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Uncertainty and global sensitivity analysis for the optimal design of distributed energy systems

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HIGHLIGHTS

- A framework for uncertainty investigation in model-based DES design is presented.
- A deterministic DES design model based on the energy hub concept is formulated.
- Probabilistic descriptions of all the relevant uncertain parameters are developed.
- Monte Carlo uncertainty analysis examines the variation of the design model outputs.
- Two-step sensitivity analysis identifies the most influential uncertain parameters.

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ABSTRACT

The effective design of Distributed Energy Systems (DES) is subject to multiple uncertainties related to aspects like the availability of renewable energy, the building energy demands, and the energy carrier prices. Nevertheless, current practices involve the use of deterministic design models, which overlook uncertainty and can lead to suboptimal DES configurations that fail to deliver the desired performance.

A necessary condition in order to obtain robust DES designs against uncertainty is the understanding of uncertainty's impacts and main drivers. Therefore, this paper presents a novel methodological framework for the investigation of uncertainty in the context of DES design, which combines optimisation-based DES models and techniques from Uncertainty Analysis (UA) and Global Sensitivity Analysis (GSA). Moreover, the application of the framework is illustrated with a case study for the optimal DES design of a Swiss urban neighbourhood.

Embarking from a deterministic DES design model, first, all sources of uncertainty are identified and appropriate probabilistic descriptions are assigned to all uncertain model parameters. UA is then performed using Monte Carlo (MC) simulations to quantify the impacts of uncertainty. Results reveal substantial variations in terms of economic and carbon performance of the optimal DES, but also in terms of optimal DES configurations. Moreover, the UA results indicate that the optimal system costs are mostly higher than the deterministic cost estimates, while the inverse is observed for the case of carbon emissions. Additionally, in many of the MC simulations, the resulting optimal DES configurations deviate significantly from the deterministically obtained designs, which confirms the risk of suboptimal decisions in deterministic design processes. Moreover, the results of UA can function as decision support by identifying the DES configurations that are optimal for most realisations of uncertainty.

Finally, to identify the uncertain parameters that are mostly responsible for the variation of the economic performance of the DES, a two-step GSA is launched, combining the Morris method and the variance-based Sobol method. Results of the GSA indicate the energy demand patterns and the energy carrier prices as primarily responsible for the variability of the optimal system cost, while parameters like the investment costs and the technical characteristics of the technologies exert only minimal influence. The results of GSA, besides offering a better understanding of uncertainty to DES designers, also identify the parameters for which additional effort needs to be invested to reduce their uncertainty and, as a result, the uncertainty associated with DES design.

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1. Introduction

1.1. Background and previous work

One goal of the United Nations' *'2030 Agenda for Sustainable Development'* [1] is the transition to a more efficient, sustainable energy future that will include high shares of renewable energy in the global energy mix. A promising pathway towards this vision lies in the adoption of Distributed Energy Systems (DES). DES are placed in proximity to the energy end-use sector they serve, hence, minimising energy transmission losses [2] and incorporating locally available energy resources. Moreover, they typically incorporate multiple energy carriers and renewable and other efficient technologies that convert, store and deliver energy in the form of heating, cooling, and electricity or as other energy carriers (*e.g.* hydrogen) [3], which allows them to increase operational flexibility Overall, DES deliver a series of economic, environmental and technical benefits as discussed in [3–5].

The effective design of DES is critical for the realisation of their benefits. As a result, mathematical optimisation models are commonly developed to assist with their design [6–26]. For instance, Merkel et al. [14] developed an optimisation model for the design of cost-optimal micro-CHP systems for a set of residential buildings. Carvalho et al. [20] developed an optimisation model to determine the optimal synthesis of a hospital's trigeneration plant investigating the trade-off between system costs and carbon emissions. Finally, Di Somma et al. [26] presented a model for the design of a DES for 30 residential buildings with the major innovation of their study being the integration of exergetic objectives in the design. All these DES design models, though, are characterised as deterministic, because they assume perfect knowledge of all model parameters. However, the DES design process combines multiple economic, technical, and policy aspects, which can render model input parameters *uncertain*. Such aspects include the stochastic nature of renewables and the unknown future energy carrier prices, among others.

Uncertainty in DES design introduces additional complexity alongside the risk of suboptimal decisions in cases when the actual parameter values deviate from the ones assumed during the design. Under such circumstances, it is beneficial to understand how uncertainty influences the optimal DES designs and to identify the most influential uncertain parameters. *Uncertainty Analysis* (UA) and *Sensitivity Analysis* (SA) are methods that are exactly aimed to address such concerns.

UA investigates the variability of a model's output given uncertain input parameters; hence, it allows modellers to answer the question "*How uncertain is my model output?*" UA is mostly performed via *Monte Carlo (MC) simulations* in which a deterministic model is evaluated repeatedly for different uncertain parameter samples. UA then seeks to statistically characterise the variable model output by calculating statistical measures, identifying patterns etc.

A number of studies have performed UA in the context of DES. MC analysis of the optimal dispatch of an energy hub system is performed in [27] considering uncertain energy carrier prices. Mavrotas et al. [28] performed UA for the design of a DES considering uncertain discount rate and energy carrier prices. In [29], UA is performed for the design of a multi-generation system considering uncertainty pertaining to investment costs, the price of ethanol, and the CO_2 emissions displaced by ethanol. Besides economic parameters, UA was used in [30] to investigate the impact of wind power uncertainty on the design of a microgrid. Similarly, Li et al. [31] performed MC simulations to account for uncertain energy demands in the design of a trigeneration system. Finally, Dufo-López et al. [32] investigated the uncertainties of solar radiation and energy demands for the design of an off-grid energy system using UA.

Overall, though, the number of studies performing UA remains limited, while the focus is commonly placed only on a few uncertain parameters with some studies considering economic parameters (*e.g.* energy prices) and others renewable energy availability and building energy demands. A final shortcoming pertains to the treatment of uncertain time series parameters like the energy demands and solar/wind patterns. Typically, each time interval is assigned a probability distribution (*e.g.* the Weibull in [30] and the Normal in [31,32]) and is treated independently from the rest. Variable profiles are generated by sampling random values from the specified distributions for each time step. However, this approach neglects the autocorrelation of these time series. Moreover, correlations and interactions between parameters are not considered (*e.g.* between a building's heat demand and solar radiation/solar gains). Finally, specific aspects that cause the uncertainty of these parameters like occupant behaviours cannot be explicitly considered.

Sensitivity Analysis (SA) is complementary to UA and aims to *quantify the importance of uncertain parameters* regarding their contribution to model output variability [33]. The most common SA method is *Local Sensitivity Analysis* (LSA), which investigates parameter importance by varying one parameter at a time, while keeping all other parameters fixed. The popularity of LSA stems primarily from its simplicity and ease of understanding [34]. However, LSA is an *inadequate practice* as it does not effectively cover the input parameter space. Additionally, parameter interactions cannot be studied as this would require simultaneous variation of the input parameters [34]. The drawbacks of LSA are alleviated by using *Global Sensitivity Analysis* (GSA), which varies all uncertain parameters simultaneously, hence, offering better coverage of the uncertain parameter space and allowing for the study of parameter interactions. A wide range of GSA techniques is available [35] and up-to-date reviews of GSA developments are given in [36,37].

Despite the maturity of GSA methods and their great diffusion in relative fields to DES, such as Building Performance Simulation (BPS) [38], the majority of the studies in DES design use LSA to investigate parameter importance (*e.g.* [13,14,39–49]) and only a limited number of studies have applied GSA. For instance, Moret et al. [50] have used the GSA Morris method [51], on the problem of optimal design of a residential energy system, considering multiple technical, economic and energy demand uncertainties. Lythcke-Jørgensen [29] also applied the Morris method to assess the relative importance of each input parameter on output variability.

1.2. This paper

In summary, previous efforts that used UA to investigate uncertainty in DES design considered only a subset of the relevant uncertain model parameters instead of the whole set, while the probabilistic descriptions assigned to time series parameters exhibit certain drawbacks. Moreover, studies that aimed to investigate parameter importance with SA mostly chose to perform LSA instead of the more accurate GSA.

This paper aims to address these shortcomings via the following contributions:

i. The development of a complete methodological framework that integrates state-of-the-art methods for UA and GSA with optimisation-based DES design models.
ii. The consideration of the full set of uncertain model parameters in a DES design model.
iii. The development of a modelling scheme for the generation of variable building energy demand and solar radiation profiles, which better reflect their stochastic nature and correlations. The scheme incorporates aspects like stochastic occupant behaviours and climate change projections and is coupled with a Building Performance Simulation (BPS) tool.
iv. The application of the framework to a case study to illustrate the insight that can be generated and to highlight the importance of uncertainty considerations.

Hence, the main novelty of this paper is that it is the first study in