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Evaluating shortfalls in mixed-integer programming approaches for the optimal design and dispatch of distributed generation systems

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HIGHLIGHTS

- We model the optimal design and dispatch of a distributed generation system.
- Our model includes performance characteristics often not considered in simpler models.
- A simpler model underestimates the optimal system capacity compared to our model.

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ABSTRACT

The distributed generation (DG) of combined heat and power (CHP) for commercial buildings is gaining increased interest, yet real-world installations remain limited. This lack of implementation is due, in part, to the challenging economics associated with volatile utility pricing and potentially high system capital costs. Energy technology application analyses are also faced with insufficient knowledge regarding how to appropriately design (i.e., configure and size) and dispatch (i.e., operate) an integrated CHP system. Existing research efforts to determine a minimum-cost-system design and dispatch do not consider many dynamic performance characteristics of generation and storage technologies. Consequently, we present a mixed-integer nonlinear programming (MINLP) model that prescribes a globally minimum cost system design and dispatch, and that includes off-design hardware performance characteristics for CHP and energy storage that are simplified or not considered in other models. Specifically, we model the maximum turn-down, start up, ramping, and part-load efficiency of power generation technologies, and the time-varying temperature of thermal storage technologies. The consideration of these characteristics can be important in applications for which system capacity, building demand, and/or utility guidelines dictate that the dispatch schedule of the devices varies over time. We demonstrate the impact of neglecting system dynamics by comparing the solution prescribed by a simpler, linear model with that of our MINLP for a case study consisting of a large hotel, located in southern Wisconsin, retrofitted with solid-oxide fuel cells (SOFCs) and a hot water storage tank. The simpler model overestimates the SOFC operational costs and, consequently, underestimates the optimal SOFC capacity by 15%.

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1. Introduction

The on-site generation of heat and power, commonly referred to as distributed generation (DG), is gaining interest in the commercial building sector. A DG system can consist of renewable or non-renewable sources of power generation (e.g., photovoltaic (PV) cells, fuel cells, and other prime movers), electric energy storage (e.g., batteries), heat generation (e.g., heat exchangers and boilers), and/or thermal energy storage (e.g., hot water). For some markets, volatile utility pricing and high technology capital costs reduce the economic viability of DG. However, even in the most economically favorable markets, commercial building application remain limited to uninterrupted or backup power systems. Barriers to widespread adoption of DG at the commercial scale (< 1 MW) can be due to high grid interconnection fees and permitting wait times, as well as the perceived risk in installing new technologies. The lack of DG implementation is also due to the inadequacy of existing tools to determine the optimal configuration, size, and operation of complex, combined heat and power (CHP) systems. We refer to this task of determining the lowest cost mix, capacity, and operational schedule of DG technologies as the design and dispatch problem.

Existing efforts (see [1]) to solve the design and dispatch problem apply techniques that include simulation, evolutionary algorithms (e.g., genetic algorithms), or more traditional

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mathematical programming algorithms (e.g., simplex or branch-and-bound). The leading simulation model in the literature is the Hybrid Optimization Model for Electric Renewables (HOMER) (see [2–5]). HOMER enumerates DG system designs that have sufficient capacity to meet the annual demand of a building of interest, calculates the hourly dispatch associated with each system design, and rank orders the designs based on life-cycle cost. However, the dispatch strategy is pre-specified by the user, rather than determined by the model. The inability to optimally select the system dispatch is particularly troublesome when the system design includes storage, because the model cannot consider the demand in future time periods when choosing the dispatch in the current time period. Thus, as with any simulation model (see also [6–9]), the results are inherently *de*scriptive rather than *pre*scriptive.

Prescriptive models of the design and dispatch problem include variables for the configuration, capacity, and time-varying operation of the technologies in the system. The values of these variables are determined by solving instances of the model with an appropriate algorithm. Evolutionary algorithms (EAs) are applied in a number of studies to determine the dispatch of an existing DG system (see [10,11]) or the design and dispatch of a new system (see [12–14]). Although these studies are capable of prescribing a system design and/or dispatch, the EA approach is fundamentally different than that of more traditional algorithms. In general, search heuristics such as EAs do not include methods for bounding the optimal objective function value and terminate based solely on decreased improvement in the objective. Thus, there is often no way of determining whether the solution which results from the algorithm is close to globally (or even locally) optimal. By contrast, models which apply simplex or branch-and-bound algorithms (see [15–19]) can prescribe a provable, globally optimal system design and dispatch.

Foremost among the global optimization models in the DG literature is the Distributed Energy Resources Customer Adoption Model (DER-CAM) (see [20–23]). DER-CAM is a mixed-integer linear programming (MILP) model that is solved using the branch-and-bound algorithm to determine the number of DG technologies to acquire, along with their operating levels over time, to meet the power and heating demands of a building at minimum capital, operational, and environmental (i.e., emissions) cost. In contrast to other existing research, DER-CAM addresses both the design and dispatch of a DG system, applies a provable global optimization approach, includes both economic and environmental costs in its objective, and considers the generation and storage of both power and heat using renewable and nonrenewable technologies. Given all of these attributes, DER-CAM is the most flexible of the design and dispatch models cited thus far. But, DER-CAM does not consider many performance characteristics that constrain the dynamic (i.e., off-design) operation of DG technologies. Simplifying these characteristics permits a linear formulation of the problem with few integer variable restrictions. Thus, even large instances (i.e., instances possessing long time horizons) of the design and dispatch problem can be solved with relative ease. However, insufficiently modeling the off-design system performance could result in the prescription of unrealistic system dispatch schedules and, ultimately, in the recommendation of a suboptimal system design.

Pruitt et al. [24] address the implementation of higher model fidelity by presenting a mixed-integer nonlinear programming (MINLP) model, referred to as $(\mathcal{P})$, that prescribes a globally minimum cost system design and dispatch, and that includes dynamic[1] performance characteristics of power and heat generation and storage that are simplified or not considered in models such as DER-CAM. In addition to typical constraints on demand, capacity, and inventory balance, $(\mathcal{P})$ models the maximum turn-down, start-up fuel consumption, ramping capability, and part-load electric efficiency of power generation technologies, and models the time-varying temperature of thermal storage technologies. The consideration of these dynamic performance characteristics can be particularly important when the technologies are operated in a load-following (i.e., time-varying), rather than baseload (i.e., fixed), manner. In some applications, the DG system configuration and capacity, the building's energy demands, and/or the local utility's rates, policies, and procedures may require a time-varying dispatch from the DG technologies. In these instances, $(\mathcal{P})$ captures the real-world operation of the technologies more accurately than models which simplify or do not consider dynamic performance characteristics.

The objectives of this work are to: (i) evaluate the differences in optimal design and dispatch when using simplified or higher-fidelity models, (ii) develop insight into when higher-fidelity models are more appropriate to employ than simplified models, and (iii) provide a higher-fidelity model for enabling more detailed engineering analyses of integrated DG systems in building applications.

In this paper, we demonstrate that neglecting system dynamics can result in inaccurate prescriptions of system operation and, subsequently, in suboptimal DG investment. In order to demonstrate this, we present a simplified version of $(\mathcal{P})$, called $(\mathcal{S})$, that does not include maximum turn-down, start up, ramping, or part-load efficiency, and that models thermal storage in terms of energy inventory rather than temperature. The formulation of $(\mathcal{S})$ as a representative model that does not consider system dynamics permits both qualitative and quantitative comparisons with $(\mathcal{P})$. In so doing, we are able to highlight the scenarios for which a more detailed model, such as $(\mathcal{P})$, is preferable to a simpler model, such as $(\mathcal{S})$. The remainder of the paper is organized as follows: Section 2 discusses the specific dynamic performance characteristics considered in our research and their importance given alternative operating strategies. Section 3 provides the MINLP formulation of $(\mathcal{P})$, the MILP formulation of $(\mathcal{S})$, and concludes with an examination of the qualitative differences between $(\mathcal{P})$ and $(\mathcal{S})$. Section 4 demonstrates the numerical impact of the differences between the two formulations with a case study of a representative commercial building application. Finally, Section 5 concludes the paper.

2. System operating strategies

For the DG systems examined in this research, we consider solid-oxide fuel cells (SOFCs) as the primary source of on-site power generation. Thus, one of the goals of solving specific instances of $(\mathcal{P})$ is to determine the appropriate operating strategy (e.g., baseload versus load-following) for the SOFC system. Accurately modeling the operation of DG technologies, such as fuel cells, can require the consideration of a number of performance characteristics. Fuel cells convert the chemical energy of a fuel, such as natural gas, directly into electrical energy through electrochemical reactions. In this way, the performance and technological characteristics of fuel cells resemble those of batteries more than those of conventional, fossil fuel-based combustion generators. However, unlike batteries, fuel cells do not require charging and can continue to produce power as long as they are supplied with reactants (such as fuel and air). The materials of construction employed by SOFCs, in particular, demand high operating temperatures to achieve practical power generating efficiencies. Because SOFCs require a significant amount of time to reach operating temperature (i.e., maximum turn-down), their ability to depart standby mode (i.e., start up) and change power output between time periods (i.e., ramp) is limited (see [25]). Additionally, the ratio of their electric energy output to fuel energy input (i.e., electric efficiency)

[1] The usage of dynamic in this paper refers to both the off-design (or part-load) performance of the SOFC system and the time-dependent thermodynamic state of the water in the storage tank.