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Designing electrically self-sufficient distributed energy systems under energy demand and solar radiation uncertainty

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Abstract

This paper examines the design of autonomous Distributed Energy Systems (DES) under energy demand and solar radiation uncertainty. A two-stage stochastic program is developed that seeks cost-optimal DES designs considering probabilistic scenarios for the uncertain parameters to represent possible operating conditions. Then, energy autonomy constraints are imposed to each individual scenario, ensuring the autonomy robustness of the DES. The model is applied to a Swiss office building and results reveal that the most cost-effective DES solutions achieve an electrical autonomy of 20% relying on renewable PV electricity generation. Higher autonomy levels require additional electricity from a CHP engine, while a 100% autonomous system is achievable but requires significant amounts of thermal and electrical storage. Finally, comparing the stochastic DES designs against deterministic ones reveal significant differences, illustrating the importance of uncertainty considerations in the design of autonomous DES.

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Keywords: Distributed Energy System, Energy hub, Energy autonomy, Uncertainty, Stochastic Programming

1. Introduction

Distributed Energy Systems (DES) can increase the efficiency of energy supply to urban buildings and districts by incorporating a multitude of renewable and efficient technologies to meet the buildings' heating, cooling, and electricity demands. Besides their economic, environmental and technical benefits [1], DES can also unlock the potential for highly energy autonomous buildings and districts, which cover high shares of energy demands with local energy generation. Autonomous DES can be attractive for a series of reasons including independence from fluctuating energy markets, better control over energy decisions and local consumption of low-carbon generated energy [2].

Given the complexity of designing autonomous DES, mathematical optimisation models are commonly developed to assist with the task. Milan [3] presented a model for the design of a residential building's 100% renewable energy

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system. Orehounig et al. [4] considered energy autonomy as a performance criterion for the comparison of energy system configurations for a Swiss neighbourhood. Finally, McKenna et al. [2] performed a comparative analysis of autonomous energy systems at different spatial scales ranging from the single building to the city district scale.

All these studies, though, are performed deterministically assuming perfect knowledge of all the relevant model parameters required for the design. Nevertheless, many aspects involved in DES design (and their corresponding model parameters) are actually uncertain. Building energy demands are inherently stochastic and are influenced by weather and stochastic occupant behaviours. Additionally, solar radiation data required to predict the performance of solar technologies like photovoltaics (PV) can also be considered uncertain due to factors like measurement accuracy, inter-annual variability, the representativeness of the monitoring period etc. [5].

Neglecting the uncertainty of relevant model parameters could lead to suboptimal DES designs that do not meet the desired energy autonomy targets in cases when the actual parameters deviate from their design values. Therefore, in this paper, the aim is to present an optimisation model for the design of autonomous DES that will also directly incorporate the uncertainty associated with energy demands and solar radiation into the decision-making process.

2. Methodology

2.1. A two-stage stochastic model for the design of autonomous DES and a case study

In this work, the design of an autonomous DES is investigated for an office building in Zurich, Switzerland with a total floor area of 1620 m^2 and a total roof area of 162 m^2 for solar installations, shown in Fig. 1a. The candidate energy technologies for the office's DES shown in Fig. 1b include different types of boilers, heat pumps (air-, ASHP, and ground-source, GSHP), a cogeneration engine (CHP), PV panels, thermal storage and batteries in order to meet the building's heating and electricity demands.

The DES design task then includes the identification of the optimal DES configuration (technology selection and sizing) that will maximise the building's energy autonomy, while minimising the total system cost. Investigating the trade-offs between the two optimisation objectives can be accommodated in multi-objective optimisation. This can equivalently be expressed as a single-objective, cost-minimisation problem, in which the autonomy-maximisation objective is treated within a constraint imposing a minimum autonomy requirement. By varying the levels of the autonomy requirement and performing multiple optimisation runs, different optimal DES configurations can be obtained that represent the trade-off between system cost and system autonomy.

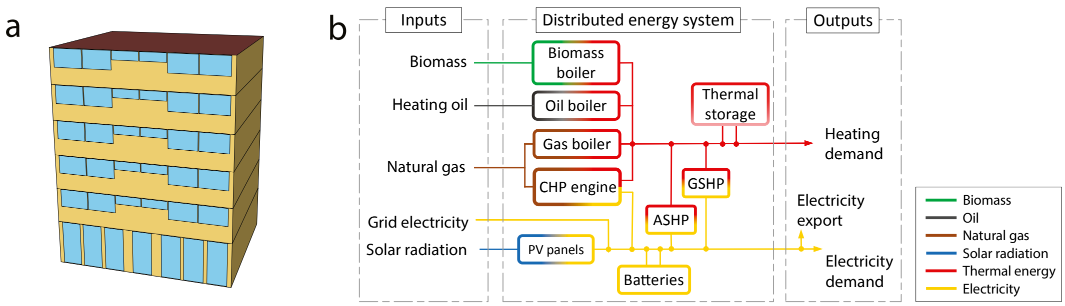

Fig. 1. (a) Illustration of the office building used as a case study; (b) set of candidate technologies considered for the autonomous DES.

The optimal DES design model's formulation for this paper is built on the basis of previous DES modelling efforts [6] that were based on the energy hub concept [7]. A requirement for this paper's model, though, is that it should explicitly account for the uncertainty in the office's energy demands and the incoming solar radiation. However, as the model in [6] is deterministic, the technique for Optimisation under Uncertainty (OU^2) called Two-Stage Stochastic Programming (SP) is used to extend it towards a stochastic formulation that explicitly considers uncertainty.

The main hypothesis of SP is that a probabilistic description of uncertainty is available in the form of scenarios $s \in \mathcal{S}$ each with a probability π_s. In two-stage SP then, decisions are split in two-stages corresponding to decisions that need to be made before (*here-and-now*) and after uncertainty is revealed (*wait-and-see*), respectively. For the task of DES design under uncertainty, design aspects, namely the selection and sizing of the DES technologies, correspond to first stage decisions as they need to be made before knowing the actual values of the uncertain parameters. The operating aspects of the DES (*e.g.* when to import electricity from the grid and how much, when to store energy etc.) belong in the second stage and are made only after uncertainty is revealed.

By explicitly including a set of scenarios s for the uncertain energy demand and solar radiation patterns, the possible conditions under which the DES will need to operate are considered. The aim of the model then, expressed in Eq. (1), is to minimise the first-stage cost, Inv, (*i.e.* the investment expenditure associated with first-stage decisions), and the expectation of the second-stage cost, $\mathbb{E}_{s\in\mathcal{S}}[Op_s]$, where Op_s includes the operational expenditure of the system for scenario s. The total cost for a specific scenario s can then be defined as $CPS_s = Inv + Op_s, \forall s \in \mathcal{S}$.

$$min \;\; Inv + \mathbb{E}_{s\in\mathcal{S}}\Big[Op_s\Big] = Inv + \textstyle\sum_{s\in\mathcal{S}}\Big(\pi_s \cdot Op_s\Big) \tag{1}$$

To reflect the scenario-dependence of the second-stage decisions, all model variables in [6] that are related to operating aspects of the DES (*e.g.* consumption of energy carriers, electricity imports and exports, energy flows to and from storage etc.) need to be expressed per scenario s. Similarly, all the model constraints in which second-stage variables are included (*e.g.* the energy balances) need to be expressed for each scenario s in addition to their current domain (*e.g.* for each time step t). On the other hand, first-stage variables and constraints should remain identical.

The final aspect of the model pertains to the energy autonomy of the DES. In this paper, the term energy autonomy refers to the degree of energy self-sufficiency *i.e.* the percentage of energy demand that is covered by local, building-integrated generation. Given that heat demands can only be covered with local generation, energy autonomy corresponds to the building's electrical self-sufficiency. The autonomy constraint for this paper is expressed in Eq. (2), which defines the degree of electrical autonomy as the part of the total electrical requirements that is not met with grid imported electricity. Electricity generated locally but exported does not contribute towards energy autonomy. Note that in its current form the constraint in Eq. (2) is nonlinear and it would need to be linearised by moving the denominator to the right-hand side. Its form is preserved like that, though, for clarity purposes.

$$1 - \frac{\text{Total grid elec. imports}}{\text{Total elec. requirement}} = 1 - \frac{\sum_{t\in T} P^{grid}_{s,t}}{\sum_{t\in T}\left(P^{ashp}_{s,t} + P^{gshp}_{s,t} + L^{elec}_{s,t}\right)} >= \text{Autonomy requirement [\%]}, \;\; \forall s \in \mathcal{S} \tag{2}$$

In Eq. (2), $P^{grid}_{s,t}$ represents the grid imported electricity, $P^{ashp}_{s,t}$ and $P^{gshp}_{s,t}$ the electricity inputs to the ASHP and the GSHP, respectively, and $L^{elec}_{s,t}$ represents the electricity demand of the building for lighting and equipment. All these indicators are indexed per time step t and scenario s. The constraint in Eq. (2) is enforced separately for each scenario s, meaning that the model will seek robust DES designs that ensure that the autonomy requirements will be fulfilled for every realisation of the uncertain energy demands and solar radiation.

2.2. Scenario generation and reduction

In order to generate scenarios for the uncertain building energy demand and solar radiation patterns, an approach using the Building Performance Simulation (BPS) software EnergyPlus [8] is used. Initially, probability distributions are assigned to the BPS input parameters and then Monte Carlo BPS simulations are launched to generate multiple scenarios for the uncertain parameters. A discussion of the uncertain BPS input parameters is given as follows:

Normal distributions are assigned to material properties, infiltration, ventilation rates and thermostat settings [9,10] using nominal values from [11] for the first two and from the Swiss norm SIA 2024 [12] for the latter two as the distributions' mean. *Triangular distributions* are assigned to the occupancy density, the capacities for lighting and appliances, and the hot water demands [10], created using the min-nominal-max values in [12]. Moreover, to represent aspects like the stochastic occupancy patterns, appliance usage etc. additional variability is introduced to the schedules used in BPS. Starting from the nominal schedules of [12], each hourly value is varied by ±15%. Then the values of each profile are resampled with replacement within specified blocks in each day [13] to introduce variability in the course of actions that each schedule represents (*e.g.* when a device is used). Finally, to represent weather uncertainty, multiple future climate projections are sourced from the CORDEX project [14] for the system's operating period (2021-2040) and transformed into BPS weather files using the 'morphing' technique [15].

In total, approx. 1500 scenarios are generated for the uncertain energy demands and solar radiation with their annual total values illustrated in Fig. 2. If all scenarios are used in the optimisation problem though, its size would lead to computational tractability issues. Therefore, a *scenario reduction technique* is needed to select a subset of the most representative scenarios and calculate their probabilities, ensuring little or no sacrifice to the model's accuracy. For this task, a *feature-based clustering* approach is applied [16]. First, statistical features (mean, variance, max, kurtosis and skewness) are extracted for the energy demand and radiation time series of each scenario to represent the original dataset. Then, the *k*-medoids clustering is applied to this statistical feature set in order to identify the most representative scenarios. External clusters are also introduced to represent scenarios with extreme low and high total annual energy demands, which might not be selected by the clustering algorithm, and scenarios whose peak demands correspond to the desired values for accurate system sizing (*e.g.* a chosen percentile of the peak energy demand distributions). The probability of each representative scenario is calculated as the percentage of all scenarios that belong in each representative scenario's cluster. In this paper, the selected subset consists of 20 scenarios, which are illustrated in Fig. 2, showing the effective coverage of all the regions in the uncertain parameter space.

Fig. 2 shows also the deterministic values for the energy demands and solar radiation, which are calculated using the nominal values of the BPS parameters and a Typical Meteorological Year (TMY). As it can be seen, the deterministic values represent "average" conditions that do not reflect the range of possibilities for the uncertain parameters.

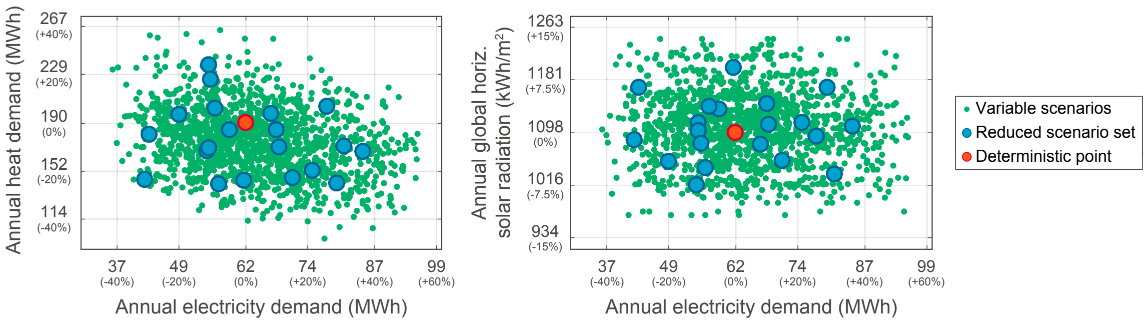

Fig. 2. Variable annual heat and electricity demands and incoming solar radiation, subset of most representative scenarios, and deterministic values (the percentage values in each axis indicate the deviation from the deterministic value)

3. Results

The results of this paper are summarised in Fig. 3. In Fig. 3a, the economic performance of the optimal system configurations is presented in terms of the mean total system cost (see Eq. (1)) and the range of the individual scenario costs, CPS_s. The lowest mean costs are observed when the system autonomy requirement is set at 0%-20%. The mean cost then increases at a relatively constant rate until the 90% point, while for the 100% autonomous system it reaches 60 kCHF. Besides the mean costs, the information regarding the CPS_s range can also be valuable for decision-makers in selecting the desired autonomy level. For instance, in the case of the 100% autonomous system, the cost for the most unfavourable scenario exceeds 70 kCHF, which, if considered extreme, could render the system an unfavourable choice. An additional performance metric presented in Fig. 3a is the system's CO_2 emissions. It can be seen that when autonomy requirements increase, the mean CO_2 emissions as well as their corresponding scenario range increase with it. These patterns can be better understood by examining Fig. 3b and Fig. 3c, which present the selected technologies and their sizes for the different systems.

For the configurations that result in the lowest total system cost (0%-20% autonomy range), the technology selection includes an oil boiler, a GSHP, PV and thermal storage. This also indicates that even when the autonomy requirement is set at 0% or 10%, the autonomy per scenario is actually higher because of PV and reaches 20%. Increasing the autonomy requirement, the first change observed is that a CHP engine is introduced in the DES configuration and its size gradually increases until it reaches 55 kW_{th} at the 100% point. The increased CHP capacities are initially accompanied by similar decreases of the GSHP size, while the oil boiler's capacity is decreased only after the 70% point. At the same time, the capacity of PV remains constant for all configurations. With regards to energy storage systems, the thermal storage tank sizes remains constant until the 70% point and is then increased almost exponentially. Thermal storage is used to store excess heat at times when electricity is generated by the CHP and the CHP's heat output exceeds the heat demand. Increased CHP sizes at higher autonomy levels increase the DES on the CHP

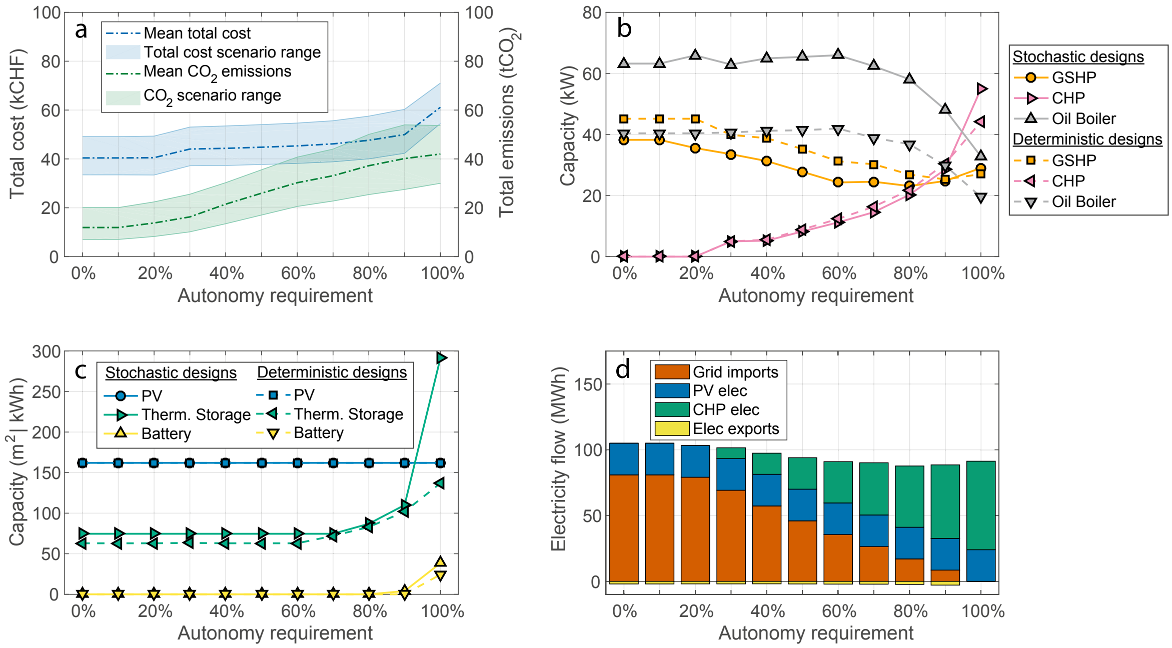

Fig. 3. (a) Mean value and scenario ranges for total system cost and CO_2 emissions; (b) Stochastic and deterministic capacities of energy generation technologies; (c) Stochastic and deterministic capacities of renewable and energy storage technologies; (d) Average electricity flows in the DES for different degrees of energy autonomy.

and, thus, need to be accompanied by higher thermal storage sizes. Finally, batteries are only introduced at a small capacity at the 90% point and reach a size of 45 kWh for the 100% autonomous system.

Besides the system configurations resulting from the two-stage stochastic program, Fig. 3b and Fig. 3c also present the optimal DES designs when the analysis is performed deterministically. These results are obtained using the same two-stage stochastic model but with only one scenario corresponding to the deterministic demand and radiation profiles. Starting from the generation technologies, it can be seen that the oil boiler tends to be undersized in the deterministic compared to the stochastic case, which can be attributed to the deterministic model's reduced knowledge about "extreme" demand scenarios. The implication of selecting the deterministic boiler capacities for the DES is that for some days in a year the DES might be incapable of covering completely the building's thermal needs. On the other hand, the deterministic GSHP capacities are mostly higher than in the stochastic case. Given the uncertainty of the building's electricity demand, the stochastic model reduces the GSHP size to lower the total electricity requirements of the building. The CHP capacities are aligned between the two models, apart from the case of the 100% autonomous system, for which given the extreme scenarios included in the stochastic case, the CHP is sized at a higher capacity. Similarly, in both cases, the maximum roof area is fitted with PV. Finally, for the thermal storage modules, the deterministic capacities are lower than the stochastic ones. Especially, at the highest autonomy requirements, the thermal storage's size is 54% smaller and the battery's 37% smaller. As a result of these differences, if the deterministic design is adopted instead of the stochastic one and given the variable energy demand and solar radiation patterns, there is the risk of not meeting the autonomy requirements of the building. This would be then attributed to both the higher electricity demands resulting from higher GSHP capacities and the smaller CHP and energy storage capacities. Overall, thus, these results illustrate the importance of stochastic analysis in the design of autonomous DES since by examining the range of possible uncertain parameter outcomes better-informed decisions are made.

The final set of information given in Fig. 3d pertains to the total annual electricity flows, averaged over all scenarios, for different energy autonomy levels. It can be seen that for the 0%-20% autonomy range, the dominating source of electricity is the electrical grid supplemented by photovoltaic generation. As the autonomy requirements increase, the grid imported electricity is gradually replaced by CHP-generated electricity until, finally, no electricity is imported for the 100% autonomous system. Overall, given the higher reliance on the CHP engine to cover the building's energy demands, the reducing GSHP capacities in Fig. 3b, and the much lower Swiss grid emission factor compared to the one for natural gas [17], these patterns can also explain why the CO_2 emissions in Fig. 3a are increasing.

Overall, it is shown that electrical self-sufficiency for the examined office building is possible even until 100%. Nevertheless, the system needs to rely heavily on natural gas for electricity generation via the CHP engine, which makes it dependent on another non-renewable resource that needs to be imported. This finding could be thus used as an indication that autonomous DES are perhaps more suitable for whole communities rather than single buildings where resources like hydro power, biomass and wind can be more easily harnessed.

4. Conclusions

In this paper, a two-stage stochastic model is presented for the design of autonomous DES under uncertain energy demand and solar radiation patterns. The model seeks optimal DES designs considering a range of scenarios for the uncertain demand and radiation patterns, which are calculated using Building Performance Simulation. By enforcing the energy autonomy requirement for each individual scenario, robust DES are obtained, which will reach the desired energy autonomy levels for any realisation of the uncertain parameters.

The model is applied to the task of designing an autonomous DES for an office building. Results show that when cost-optimality is sought, 20% of electrical energy autonomy is possible using PV panels. Increasing the autonomy levels requires additional electricity generation by a CHP engine, which in turn increases both the costs and the CO_2 emissions. Finally, a comparison between stochastic and deterministic solutions prove the superiority of stochastic analysis and illustrate the risks of suboptimal DES designs when the analysis is performed deterministically.

As future work, additional uncertain parameters like the energy carrier prices will be included in the model. Moreover, the design of autonomous DES will be investigated at the whole-community scale, where more diverse resource portfolios that include hydro or wind energy can contribute towards energy autonomy.

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