

Energy Management of a Renewable-Powered Alkaline Electrolyzer System: A Comparative Study of Nonlinear Optimization Methods

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ABSTRACT

Energy management plays a crucial role in achieving efficient and sustainable operation of industrial energy systems. With the increasing integration of renewable electricity and the growing complexity of hydrogen production networks, effective control strategies are required to minimize operational costs and carbon footprint. However, the uncertain nature of renewable energy sources, such as photovoltaic (PV) power, complicates their accurate forecasting and challenges the optimal energy management of system components. To deal with uncertainties, the rolling horizon approach (RHA) provides a practical framework for adaptive decision-making by repeatedly solving optimization problems over moving time windows while updating system data in real time. In RHA-based energy management, linear or linearized system models are often employed and optimized by linear methods to reduce computational complexity; however, these simplifications can compromise physical realism and lead to suboptimal decisions. Although RHA can also incorporate local, or global deterministic and stochastic algorithms for nonlinear problems, such approaches frequently suffer from high computational effort, slow convergence, local optima, and difficulty in ensuring constraint satisfaction in large-scale nonlinear systems. To overcome these limitations, this work employs the novel hybrid optimization method "BO-IPOPT"—a combination of Bayesian Optimization (BO) for global exploration and the Interior Point OPTimizer (IPOPT) for rapid local refinement. Applied to an industrial hydrogen production system, BO-IPOPT outperforms state-of-the-art approaches in accuracy and robustness by achieving lower operational costs at the same CPU time while satisfying all constraints. Finally, the influence of the uncertainties in PV generation on the performance of the energy management system is analyzed.

Keywords: Energy management, Rolling horizon approach, BO-IPOPT, Renewable hydrogen system

INTRODUCTION

Energy utility systems play a central role in industrial operations, and their efficient management is increasingly crucial as sustainable energy technologies are integrated. The growing penetration of renewable energy sources and energy storage systems has increased the system complexity, making optimal energy management essential [1]. Key objectives include minimizing operating costs, reducing CO₂ emissions, and improving the overall energy efficiency [2]. However, these goals are

challenged by the variability of renewable generation, fluctuating process demands, grid stability requirements, power quality constraints, and uncertainty in energy forecasts [3].

Conventional control strategies, such as PID controllers and rule-based scheduling [4, 5], remain widely used but are inherently limited. These approaches react only to current errors, lack predictive capabilities, struggle with multi-objective optimization and system-wide constraints, and are poorly suited to dynamic and uncertain operating conditions. As a result, more advanced

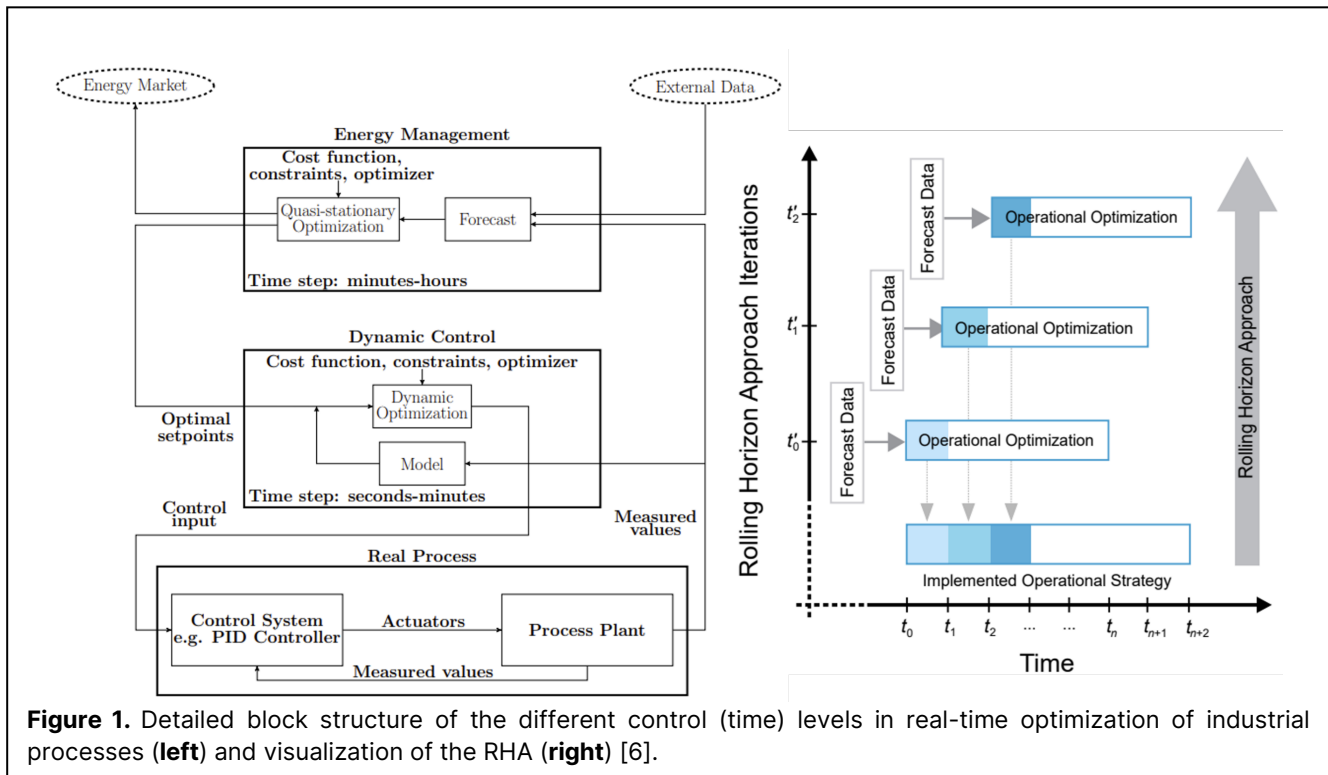


Figure 1. Detailed block structure of the different control (time) levels in real-time optimization of industrial processes (left) and visualization of the RHA (right) [6].

energy management strategies that can anticipate future conditions, coordinate multiple system components, and explicitly account for uncertainty are increasingly necessary.

The role of energy management within the broader framework of real-time optimization is displayed in **Figure 1** on the left [6]. At the highest level, predictive optimization computes optimal setpoints for energy flows, temperatures, and power exchange over time horizons ranging from minutes to hours, with the objective of minimizing operating costs and emissions. These setpoints are passed to the second level, where component-level controllers ensure stable and reliable system behavior by tracking the prescribed targets. The third level describes the physical process itself, including the plant, instrumentation, and actuators that execute the control actions in real time. While all three levels are essential for system operation, this work focuses exclusively on the system (highest) level, i.e., the energy management layer.

To address the uncertainties in energy systems, various methods have been proposed, including stochastic programming, robust optimization, fuzzy logic, and Monte Carlo simulation [6]. Although effective, these methods often entail high computational effort, limiting their applicability in time-sensitive operational contexts. To address this limitation, the rolling horizon approach (RHA) has emerged as a practical and widely adopted solution [6]. By repeatedly solving a finite-horizon optimization problem using updated forecasts and measurements (see **Figure 1** on the right), rolling horizon optimization enables adaptive, real-time decision-making

under uncertainty. This makes it particularly well suited for industrial energy systems with high renewable penetration and rapidly changing operating conditions.

The performance of RHA is closely linked to the choice of the optimization method, which governs how decisions are updated as forecasts and system conditions evolve. Most RHA applications rely on linear or mixed-integer linear formulations, as these enable efficient handling of continuous and discrete variables and offer favorable computational scalability [7, 8]. However, the simplifications inherent in linear and linearized models often reduce physical accuracy, particularly in systems exhibiting strong nonlinear behavior, wide operating ranges, or complex component interactions. In such cases, linear approximations may lead to suboptimal operational decisions. In addition, linearization requires careful balance between accuracy and computational efficiency for the grid fineness. Introducing additional variables—particularly in systems exhibiting pronounced nonlinear dynamics or complex component interactions—rapidly transforms linearization into a computationally demanding process.

Nonlinear optimization methods are less frequently adopted in RHA-based energy management due to their computational burden. Deterministic global solvers are generally impractical under real-time constraints because of exhaustive region enumeration and slow convergence, especially for large-scale nonconvex problems [6]. Stochastic global optimization techniques, such as genetic algorithms, have been explored to better capture nonlinearities and avoid local optima, particularly in

renewable and hybrid energy systems. Nevertheless, their high computational cost, extensive function evaluations, and slow convergence limit their suitability for high-dimensional, constrained, real-time applications [6].

To overcome the computational and convergence limitations of conventional stochastic optimization methods, this work incorporates the recently proposed BO-IPOPT algorithm into the energy management framework for industrial systems. BO-IPOPT is a hybrid approach that combines the global exploration capability of Bayesian optimization with the efficient local convergence and constraint handling of IPOPT [9, 10]. Previous studies have shown that this method can reliably solve large-scale, nonlinear, and constrained optimization problems, delivering significantly improved solution quality and robustness compared to existing approaches under comparable computational effort [6, 11].

In this work, BO-IPOPT is applied to the energy management of an industrial hydrogen production system that includes a 40 MW alkaline electrolyzer (AEL), photovoltaic (PV) generation, grid electricity, an organic Rankine cycle (ORC) unit for waste heat recovery, a high-pressure hydrogen (H_2) storage, a configuration that is inherently nonlinear. The study benchmarks BO-IPOPT against state-of-the-art optimization methods to evaluate its performance in terms of solution quality, robustness, and computational efficiency under realistic operating conditions. Additionally, the investigation addresses the impact of solar data uncertainties on energy management decisions, examining how prediction errors in PV generation influence operational strategies and the overall system performance.

This paper is organized as follows: Section 2 introduces the considered industrial system and Section 3 the optimization methods whose performance is investigated in this work. In Section 4, the prediction model and strategy for multi-step-ahead forecasting are presented. Section 5 shows the influence of different settings on the energy management performance of the industrial system. Finally, Section 6 summarizes the main conclusions and provides a perspective for future work.

USE CASE

In this section, the underlying industrial hydrogen production system is briefly introduced as well as the corresponding optimization problem.

System Description

The industrial system illustrated in **Figure 2** is built around a 40 MW pressurized AEL that supplies hydrogen to a refinery. Its main power source is a PV plant, complemented by electricity generated from refinery waste heat via an ORC unit. When required, additional

power can be drawn from the grid as an auxiliary energy source. The AEL comprises eight stacks, each operating at a pressure of 20-25 bar and consuming 5 MW when running at full capacity. The produced hydrogen is compressed and stored in a high-pressure system operating at 350 bar before being delivered to the refinery. The overall operation ensures that the refinery's hydrogen demand is continuously met at each time step.

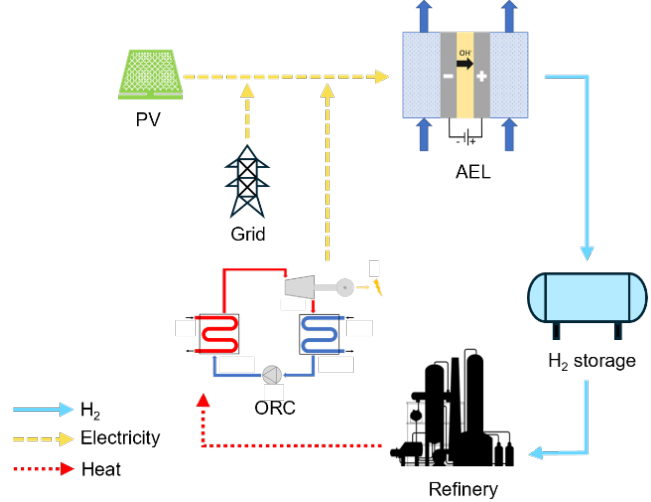


Figure 2. Visualization of the industrial hydrogen production system.

Optimization Problem

For the cost-optimal operation of the industrial hydrogen production system, a constrained, nonlinear, and nonconvex optimization problem is formulated within a multi-period framework. The optimization horizon is discretized into n uniform time steps with the duration Δt , such that the decision variables are evaluated at discrete time points t_k , with $k = 1, \dots, n$. The objective is to minimize the total operational costs consisting of grid electricity costs (first term) and AEL startup costs (second term):

$$\min \sum_{k=1}^n P_{\text{grid}}^k g_{\text{grid}}^k \Delta t + \sum_{k=1}^n \sum_{s=1}^{N_{\text{stack}}} g_{\text{su}}^{k,s} z_{\text{su}}^{k,s}, \quad (1)$$

where P_{grid}^k represents the grid electricity consumption, g_{grid}^k the grid electricity price, $g_{\text{su}}^{k,s}$ the cost per startup of an AEL stack, and $z_{\text{su}}^{k,s}$ a binary variable denoting the startup of a stack, with s describing the AEL stack indices. At each time step, the power balances among all generation and consumption units are maintained as:

$$P_{\text{PV}}^k + P_{\text{ORC}}^k + P_{\text{grid}}^k = P_e^k + P_{\text{comp}}^k, \quad (2)$$

where P_{PV}^k and P_{ORC}^k denote the PV and ORC power generation, P_e^k the AEL consumption, and P_{comp}^k the power consumption for hydrogen compression modeled based on [12]. The hydrogen production rate of each AEL stack is given by Faraday's law as:

$$\dot{m}_{\text{prod, stack}}^{k,s} = \frac{\eta_{\text{Faraday}}^{k,s} I_{\text{cell}}^{k,s}}{2F} M_{\text{H}_2} N_{\text{cell}} Z_{\text{on}}^{k,s}, \quad (3)$$

where η_{Faraday} is the Faraday efficiency, F the Faraday constant, I_{cell} the cell current, N_{cell} describes the number of cells in the stack, and M_{H_2} denotes the molar mass of hydrogen [13]. The total hydrogen production is the summation over all stacks:

$$\dot{m}_{\text{prod}}^k = \sum_{s=1}^{N_{\text{stack}}} \dot{m}_{\text{prod, stack}}^{k,s}. \quad (4)$$

The AEL power consumption P_e^k is modeled according to [13]. In addition, the AEL operates in on/off/standby modes, which are enforced through AEL operational constraints. The PV power generation is modeled as a function of solar irradiance and ambient temperature:

$$P_{\text{PV}}^k = A_{\text{PV}} G_{\text{PV}}^k \eta_{\text{PV, inv}} \eta_{\text{PV, mod}}^k (1 - x_{\text{PV, cur}}^k), \quad (5)$$

where A_{PV} is the module area, G_{PV}^k denotes the solar irradiance, $\eta_{\text{PV, inv}}$ the inverter efficiency, and $\eta_{\text{PV, mod}}^k$ the module efficiency. The latter depends on its part-load behavior, nominal module efficiency, nominal solar irradiance, ambient temperature, and nominal temperature [6]. The variable $x_{\text{PV, cur}}^k$ accounts for the restriction or deactivation of the PV operation. All PV model parameters are taken from [6].

The ORC unit is represented by a surrogate model as a quadratic function of its hot-source temperature $T_{\text{ORC, source}}^k$ and ambient temperature T_{amb}^k :

$$P_{\text{ORC}}^k = f(T_{\text{ORC, source}}^k, T_{\text{amb}}^k). \quad (6)$$

The dynamics of the hydrogen storage are modeled by the differential mass balance:

$$m_{\text{sto}}^k = m_{\text{sto}}^{k-1} + (\dot{m}_{\text{sto, in}}^k - \dot{m}_{\text{sto, out}}^k) \Delta t, \quad (7)$$

where m_{sto}^k is the amount of hydrogen stored, $\dot{m}_{\text{sto, in}}^k$ denotes the hydrogen mass flow entering the storage, and $\dot{m}_{\text{sto, out}}^k$ the hydrogen mass flow withdrawn from the storage. Additional constraints prevent simultaneous charging and discharging, while $\dot{m}_{\text{sto, in}}^k$ and $\dot{m}_{\text{sto, out}}^k$ are limited by the maximum inlet and outlet flowrates of the storage. The resulting formulation describes a nonlinear, nonconvex optimization problem with continuously differentiable constraints, avoiding binary or integer variables through smooth approximations in the hydrogen storage and the AEL, added as penalty terms in the objective function.

This optimization problem employs two different time resolutions to accommodate the available input data characteristics. Grid electricity consumption, PV, storage dynamics, and AEL operation are controlled at 15-minute intervals to capture short-term fluctuations, while the ORC power output follows an hourly resolution by maintaining the heat source temperature $T_{\text{ORC, source}}^k$ constant over each hour (via additional equality constraints). The 15-minute timestep aligns with common intraday

electricity market trading practices [14]. The optimization requires input data including electricity prices, solar irradiance, ORC heat source temperature, hydrogen demand profile, and ambient temperature, with only the solar data forecasted in this work while all other inputs are treated as known.

OPTIMIZATION METHODS

To solve the aforementioned constrained, nonlinear, and nonconvex optimization problem at each iteration of the RHA, several optimization algorithms are examined. These include one widely known stochastic approach, namely GA; the local deterministic optimizer IPOPT applied in single-start form (with and without warm-starting); and the recently proposed hybrid algorithm BO-IPOPT. Although local deterministic solvers are not commonly employed within RHA-based energy management frameworks, their performance is explored here due to their broad applicability and strong efficiency in solving large-scale problems. Owing to the size and complexity of the optimization problem, global deterministic solvers such as BARON are not considered, as they become computationally impractical for problems of this scale (over 100 decision variables) [10]. The following subsections briefly describe the optimization methods evaluated in this study.

Stochastic Method

GA is a well-established stochastic optimization technique inspired by natural processes. GA [15] operates by evolving a population of candidate solutions through selection, crossover, and mutation operators. Constraints are typically addressed by incorporating equality and inequality violations into the objective function via penalty terms [16]. While GA is well suited for exploring large and complex search spaces and capable of escaping local optima, it generally requires a large number of function evaluations, leading to high computational effort and long convergence times, particularly in complex optimization settings.

Deterministic Methods

IPOPT [17] is a deterministic optimization algorithm designed for large-scale nonlinear programming problems. It employs an interior-point framework to enforce constraints and efficiently converges to locally optimal solutions. IPOPT is widely used in scientific and engineering applications due to its robustness and computational efficiency; however, as a local solver, it may converge to suboptimal local minima depending on the initial conditions. Warm-start (WS) strategies are often applied to accelerate convergence by exploiting information from previous solutions, especially when a sequence of related optimization problems is solved, as in RHA-based

approaches [18]. Nevertheless, inappropriate or poorly chosen warm-start information can adversely affect the solution quality.

Hybrid Method

BO-IPOPT is a hybrid optimization method originally proposed in [9] and further developed in [10], which integrates Bayesian optimization (BO) with IPOPT. The method combines BO's capability for global exploration with IPOPT's strength in local refinement and constraint handling. In this optimizer, BO constructs a surrogate model—based on Gaussian processes—to approximate both the objective function and constraints, guiding the search toward promising regions of the decision space without requiring a highly accurate global surrogate. Even if the surrogate model does not fully capture the objective landscape in high-dimensional spaces, its role in BO-IPOPT is primarily to guide the search, while its impact on the performance of the hybrid method will be further investigated in future work. Constraint handling within BO is achieved using an augmented Lagrangian formulation, where inequality constraints are converted into equalities through slack variables, resulting in a sequence of simpler optimization subproblems. IPOPT is then employed to perform local optimization within these regions while efficiently enforcing the constraints. By alternating between BO-driven global exploration and IPOPT-based local refinement, the BO-IPOPT framework is able to effectively address high-dimensional, constrained optimization problems, overcoming many of the limitations associated with purely stochastic or purely deterministic approaches.

UNCERTAINTIES IN SOLAR DATA

Solar irradiance is inherently uncertain due to its strong dependence on atmospheric conditions and cloud dynamics, directly affecting photovoltaic power generation and operational decision-making. Reliable short-term forecasting is therefore essential for the RHA considered in this work.

As discussed in [6], physical forecasting methods rely on atmospheric modeling, numerical weather prediction, and satellite data, resulting in high computational complexity and significant data requirements. Moreover, physical methods are generally more suitable for long-term prediction horizons (> 6 hours ahead), while data-based approaches have been shown to perform better for short-term forecasts of up to six hours ahead. These characteristics make physical models unsuitable for real-time and iterative optimization frameworks, and they are therefore not considered in this study. Instead, data-based forecasting methods are considered, as they leverage historical time-series data and require substantially lower computational effort.

In [6], several data-driven models were evaluated, including linear and nonlinear regression, statistical methods, and machine and deep learning approaches. The results demonstrated that linear regression provides the most favorable trade-off between forecasting accuracy and computational efficiency, especially for both one-step and multi-step ahead predictions. Consequently, linear regression is selected as the solar irradiance forecasting model in this work. Based on the feature selection presented in [6], the resulting multiple linear regression model (MLR) used to predict solar irradiance is expressed as:

$$G_t = f(G_{t-1}, G_{t-2}, G_{t-3}, G_{t-4}, G_{t-\text{day}}, G_{t-\text{year}}, SD_{t-\text{day}}, T_{t-\text{day}}, p_{t-\text{day}}), \quad (8)$$

where G denotes the solar irradiance, SD the sunshine duration, T the air temperature at two meters, and p the air pressure station level.

To propagate uncertainty over the prediction horizon, a recursive multi-step forecasting strategy is employed. Following the approach described in [6], a single one-step-ahead model is trained and applied iteratively, with each predicted value fed back as an input for the subsequent time step. This process continues until the full forecasting horizon is covered. The one-step-ahead forecast at time t is given by:

$$\hat{G}_t = f(G_{t-1}, G_{t-2}, G_{t-3}, G_{t-4}, G_{t-\text{day}}, G_{t-\text{year}}, SD_{t-\text{day}}, T_{t-\text{day}}, p_{t-\text{day}}), \quad (9)$$

while the two-step-ahead forecast is obtained recursively as:

$$\hat{G}_{t+1} = f(\hat{G}_t, G_{t-1}, G_{t-2}, G_{t-3}, G_{t+1-\text{day}}, G_{t+1-\text{year}}, SD_{t+1-\text{day}}, T_{t+1-\text{day}}, p_{t+1-\text{day}}). \quad (10)$$

ENERGY MANAGEMENT

This section introduces the scenarios used for the energy management of the industrial hydrogen production system and the corresponding results.

Scenarios

In this work, two one-week solar data scenarios are considered, representing winter and summer conditions with lower and higher solar irradiation respectively, with a 15-minute resolution. Moreover, the electricity price g_{grid} is fixed at 0.12 €/kWh and the price g_{su} per startup event in each AEL stack at 435 €. The chosen scenarios and values are representative for the considered refinery.

Results

The performance of the energy management strongly depends on the selected optimization algorithm. In this section, we assess the stochastic algorithm "GA",

IPOPT in single-start mode (with and without warm-starting), and the hybrid BO-IPOPT within the RHA-based energy management framework. All methods are implemented in Python 3.12; IPOPT is accessed via Pyomo with default settings, GA uses parameter values recommended in [19], and BO-IPOPT follows the configuration proposed in [10], with the four best candidates selected per outer iteration to match the four available CPU cores. To enhance computational efficiency, the IPOPT evaluations within BO-IPOPT are executed in parallel on four cores using the multiprocessing library, whereas the stochastic search component of BO-IPOPT is kept sequential to ensure a fair comparison with GA. All simulations are performed on a machine equipped with an Intel(R) Core(TM) i7-8665U processor.

In this study, the optimizer CPU running time denotes the fixed time budget assigned to GA and BO-IPOPT at each RHA iteration to compute the best available minimum, i.e., the optimal trajectories for the system setpoints. By contrast, IPOPT and WS-IPOPT are started only once and perform a local search, typically terminating before the end of the fixed time window (average termination time about 40 seconds). Since all considered algorithms contain inherent randomness (e.g., random initializations, sampling), each numerical experiment is repeated 10 times, and the reported results are based on these repeated runs to average out stochastic effects. As a reference configuration, we employ a 24-step optimization horizon, corresponding to 6 hours with 15-minute intervals, resulting in an optimization problem with 4,248 decision variables. This horizon strikes a balance between incorporating enough future steps for robust operational planning and the accuracy of data-based solar forecasts (limited to ≤ 6 hours ahead). Since the true global optimum is unknown, the best solution obtained among BO-IPOPT and GA with a CPU time of 5 minutes per RHA iteration is used as a benchmark for evaluating all algorithms.

We first investigate the effect of the different optimizers when included in the RHA, neglecting any uncertainty in the input data to ensure a fair comparison. In agreement with the refinery, the CPU time for each optimizer is fixed to 50 seconds per RHA iteration, which was chosen so that the resulting control actions and system responses can be updated sufficiently fast for practical implementation. The optimization outcomes for the winter and summer weeks are summarized in **Figure 3**, which presents box plots of the minimum accumulated objective function values for each method over the repeated trials. The results indicate that BO-IPOPT achieves the lowest operating costs and the tightest spread of values among all algorithms. On average (relative to the median), BO-IPOPT attains a relative error of about 0.01 % with respect to the benchmark in the winter week, whereas GA, IPOPT, and WS-IPOPT exhibit errors of

approximately 314 %, 3 %, 0.2 %, respectively. For the summer week, the average error of BO-IPOPT is about 0.2 %, while GA, IPOPT, and WS-IPOPT show relative errors of around 505 %, 4 %, 2 %, respectively. BO-IPOPT is the only method that consistently reaches the benchmark solution in both weeks. As expected, IPOPT and WS-IPOPT show worse performance than BO-IPOPT due to their single-start limitations and suboptimal warm-starts, which lead to wide variability in objective values, higher operating costs, and the need for multiple restarts.

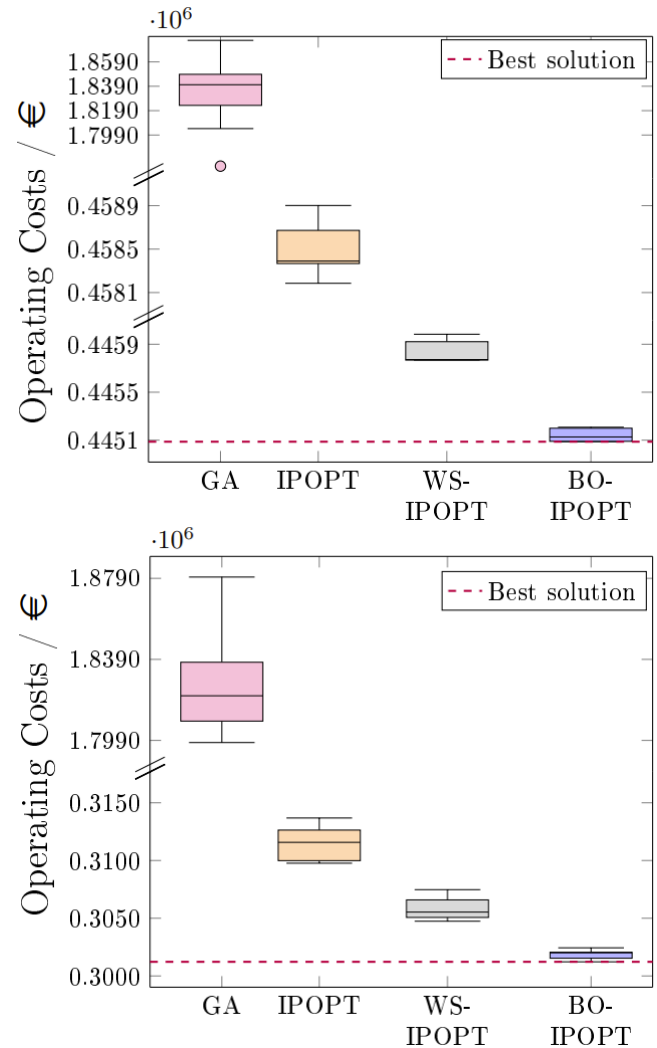


Figure 3. Comparison of operating costs over 10 trials for different optimizers in winter (**top**) and summer (**bottom**). The circles in the box plots represent outliers.

Among single-start methods, WS-IPOPT delivers lower objective function values and a tighter range of results than IPOPT, benefiting from more informed starting guesses that reduce sensitivity to starting points and enhance consistency across repeated runs. The stochastic optimizer “GA” encounters significant challenges: its population-based mechanism and random perturbations

demand numerous iterations to find feasible, low objective function solutions. Within the tight per-RHA-iteration time limits, it fails to adequately search the space or address constraint violations—yielding infeasible results with violations on the order of 10^{12} and much higher operating costs than the other solvers.

It is worth noticing that higher solar irradiation in summer makes the optimization problem more challenging, adding system variability and operational flexibility, thus widening performance gaps between the solvers.

Although IPOPT and WS-IPOPT are single-start local solvers, they frequently fail to converge on the first try, requiring restarts. In this system, IPOPT needed them in 25 % of winter RHA iterations and 43 % in summer. WS-IPOPT improved to 3 % (winter) and 12 % (summer) restart rates. This further supports the advantage of BO-IPOPT, which improves both the solution quality and the convergence to a feasible solution at each RHA iteration.

Although this analysis assumes perfect input data (no uncertainties), **Figure 4** demonstrates that solar uncertainties handled via MLR remain close to the perfect case, with 0.2 % cost deviations in the winter week and 1.6 % cost deviations in the summer week—making this forecasting model suitable for real-time applications (CPU training time < 1 second).

CONCLUSION

This study evaluates the effectiveness of the novel hybrid BO-IPOPT method in the energy management of an industrial hydrogen production system introduced in this work. We first compared BO-IPOPT against state-of-the-art optimizers—IPOPT, WS-IPOPT, and GA—assessing their accuracy and robustness. BO-IPOPT consistently outperformed the alternatives, achieving higher accuracy and robustness, without facing any convergence issues or constraint violations. IPOPT and WS-IPOPT underperformed due to reliance on single-start strategies and suboptimal WS initialization. In addition, both solvers often struggled with convergence failures, frequently needing multiple restarts at individual RHA iterations. Beyond these difficulties, both deterministic methods showed substantial variability in the objective values across repeated runs compared to BO-IPOPT. Although WS-IPOPT offered better accuracy and robustness than IPOPT by reducing the restart frequency and outcome variability, these issues were not fully resolved. Moreover, GA failed to satisfy the system's constraints within the defined computational limits, compromising solution quality.

Another important observation from this energy management analysis is that scenarios with higher solar power availability made the optimization problem more challenging due to greater system variability and operational flexibility. Thus, employing a reliable and efficient

optimizer like BO-IPOPT proves especially critical in such cases. In addition, uncertainties in solar data have also been incorporated into this work. The simple MLR delivered consistently robust results with very low computational demands. Across both solar scenarios, the linear model limited the operating cost deviations up to 1.6 % relative to perfect foresight cases, rendering it highly suitable for real-time applications requiring rapid retraining.

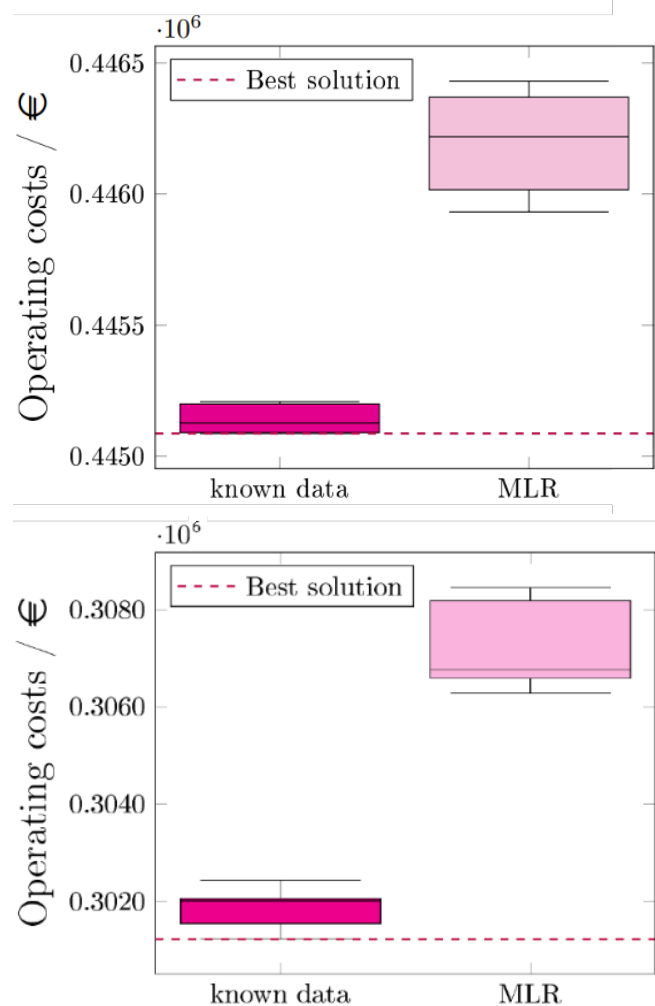


Figure 4. Comparison of operating costs over 10 trials using BO-IPOPT with and without uncertainties modeled via MLR for the solar data in winter (**top**) and summer (**bottom**).

Future work will first benchmark BO-IPOPT against Gurobi on a linearized system using experimental data to determine the superior approach, and investigate hybrid methods such as using Gurobi solutions to initialize BO-IPOPT. Next, different optimization horizons will be investigated to balance forecasting accuracy of input data (which decreases with longer horizons) with computational feasibility (which may worsen as the problem size grows with the horizon length) and predictive planning

(larger horizons help incorporate future conditions into the optimal operating strategy). In addition, we aim to incorporate variable electricity prices alongside uncertainties in hydrogen demand and ORC source temperature. Moreover, implementation in a Hardware-in-the-Loop or real plant setup will then evaluate closed-loop performance with real-time sensor feedback. Finally, the performance of BO-IPOPT will be assessed on even larger systems in future research, including the impact of its surrogate accuracy on the method's performance.

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