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Design of distributed energy systems under uncertainty: A two-stage stochastic programming approach

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HIGHLIGHTS

- A two-stage stochastic program for optimal DES design under uncertainty is presented.
- Multiple sources of uncertainty are considered in the model.
- Probabilistic uncertainty scenarios are generated using statistical approaches.
- Cost-optimal DES designs are obtained for different CO_2 limiting strategies.
- A comparison between stochastic and deterministic DES designs is provided.

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ABSTRACT

Uncertainty introduces significant complexity to the design process of distributed energy systems (DES) and introduces the risk of suboptimal decisions when the design is performed deterministically. Therefore, it is important that computational DES design models are able to account for the most relevant uncertainty sources when identifying optimal DES configurations. In this paper, a model for optimal DES design under uncertainty is presented and is formulated as a Two-stage Stochastic Mixed-Integer Linear Program. As uncertain parameters, energy carrier prices and emission factors, building heating and electricity demands, and incoming solar radiation patterns are considered and probabilistic scenarios are used to describe their uncertainty. The model seeks to make cost-optimal DES design decisions (technology selection and sizing) before these uncertain parameters are known, while it also identifies the optimal operation of the selected DES configuration for multiple uncertain scenarios. Moreover, two strategies for emission reduction are employed that set CO_2 limits either to the system's average emissions under uncertainty ('neutral' strategy) or individually to the system's emissions for every possible uncertainty outcome to ensure a more robust emission performance ('aggressive' strategy).

To illustrate the model's application, the design of a DES for a Swiss urban neighbourhood of 10 buildings is investigated. Multiple optimal DES configurations are obtained by using the 'neutral' and 'aggressive' emission reduction strategies and the trade-offs between the systems' economic and emission performance are analysed. Moreover, the optimal DES are contrasted in terms of technology selection and energy consumption shares among fossil fuels, grid electricity and renewable energy. Finally, all model outputs are compared to results obtained from a deterministic design model. The comparison showed that the deterministic model leads to underestimations of the system costs and inaccurate estimates of the system's CO_2 emissions. Moreover, the deterministic designs, in many cases, underestimate the renewable energy capacity that is required to meet the imposed CO_2 limits. These significant differences between the stochastic and the deterministic model results can serve to confirm the shortfalls of deterministic design.

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1. Introduction

1.1. Background and previous work

Given the energetic importance of cities[1] and the increasing urbanisation trends[2], many of the global energy-related challenges are expected to be solved in an urban context. A promising avenue towards creating sustainable cities lies in the transformation of the urban energy supply with *Distributed Energy Systems* (DES) covering large shares of the energy requirements of the urban building stock. DES are placed in close proximity to the buildings whose energy demands they need to cover, and typically accommodate multiple energy carriers, and energy generation, storage and distribution technologies [3]. As a result of their placement, DES can minimise energy distribution losses, while they also allow the integration of locally available renewable energy sources. An overview of DES alongside their economical, technical and environmental advantages is given in [4–6].

The design of DES can be a challenging task though, given the numerous available energy technologies to compose a DES, the need to simultaneously cover multiple energy demand types (heating, electricity, cooling, etc.), and the multiple conflicting objectives involved in DES design (*e.g.* economic, environmental, etc.). Therefore, designers frequently rely on optimisation models to assist them with identifying the DES technology portfolio that will optimise desired performance criteria [7].

The worth of any computational model used in scientific and engineering disciplines depends on how reliable and accurate its output is. Any uncertainty in a model's input parameters, due to either lack of knowledge or inherent system stochasticity [8], can render its output uncertain as well. In DES design, uncertainty can be traced to multiple aspects, such as the stochastic nature of renewable energy and building energy demands or the unknown evolution of energy carrier prices during the DES lifetime. Overlooking uncertainty could lead to sub-optimal DES designs that do not deliver the economic or environmental performance for which they are designed. Nevertheless, in the majority of studies DES design is still performed deterministically (*e.g.* [9–16]).

Uncertainty Analysis (UA) and *Sensitivity Analysis* (SA) are commonly used to investigate uncertainty in a model. UA examines the output variations given uncertain model inputs, while SA aims to identify the uncertain parameters that act as the main drivers of the output variation. UA, for instance, can illustrate the variations of optimal DES designs for different realisations of the uncertain parameters. Such an investigation is valuable as it informs designers about the impacts of uncertainty. However, it cannot identify a *single DES design* that will be optimal against uncertainty. Therefore, decision-makers can find themselves in a quandary about how to further proceed, especially in the case that different designs emerge as optimal when alternative input values are used.

Identifying an optimal DES design in the face of uncertainty can be performed using techniques of *Optimisation under Uncertainty* (OU^2) [17]. *Stochastic Programming* (SP) is perhaps the most utilised OU^2 method[3], with its roots tracing back to the publication by Dantzig [19]. Stochastic Programs are mathematical programs, in which some of the parameters are subject to uncertainty. The main premise of SP is that probabilistic descriptions of the uncertain parameters are available (or can be estimated), either in the form of probability distributions or as scenarios with associated probabilities. The goal of the stochastic program is to identify a policy that ensures feasibility for all (or almost all) possible realisations of uncertainty, while optimising for a performance measure that includes the decision and the uncertain parameters, *e.g.* the expected or the worst-case performance. For a detailed overview on SP we refer the reader to [20].

The *two-stage stochastic program with recourse* (two-stage SP) is the most common stochastic program type. In a two-stage SP, decisions and their associated variables are split in two groups, namely the first- and the second-stage decision variables. The first-stage variables represent *"here-and-now"* decisions, *i.e.* ones that need to be made before the realisation of the uncertain parameters. After uncertainty is revealed, a second set of decisions are made, called *recourse* or *"wait-and-see"* decisions, which depend on the actual value of the uncertain parameters, but also on the first-stage decisions.

The problem of optimal DES design under uncertainty can be suitably accommodated in the decision-making structure of a two-stage SP. DES design decisions (*i.e.* technology selection and sizing) are included in the first-stage, as they need to be made before the actual values of the uncertain parameters (*e.g.* building energy demands) are known. On the other hand, DES operating decisions (*i.e.* when to generate, store, import and/or export energy) belong in the second-stage as they only need to be made after uncertainty is revealed.

Multiple authors have adopted two-stage SP in studies investigating DES design under uncertainty [21–28]. These studies have investigated optimal DES design in various settings including residential buildings and complexes [27,28], hospital buildings [21,22], and rural communities and cities [25,26]. These studies vary also in terms of the uncertainty sources that they consider. For instance, Rezvan et al. [21] considered only energy demand uncertainty, Zhou et al. [23], in addition to energy demands, considered solar and wind energy availability as uncertain, while Yang et al. [22] considered uncertain energy demands, energy carrier prices, and renewable energy (solar and wind) availability. Finally, in all studies, the minimisation of the total DES cost is included as the design objective. In most cases this was the only objective used, but multi-objective formulations have also been used in [27,28] to also investigate the minimisation of CO_2 emissions and the maximisation of renewable energy shares.

Please note that aspects, which are most often associated with stochastic programming and optimisation under uncertainty, such as the "two-stage optimisation" and the use of multiple scenarios, have also been used in the context of deterministic DES design in [29,30]. In these studies, the term two-stage is also used to differentiate between design and operating decisions. However, unlike in two-stage stochastic programming, these studies present a deterministic model, in which given the availability of perfect information, the decisions in the two stages are made at the same time. Regarding the second aspect, the models in [29,30] also consider *multiple scenarios* for which the DES operation is calculated; however, in this case, these scenarios correspond to representative days selected from *within a single year* and do not reflect the uncertain nature of the model parameters like energy demands and prices. This approach, in the literature, is mostly commonly referred to as the "typical days" approach. The aim is to select a set of typical/representative days from a single year that can represent the full yearly horizon and reduce the model's size and computational requirements. Typical days have been used in multiple studies (*e.g.* [31–33]).

Besides DES design problems, the techniques of two-stage and multi-stage stochastic programming have also been used in studies investigating optimal energy system operation under uncertainty [34–47]. The decision structure of a two-stage stochastic program for optimal energy system operation could, for instance, in the first stage, involve day-ahead operation commitment decisions for the DES equipment. The second-stage could then involve the real-time dispatch decisions that need to be made according to the actual realisation of uncertain energy demands, solar patterns, etc. For instance, Mohan et al. [44] presented a two-stage SP for the optimal day-ahead energy management of a DES with multiple renewable sources. Forecast uncertainties for the day-ahead energy demand, wind and solar patterns are considered, as well as uncertainty from generator outages. In

[1] Cities today account for 64% of the global primary energy demand and for 70% of the total energy-related CO_2 emissions [1]

[2] The percentage of urban population is projected to increase to 66% in 2050 from 54% in 2014 [2]

[3] Other methods for OU^2 include Robust Optimisation, Fuzzy Programming, Interval Programming, etc. For an overview see [17,18].