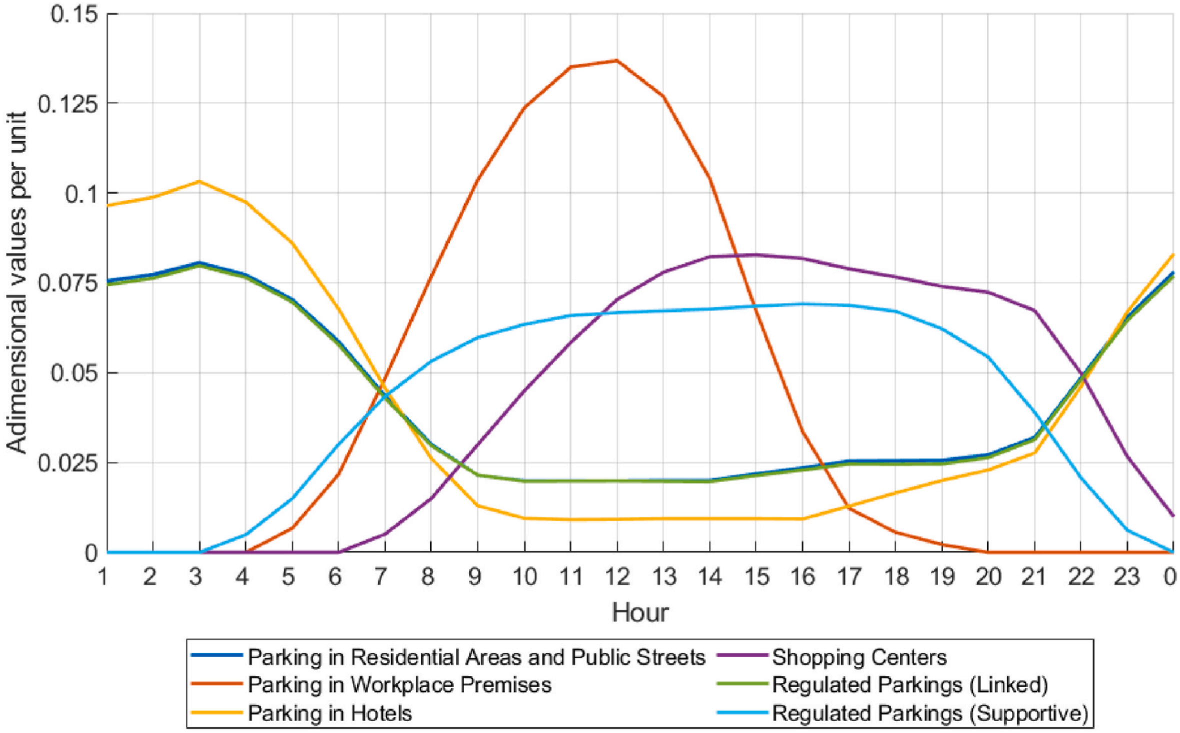

Fig. 6. *Major profiles of EV charging (based on* [32]*).*

Nonetheless, considering the inherent uncertainty in EV deployment, with an expected range between 1.6 million and 2.2 million, a scaling factor of 0.84–1.16 has been incorporated into the uncertainty study. Given the scarcity of detailed information and the difficulty in precise predictions, a uniform distribution has been assumed for this parameter, drawing on the principles of the maximum entropy theorem [46]. Once the EV demand curve has been appropriately scaled, it is combined with the base electricity demand to derive the comprehensive forecast for 2040.

The efficiency factor (f_EFFI) is also a significant consideration in the forecasting process, accounting for the anticipated improvements in general equipment efficiency across residential, industrial, and other sectors. With a baseline reduction of 1.2 TWh projected for 2040, an uncertainty analysis is carried out using a coefficient following a uniform probability ranging from 0.75 to 1.25 to account for potential variations in efficiency enhancement.

Nevertheless, when renewable energies make a significant contribution to the energy mix, a natural decoupling occurs between the generation curve, primarily driven by solar PV generation during the central hours of the day, and the demand curve, which remains relatively steady throughout the 24 h, especially with the contribution of EVs. This situation poses a challenge that requires a substantial storage capacity to absorb excess generation and make it available when needed or an oversizing of the system to ensure a constant energy supply to meet demand. Hence, particularly in the case of a significant solar production contribution, it is advisable to combine demand with generation as closely as possible, shifting the demand curve towards the central daylight hours. Several studies have been conducted to address this issue, with some focusing on the unique circumstances of the Canary Islands, of particular interest is the one of Vargas-Salgado et al. which explores the DM effect on the demand coverage for the whole archipelago [17]. One notable study by Deloitte Monitor suggests that demand management measures can shift up to 30% of demand to the central hours. Similarly, a report by the Canarian government on smart grids provides a sector-specific table that indicates a similar degree of manageability [47].

Fig. 7 illustrates the resulting new hourly demand curve obtained by implementing demand management at its maximum achievable level while maintaining the overall consumption. The uncertainty analysis considers varying degrees of demand management (f_DM), ranging from 0 (blue line in Fig. 7) to 1 (red line in Fig. 7).

Table 4 presents a summary of the electricity demand factors that were considered, including the information on their range. This table offers an organized view of the variability and extent of the uncertain variables considered in this study for the increase or decrease in electric demand. The contribution of economic growth has been represented with a normal distribution, according to the growth history analyzed, while uniform distributions have been used for the rest of the parameters, homogenizing the variability within the range considered.

4. Results and discussion

Four sub-sections of results are developed hereunder. A general presentation of the sampling carried out in the wilks' methodology is presented in the first one, while a summary of the significant results for the methodology will be displayed in section 4.2, the one on which the performance of the base scenario is tested. As described below, the system cannot cover the demand in all 59 sampled scenarios. Then, the recalculation process that must be made to reach 100% demand coverage for all the tested scenarios will be described in section 4.3. Finally, the last one provides a summary of the major findings and a summary of the results presented.

4.1. Wilks' methodology sampling

The 59 cases with uncertainties associated with variable generation sources and demand applied to the base scenario (energy mix described in section 2) may lead to many cases in which it cannot meet demand. Therefore, the generation and storage capacity should be increased so that there is no shortage under any circumstances, i.e., the new proposed mix can cover the demand in the 59 simulations proposed following the BEPU methodology. However, the system can lead to considerable

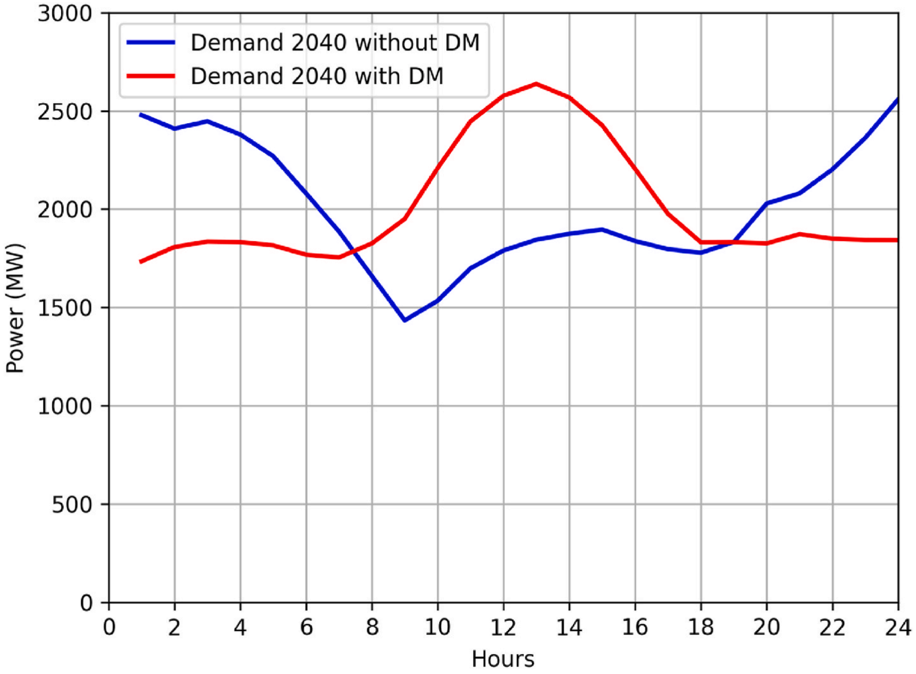

Fig. 7. Hourly average demand curve with and without demand management (DM).

Table 4
Summary of the energy parameters and the used PDF to perform the BEPU analysis.

Parameter	Distribution	Variation Range/PDF Parameters
f_EG	Normal	$\mu = 2, \sigma = 0.5$
f_EFFI	Uniform	[0.75, 1.25]
f_ELE	Uniform	[0.5,1.5]
f_EV	Uniform	[0.841, 1.159]
f_DM	Uniform	[0,1]

surpluses, mainly when the shortage is null.

To have an initial idea of the effect of studying the uncertainties associated with the different input variables, the evolution of the hourly demand curves during a typical winter week is shown in Fig. 8. The displayed predicted demand takes into account the uncertain factors detailed in Section 3, i.e. economic growth, usage of electric vehicles, improved efficiency and demand management strategies. Then, integrating statistical methodologies and input variable-based analyses provides a reliable estimation, offering insights into the potential variability and factors that can shape the energy landscape in the coming years. In particular, Fig. 8 illustrates the projected electricity demands for the 59 cases and the electricity demand base case (energy mix described in section 2) of the third week of January serving as an example. The forecasted demands are displayed using grey lines within a blue band, while a red line depicts the base-case demand. The differences between working days and weekends (hours 120 to 168) are evident for both the base and sampled cases. The influence of demand management becomes particularly apparent during midday, when the demand closely aligns with solar generation. In addition, as night falls, a shift occurs in demand dynamics, significantly influenced by the charging patterns of electric vehicles, exerting a pronounced impact on nighttime electricity consumption.

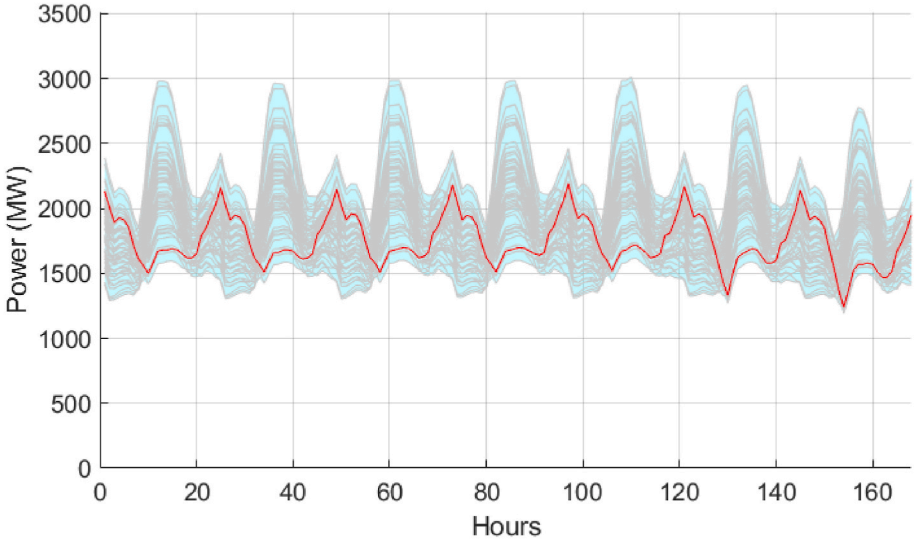

Fig. 8. Hourly average demand curves for a typical winter week using the BEPU methodology.

Regarding Fig. 9, the hourly average sun irradiance curves for the same winter week can be seen. These curves were derived using the BEPU methodology. This visualization helps to understand the changing patterns of solar irradiance. The inclusion of a zoom feature amplifies the detail, offering a perspective on the synthetic curves.

Fig. 10 provides an hourly average of the wind speed curves obtained through the BEPU methodology. This graph depicts the fluctuating nature of wind speeds, which is critical to comprehend the intermittent and variability of wind power during the analyzed winter week.

The methodology used for creating synthetic curves of wind speed or sun irradiance has a main drawback: it does not account for the variability within a day and may not explicitly consider the transition or relationship between hours within a day, but it is a major advance over the usual way of considering it in deterministic methods, in which only the values of a typical year are used.

4.2. Wilks' methodology calculations

Fig. 11 represents the capacity shortage and surpluses for the 59 simulated cases performed to account for the uncertain input variables. Only three simulations have zero shortage when carrying out the simulations (highlighted with circles in capacity shortage, cases 6, 42 and 51). This means the mix that was supposed to meet demand in all circumstances does not. Further analysis of these simulations shows that the highest electric shortage (around 4% of the supplied energy) occurs in two cases. These two worst-case scenarios are highlighted with a line (blue in case 8 and orange in case 30). While the remaining 54 cases all present energy shortages, between zero shortage and 4% of the electricity demand.

The system must provide sufficient energy to meet the demand for electricity. Consequently, the variable of interest is the capacity shortage (energy percentage that the system cannot provide). Still, the electric surplus is also important, as it quantifies how efficient the system is since it provides the energy percentage that the system is not able to use but that is lost. Then, to optimize the energy mix so that the system can cover the energy demand even in the worst-case scenario, the input variables that have more influence or correlate with the variables of interest should be identified. In the current study, the input uncertain variables are solar annual average irradiance, wind annual average speed and those related to the demand: economic growth (*f_EG*), efficiency factor (*f_EFFI*), electrification (*f_ELE*), the implementation of the EV (*f_VE*) and demand management (*f_DM*).

Being precise in identifying and acknowledging the significant parameters through sensitivity analysis helps in taking a proactive approach towards future planning. Integrating these highly influential factors into upcoming strategic planning empowers a more accurate anticipation and preparedness for potential changes or developments. Spearman correlation coefficients assess the correlation between input

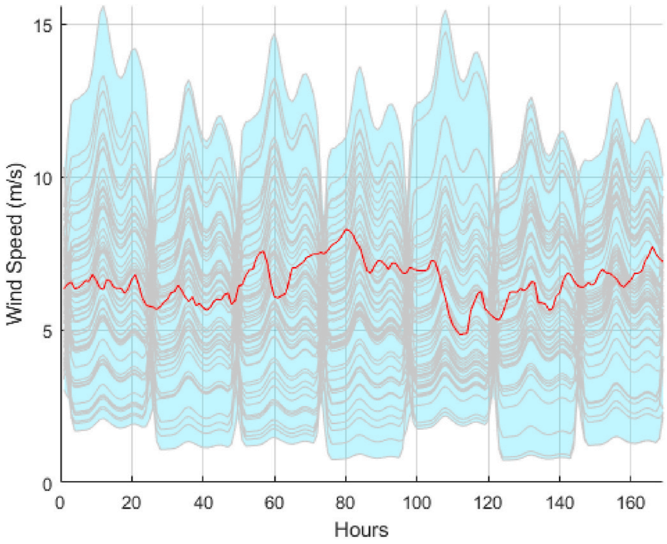

Fig. 10. Synthetic Hourly Profiles for wind speed curves for a typical winter week.

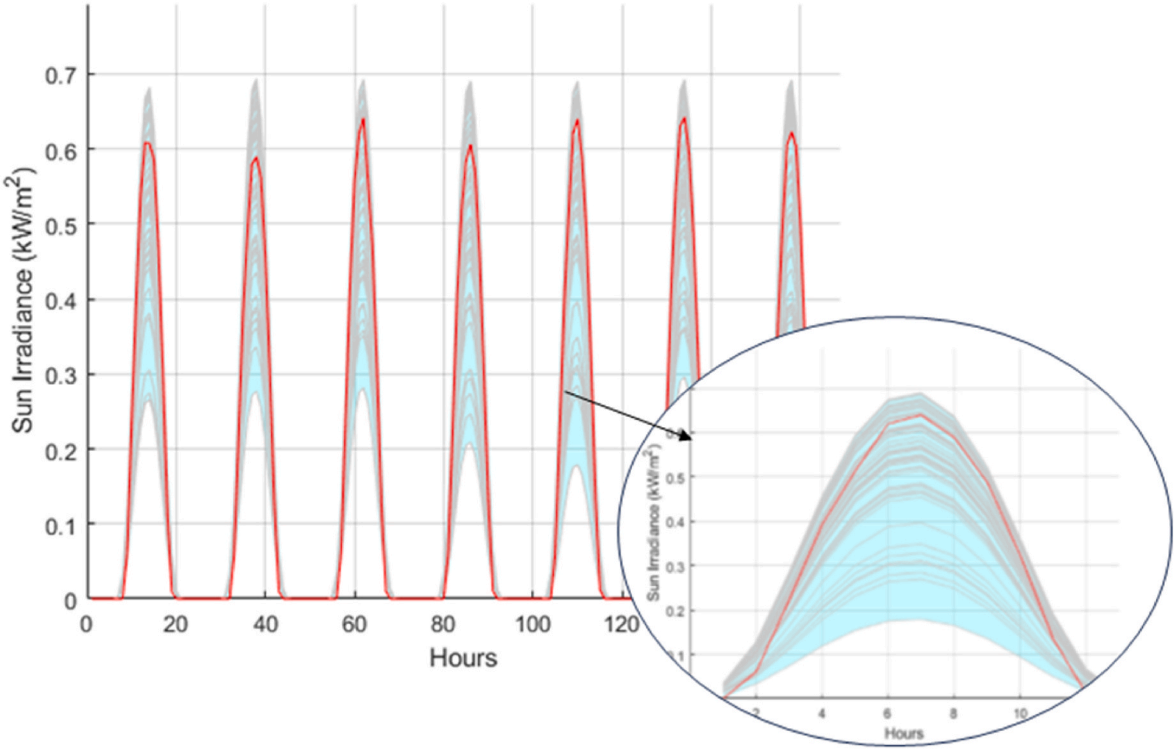

Fig. 9. Synthetic Hourly Profiles for sun irradiance for a typical winter week.

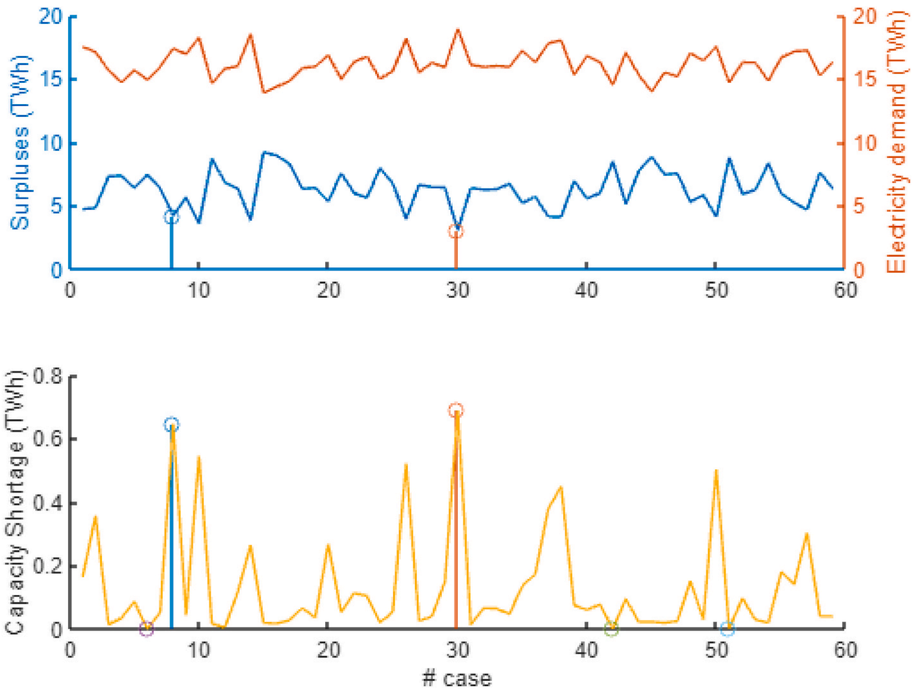

Fig. 11. Capacity Shortage and Surpluses for the 59 Wilks' sampled cases.

and output variables. In addition, the partial connection coefficients (PCC) are presented, as they are more appropriate when there are correlations between input variables, measuring the linear relationship between an input and the output [48]. Figs. 12 and 13 show the Spearman and PCC coefficients for the electric shortage. In both cases the coefficients range from −1 to +1, meaning 0 no correlation and ±1 strong correlation, direct or inverse, respectively. Both figures show that both methodologies provide similar results, but PCC provides additional information since not only gives a correlation coefficient and an error band. In this case, there is a positive correlation between economic

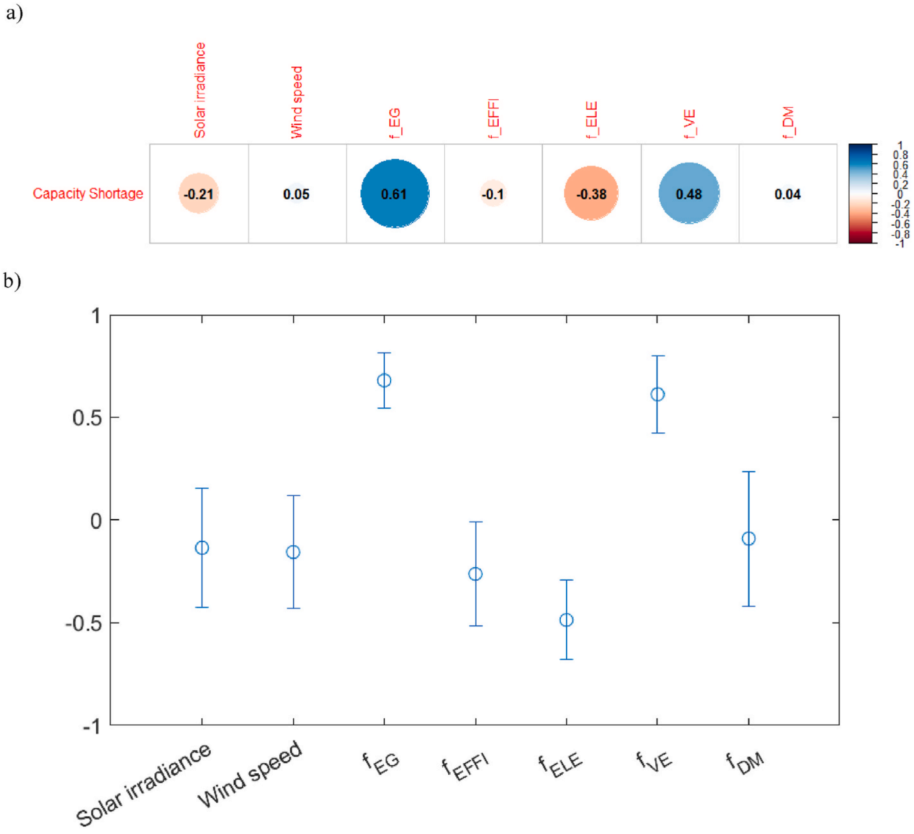

Fig. 12. Coefficients for the Capacity Shortage: a) Spearman; b) PCC.

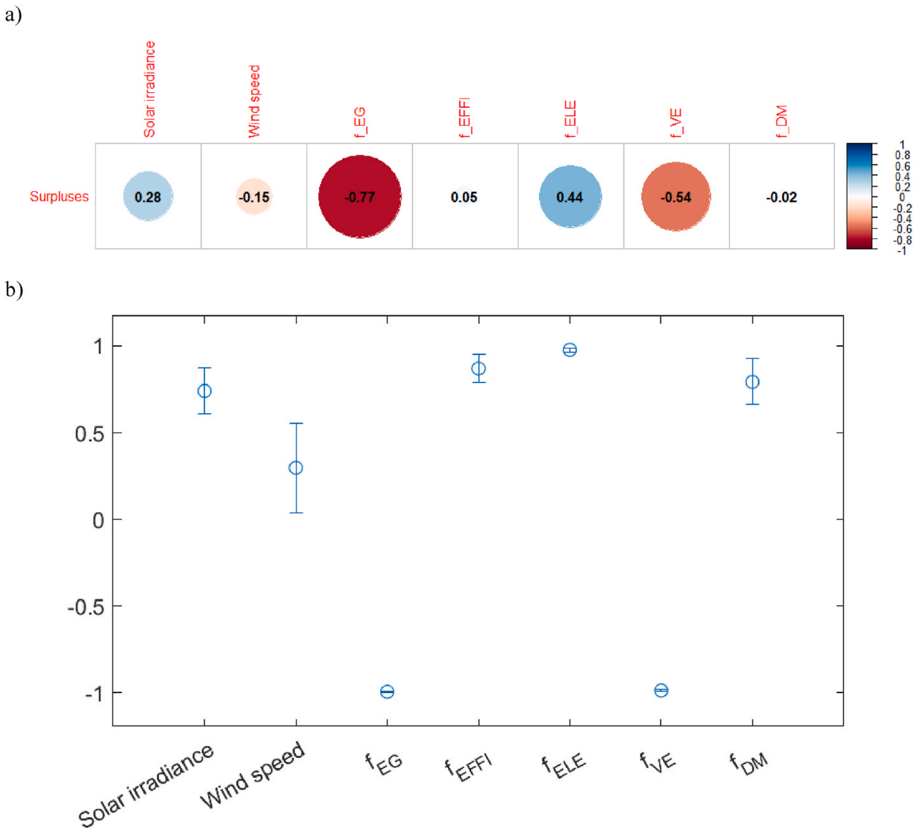

Fig. 13. Coefficients for the Electric Surpluses: a) Spearman; b) PCC.

growth and EV penetration, with small error bands when showing the PCC. The opposite behavior is shown for the electrification (mainly in buildings), solar annual irradiation, and wind and efficiency coefficients, even though the last two are nearly zero. However, the PCC shows that their influence presents an appreciable error band. Finally, the demand management measures have correlations with the shortage, although the error band provided by the PCC is somewhat high.

As previously mentioned, the excess energy should be controlled, so the same analysis has been done for the surpluses. As a general trend, the behavior of the excesses with uncertain parameters, as it seems logical to think, is precisely opposite to the one presented by the shortage. A strong negative correlation between economic growth and the EV can be seen and a direct correlation with electrification and efficiency. However, some discrepancies between the coefficients obtained by both techniques and those presented in the shortage should be noted. It should be noted that Spearman did not show any correlation between excesses and demand management, while this correlation is quite strong in the PCC. Additionally, wind has an inverse correlation in both output variables, which would not be logical, but the relative weight of this source is relatively low and, in the PCC, the uncertainty bands contain zero in both variables, i.e. no significant influence.

Although there are some correlations, the PCC has emphasized the importance of precision when it comes to understanding the effect of uncertain parameters on energy shortage and surplus. In summary, the analysis highlights the critical role of economic growth, electric vehicle penetration, electrification, and efficiency factors in shaping capacity shortage and electric surplus in the energy system. While some correlations are evident, the presence of uncertainty underscores the need for a more precise understanding of these factors' influence.

4.3. *Optimized scenario through statistical analysis*

Given the unpredictable nature of various factors affecting a project, it is imperative to ensure that the required installed capacity is increased to meet the project's demands. Without a precise understanding of the variables at play, it is important to account for potential variations and uncertainties to avoid any potential shortfalls and ensure optimal project performance. Therefore, it is recommended to increase the installed capacity to mitigate any potential risks. After analyzing the results, the main goal is to resize the system to ensure it can meet demand. The new mix can handle all scenarios by recalculating the system's performance for the most adverse cases previously sampled. The system is resized to eliminate shortages, with the worst-case scenario identified as #8 among the 59 simulated cases with the highest shortage percentage. Resizing ensures a 0% shortage and minimizes electricity surpluses as a secondary criterion. However, an important counterpart will be the increase in the energy surpluses because of this system's resizing.

After carrying out the above analysis using the software, the optimal system that has reached 0 shortage in all cases of the sample is presented in the second column of Table 5. Starting by commenting that the main change between the two systems has occurred in storage, although the installed capacity in solar PV has also decreased, increasing wind generation. Note that the reversible pumping system has been maintained since it was maximized in the initial scenario. Consequently, the mega-battery sub-system has increased significantly to provide the demanded extra-storage capacity, from approximately 35 to 55 TWh. The installed capacity of solar generation has decreased, which has reduced the peak generation during the central hours of the day. However, this decrease has been offset by a similar increase in installed wind generation capacity (−1.1 GWs of solar PV and +1.164 GWs of wind generation).

Additionally, wind generation has a much higher capacity factor than solar generation (60% versus approximately 27%), which has led to a significant increase in generation (from 25.5 TWh to 28.3 TWh per year). Despite the significant increase in storage capacity, the system has much higher energy surpluses, from 14% to 24%. In economic terms, the LCOE has gone from just over 10 to almost 14c€/kWh, while the total

Table 5
Summary of the initial generation system and the resized because of the uncertainty analysis.

	Worst Case #8	Worst-Optimized Case #8
Generation System Characteristics		
Renewable sources		
Solar PV (MW)	11,000	9900
Wind (MW)	390	1553.9
Biomass (MW)	150	150
Total power (MW)	11,540	11,604
Storage systems		
Hydro pump (MW)	2050	2050
Battery system power (MW)	3500	5544
Total power (MW)	5565	7609
Pumped storage capacity (GWh)	16.636	16.636
Battery system capacity (GWh)	34.672	54.920
Total storage capacity (GWh)	51.308	71.556
Performance of the Generation System		
Renewable sources		
Solar PV (GWh)	23,598	21,239
Wind (GWh)	1779	7014
Biomass (GWh)	62	62
Total (GWh)	25,439	28,314
Storage systems		
Hydro pump (GWh)	4327	4063
Battery (GWh)	5024	2683
Total (GWh)	9351	6746
System excesses		
Surpluses (%)	14	24
Capacity Shortage (%)	3.61	0
Economical aspects		
LCOE (€/MWh))	104.8	138.1
Total cost (M€)	39,606.8	53,720.3

investment over the project lifetime increased by 14,000 M€ (from almost 40,000 to 54,000 M€).

Consequently, the resized system has zero shortage in the most adverse situation sampled (Table 6). This leads to a much more comfortable performance in all other situations, resulting in higher generation and reduced usage of batteries and the pumping system. Consequently, its surpluses and LCOE will be much higher. Specifically, in the most favorable case (case #51), surpluses increased from 24 to almost 41%, while LCOE increased from 14 to 17c€/kWh. The system costs have increased from 40,000 to 54,000 M€ (nearly 15,000 M€), i.e. by around 25%. It should be noted that these increases are mainly due to the decrease in demand (uncertain value in the sampling) since production has remained practically unchanged compared to case #8, which means that the storage system has a much lower use (from almost 7 TWh/year re-feed into the grid between both systems to just over 3 TWh/year, primarily the batteries have hardly been used, they have dropped from reinjecting more than 2.5 TWh/year into the grid to little more than 0.3 TWh/year).

Table 6
Summary of the resized system performance as a function of the uncertain sampling parameter values.

	Worst-Optimized Case #8	Best-Optimized Case #51
Renewable sources		
Solar PV (GWh)	21,239	21,505
Wind (GWh)	7014	7142
Biomass (GWh)	61	32
Total (GWh)	28,314	28,679
Storage systems		
Hydro pump (GWh)	4063	2935
Battery (GWh)	2683	323
Total (GWh)	6746	3258
System excesses		
Surpluses (%)	24	40.8
Annual Energy Demand (GWh)	17,868	14,655
Economical aspects		
LCOE (€/MWh)	138.1	168.8

4.4. Main findings and summary of the results discussion

The EU and, consequently, Spain are directing significant efforts toward GHG reduction, aiming to achieve complete decarbonization of the European economy by 2050. Various programs have been initiated to encourage and expedite the transition to green energy. Specifically, in the Canary Islands, the Instituto Tecnológico de Canarias has developed up to seven documents over the past years, analyzing the key aspects for the future energy transition. Notably, a foundational document for the PTECan 2030 (Energy Transition Plan of the Canary Islands 2030) [31] outlines the strategic planning to accomplish the comprehensive decarbonization of the Canary Archipelago, with a timeline set a decade earlier than the established deadline for the rest of the State [30].

It is essential to underscore that achieving complete economic decarbonization poses numerous intricate challenges. The islands, given their geographic isolation, face even greater complexities. Nevertheless, islands also present distinct advantages, such as abundant natural resources. This study estimates the decarbonization of the archipelago, considering total electric consumption. Following the calculations carried out with the software and the subsequent analysis through Wilks' methodology, the primary findings pertaining to the electric system in the Canary Islands and the proposed uncertainty analysis are delineated. The subsequent bullet points summarize the principal findings derived from the analysis conducted in this study.

- The study highlights the availability of primary energy sources like PV and wind power, emphasizing their unpredictable nature, necessitating oversizing systems or large-scale energy storage and optimization strategies.
- According to recent studies and reports, the energy demand is expected to double by 100% due to economic growth, electric vehicle usage, and efficiency measures. This increase in demand brings a significant level of unpredictability, as reflected in the uncertainty analysis, which showcases wide variation ranges in these variables.
- The use of random sampling is necessary for highly variable factors such as electricity demand, solar irradiance, and wind speed. The Wilks methodology generates 59 combinations, allowing for 95% confidence and coverage levels in one-sided output variables. This underlines the importance of oversized systems to effectively meet demand across diverse sampled conditions. By considering the variability and transitions between inputs, this method addresses the limitations of traditional deterministic methods. Wilks methodology application reveal that only 3 out of 59 cases initially meet energy demand, indicating a shortage of almost 4%. This highlights the need to resize the generation mix to meet the demand adequately.
- The analysis of shortages and surpluses in relation to various factors indicates clear connections. Economic growth and the adoption of electric vehicles have a direct correlation with shortages and an inverse correlation with surpluses. Conversely, efficiency measures and electrification display a direct correlation with surpluses and an inverse correlation with shortages. Despite their variability, wind speed and solar irradiance exhibit minimal impact on the output variable, indicating no detectable correlation. Similarly, demand management does not reveal any clear trends concerning shortages but potentially correlates directly with surpluses. This potential correlation might be associated with system failures that occur when energy resources are unavailable due to cloudy or calm weather conditions.
- The proposed new energy mix is designed to meet the energy demand without any shortage at the desired confidence and coverage levels. According to the best-case scenario analysis by Wilks method,

the new energy mix guarantees that there will be no shortage, but it comes with the drawback of producing a high percentage of surpluses, approximately 40%. However, this new energy mix comes at a cost. The rescaled system cost increased by almost 15,000 M€, a 25% increase over the base energy mix. Additionally, there is an increase of about 3c€/kWh for the system LCOE.

- The Wilks method demonstrates adaptability in handling uncertainties but heavily relies on precise sampled data while estimating PDFs introduces limitations from expert opinions or historical data or requires extensive simulations for higher confidence levels.
- Fully renewable systems showcase operational reliability but at a significant additional cost due to inherent variability and unpredictability. If high reliability values are to be achieved in the demand coverage, the system must be heavily oversized. Otherwise, the reliability of the system will drop drastically. Even with a very high oversizing of the system there would be a small probability of blackout. In the current scenario, a relatively large oversizing has been used and the system has worked at 95% confidence and coverage levels. At these levels, the oversizing of the system has been considerable, a small increase in the generation power (from 11,540 to 11,604 MW), since it has proved more efficient to increase the storage capacity to achieve the aforementioned system reliability (from 51,308 to 71,556 GWh). It should be noted that if the system reliability had been increased to 99%, the oversizing would have been significantly higher.
- In summary, it is impossible to be entirely confident in practical scenarios, making backup systems or contingency plans crucial for unforeseen uncertainties. In zero GHG scenarios, reliable backup technologies must come from sources like biomass and nuclear facilities or additional oversizing of storage systems. Regardless, these techniques highlight and quantify the limitations of employing deterministic methodologies.

5. Conclusions

The study highlights the relevance of primary energy sources such as PV and wind power, emphasizing the problems associated with their unpredictable nature and the need for oversizing systems or large-scale energy storage. Forecasts for the Canary Islands archipelago by 2040 anticipate a doubling of current electricity demand, driven mainly by economic growth and the adoption of electric vehicles, conditions which introduce even greater unpredictability that is reflected in wide ranges of variation. Best Estimate Plus Uncertainty methodologies, implemented by means of random sampling, have been presented in the current research. Using Wilks' methodology, the generation of 59 random combinations must be addressed to consider variability. This random sampling considering input variables' uncertainty is applied to a deterministic generation mix, which fully covered the electric demand. Finally, only 3 cases met the energy demand initially, indicating a nearly 4% maximum shortage. Consequently, the initial generation mix, reached using a deterministic approach that was supposed to always meet the demand, necessitates a redesign to effectively cover the demand at desired coverage and confidence levels.

Further analysis reveals connections between shortages and surpluses and various factors, highlighting correlations with economic growth, electric vehicle adoption, efficiency measures, and electrification. The proposed energy mix aims to eliminate shortages but results in approximately 40% surpluses, significantly increasing system cost and LCOE. While the Wilks method demonstrates adaptability, it relies heavily on precise data, and estimating probability density functions introduces limitations. Fully renewable systems ensure operational reliability but at an additional cost, emphasizing the importance of backup technologies or contingency plans in practical scenarios, with biomass and nuclear facilities as potential sources. Overall, the study quantifies the limitations of deterministic methodologies in addressing uncertainties.

CRediT authorship contribution statement

César Berna-Escriche: Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Yago Rivera:** Writing – review & editing, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lucas Alvarez-Piñeiro:** Writing – original draft. **José Luis Muñoz-Cobo:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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