CO-OPTIMIZING DESIGN AND OPERATION STRATEGY OF SOLID OXIDE FUEL CELL-BASED HYDROGEN-ELECTRICITY COPRODUCTION SYSTEMS

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Abstract

The rapid adoption of non-dispatchable renewable energy increases electricity market volatility and creates an urgent need for more flexible energy systems to balance supply and demand. Integrated energy systems (IES) can offer this flexibility by combining multiple technologies and providing the option to switch between multiple inputs and outputs (e.g. electricity + hydrogen). Detailed market analysis of such IES systems is a challenging task, due to nonlinear models of system operations and modeling switching between operation modes. In this work, we present a framework for rapidly evaluating IES concepts through optimization-based market-informed technoeconomic analysis (TEA). Detailed equation-oriented process models are developed in the IDAES® PSE modeling platform. We then use ALAMO to generate algebraic surrogates for operating costs, capital costs, and co-production constraints. These surrogates enable us to account for complex system dynamics in larger, time-dependent models. Finally, these surrogates are embedded in a Generalized Disjunctive Programming (GDP) model to account for mode-switching system behaviors and the GDP model is solved to output optimal size and output schedule. Here, we demonstrate the method's capabilities by co-optimization of system design and operation of a solid oxide fuel cell (SOFC) power production system and find SOFC systems have economic advantages based on electricity market projections.

Keywords

Solid Oxide Fuel Cell, Wholesale Electricity Markets, Planning & Scheduling, Integrated Energy System

Introduction

With the global climate crisis looming and populations steadily rising, electric demand is expected to continue increasing. The U.S. Energy Information Administration EIA (2022) reports that renewable energy is the fastest growing generation type. While renewable energy has clear environmental and societal benefits, its inherent non-dispatchable nature challenges the operation of the electric grid, in which supply and demand must always be in balance.

Integrated energy systems (IES) can help support renewable integration by providing flexibility to the overall energy infrastructure. IESs combine multiple technologies (e.g., natural gas combined cycles, solid oxide fuel or electrolyzer cells, carbon capture, energy storage, and renewables) and tightly couple them, creating systems that can switch between inputs and outputs (Arent et al. 2021). IESs increased flexibility make them particularly attractive with increased variable renewable energy (VRE) scenarios (Lund et al. 2012). Solid oxide fuel cells (SOFC) present unique advantages for integration with other technologies. They show excellent promise as an energy conversion technology utilizing natural gas, as they have a higher efficiency and are more environmentally friendly than competing generation technologies utilizing natural gas (Singh, Zappa, and Comini 2021). Their high operating temperature, while posing operational challenges, allows waste heat from electricity generation to be collected and used in other integrated processes such as cogeneration (Napoli et al. 2015), biofuels processing (Mehrpooya, Ghorbani, and Abedi 2020), and gas turbines (Meratizaman, Monadizadeh, and Amidpour 2014). Moreover, most technoeconomic analyses (TEA) of SOFC-based IES (Behzadi et al. 2019; Chen et al. 2019) focus on levelized cost of electricity (LCOE) and similar metrics which neglect the dynamic nature of modern wholesale energy markets.

In this work, we present a framework for conducting market-informed TEA of IES. The framework allows co-optimization of design (e.g., subsystem sizes) and operation (e.g., energy flows, modes) under different locational marginal price (LMP) signals. The problem is formulated as a generalized disjunctive programming (GDP) model and implemented in Pyomo. Detailed equation-oriented process models are developed in v1.13.0 of the IDAES® PSE modeling platform (Lee et al. 2021). We then use ALAMO v2021.12.28 (Cozad, Sahinidis, and Miller 2014) to generate algebraic surrogates for operating costs, capital costs, and co-production constraints. Using these surrogates embedded in the GDP optimization model, we can directly compare the economic performance of different IES concepts such as SOFC-based IESs that co-produce hydrogen and electricity. In this study, we consider a projected LMP scenario in the 2035 CAISO region.

Methods

Market analysis was done using a GDP model with disjunctions for operating modes of the systems. Input data for the model include LMP, π_t^p, in \$/MWh, hydrogen price, π_t^h in \$/kg, and technical characteristics of the power/hydrogen systems. These characteristics include minimum system capacities, $\underline{P}$ and $\underline{H}$, in MW and kg/s respectively, maximum system capacity, $\overline{P}$ and $\overline{H}$, in MW and kg/s respectively, fractional turndowns, τ and ϕ, both unitless, and ramp rates, r^p and r^h, in MW/hr and kg/s/hr respectively. The formulation utilizes a self-schedule price-taker approach, assuming the system sets its own schedule based on the LMPs, and the addition of this system to the grid will not have an impact on the LMPs (Dowling, Kumar, and Zavala 2017).

Sets and Variables

The GDP model is indexed over the set $t \in T = \{1, \ldots, 8760\}$, representing the timesteps in the horizon in hours. The decision variables include p_t, the power output of the system at time t in MW, and P, the maximum capacity of the power system in MW. For IES that coproduce hydrogen, decision variables h_t, hydrogen output of the system at time t in kg/s and H, maximum capacity of the hydrogen production system in kg/s, are added.

Power Only Model

For systems that produce power only (two modes: system off and system producing power) the model is as follows:

$$\max \quad \sum_{t \in T} (\pi_t^p p_t - C_{\text{fixed}}(P) - C_{\text{variable}}(p_t) - C_{\text{fuel}}(p_t)) \tag{1}$$

$$\text{s.t.} \quad p_t \leq P \quad \forall t \in T \tag{2}$$

$$\underline{P} \leq P \leq \overline{P} \tag{3}$$

$$p_t \leq p_{t-1} + r^p \quad \forall\, t \in T \tag{4}$$

$$\begin{bmatrix} C_{\text{variable}}(p_t) = 0 \\ C_{\text{fuel}}(p_t) = 0 \\ p_t = 0 \end{bmatrix} \veebar \begin{bmatrix} C_{\text{variable}}(p_t) = f_1(p_t) \\ C_{\text{fuel}}(p_t) = f_2(p_t) \\ p_t \geq \tau \times P \end{bmatrix} \forall\, t \in T \tag{5}$$

Equation (1), the objective, maximizes system profit. The first term represents system revenue from selling power on the wholesale electricity market, C_{fixed} is the fixed capital costs of the system in \$/hr and is a function of system capacity, C_{fuel} is the natural gas cost associated with system operation, a function of system output, and C_{variable} is the variable operating cost of the system in \$/hr, a function of system output. Global constraints include Eq. (2), power output must be less than the system capacity, Eq. (3), installed capacity must be within specified bounds, and Eq. (4), describing ramping behavior. Equation (5) is the disjunction describing the two modes of operation. When the system is off, variable cost, fuel cost, and power output are both zero. When the system is producing power, variable cost and fuel cost are described by surrogate equations f_1 and f_2 and the power output must be greater than the fractional turndown of maximum capacity.

Surrogate Equations

Algebraic surrogate equations for fixed costs, fuel costs, and other variable costs were developed using detailed equation-oriented models developed in IDAES-PSE (Lee et al. 2021) and trained using ALAMO (Cozad, Sahinidis, and Miller 2014). See Table 1 for the surrogates used in this case study (Eslick et al. 2022).

Table 1: Surrogate Equations for SOFC

Surrogate Equations	
Fixed Cost (MM\$/yr)	$70.37\left({}^{\mathrm{P}}/_{650}\right)^{0.77} + 49.53\left({}^{P}/_{650}\right)^{0.779}$
Fuel Cost (\$/hr)	$2.4981p_t + (0.22 \times 10^{-3})p_t^2 + (0.11 \times 10^{-5})pt^3 + 38.617$
Variable Cost (\$/hr)	$0.795309p_t + (0.16 \times 10^{-4})p_t^2 + (0.82 \times 10^{-7})p_t^3 + 10.6$

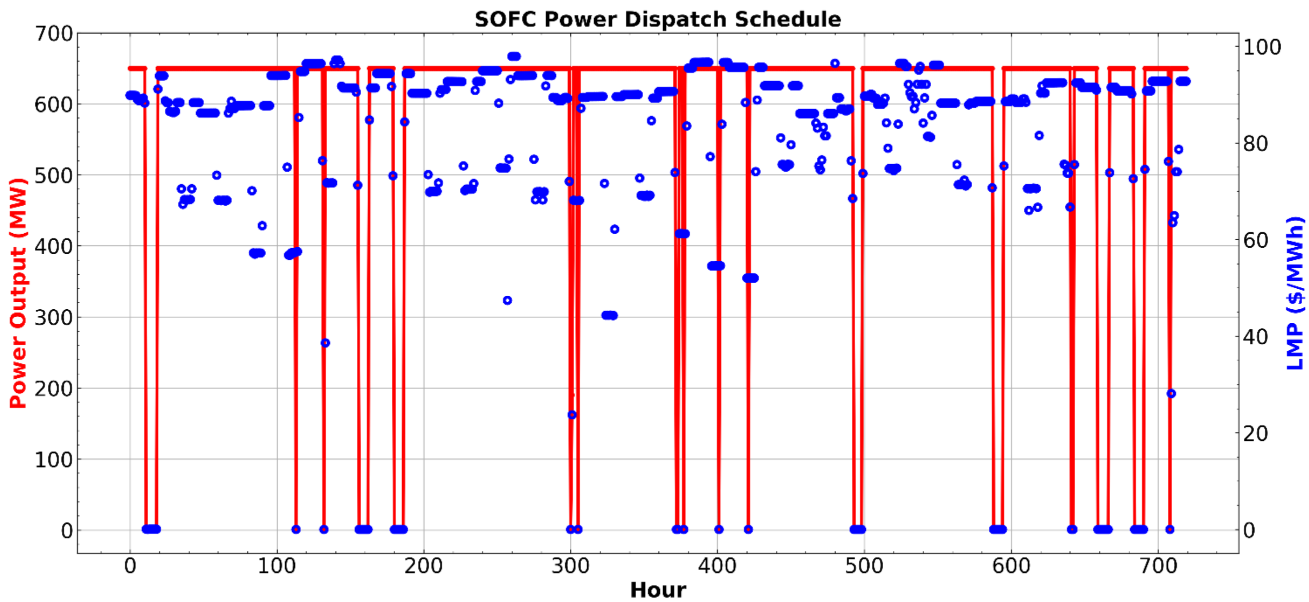

Figure 2: SOFC operation from hours 100 to 300 of the annual simulation. Power output of the system (left vertical axis) is represented by the red line and LMP (right vertical axis) at that point is represented by the blue circles.

Results and Discussion

To demonstrate the use of the proposed formulation, we co-optimize the design and operation of an SOFC system using an annual projected LMP signal modeled by implementing a $100/ton carbon tax on the 2035 CAISO region (Cohen and Durvasulu 2021). Figure 1 shows the price distribution of this LMP signal.

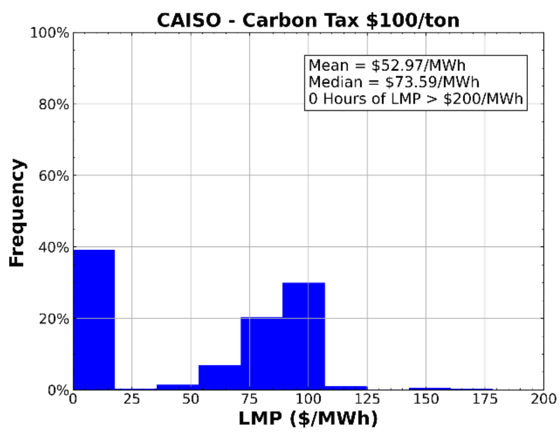

Figure 1: CAISO LMP signal used for analysis.

The system was modeled using Pyomo and solved in a two-step process: first fixing integer variables (operation mode at each time step) and solving the resulting nonlinear programming (NLP) model solving with Ipopt 3.12.8, then unfixing the integers and solving the mixed-integer nonlinear programming (MINLP) model solved using Bonmin 1.8.6 to obtain the final optimal operating strategy and system capacity.

Figure 2 shows the resulting operation scheme from hours 100 to 300 for the SOFC system. In this price scenario, the optimal plant capacity was 650 MW (maximum for the system) and the plant capacity factor was 0.61. From Figure 1, we can see this LMP signal is 39% very low prices (<$10/MWh) and 48% high prices (>$75/MWh) with a mean price of $52.9/MWh. Because of this, the plant spends the horizon either operating at maximum output or shut down. For this solution, we assumed the plant can ramp from off to maximum power in a single 1-hour time step. Adding stricter ramping limits or minimum up/down time constraints would likely impact the operating profile.

Economically, the SOFC system would be profitable under this LMP scenario. This operating strategy results in annual power revenues of M$299.3, with costs (fixed + variable + fuel) totaling M$202.6 annually. This brings annual system profit to M$96.7. These results are consistent with prior, traditional LCOE TEA showing SOFC systems have economic advantages (Adams et al. 2012)

Future Work

Here, we have demonstrated the capability of our framework to co-optimize the design and operation strategy of a power system in the market. As future work, we plan to quantify the impact of stricter ramping and minimum up/down time constraints on the optimal system operation and profitability. We plan to model seven IES concepts hybridizing NGCCs, SOFCS, SOECs, rSOFCs, and compressed air energy storage (CAES) across over ten future LMP scenarios under various carbon tax policies, ultimately developing guidance on which strategies to incorporate SOFC and SOEC technologies into IES are most promising.

Disclaimer

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