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Data-driven robust chance constrained optimization for optimal operation of a wind/hydrogen system

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ABSTRACT
The flexibility of an electrolyser enables a grid-connected wind/hydrogen system to reduce the electricity cost of producing hydrogen by energy arbitrage. Traditionally, decisions of the electrolyser operation are made based on the imperfect prediction of the day-ahead price, which inevitably makes the decision less efficient. In this paper, we further improve the operational strategy of a wind/hydrogen system by proposing a data-driven robust chance constrained method. The proposed method contributes to lower electricity costs compared to those without considering prediction uncertainty. The proposed method can be applied to systems where the price prediction is not accurate in practice.

Keywords: data-driven, robust optimization, day-ahead operation, wind/hydrogen system

NONMENCLATURE

Parameters

\[ \pi_0 \text{ Predicted electricity price (€/MWh)} \]
\[ \pi_1 \text{ Predicted electricity price error (€/MWh)} \]
\[ C^\text{HS}, C^\text{CS} \text{ Hot start cost and cold start cost (€)} \]
\[ p^{\text{ele}}, I^{\text{ele}} \text{ Power and current of electrolyser at breakpoint b (kW, A)} \]
\[ I, \bar{I} \text{ Lower and upper bound of electrolyser current (A)} \]
\[ P_s \text{ Power consumption at stand-by state (kW)} \]
\[ n_s \text{ Number of electrolyser stacks} \]
\[ MW_{H_2} \text{ Molar weight of hydrogen (kg/mol)} \]

Variables

\[ \eta_f, F \text{ Faraday efficiency and Faraday constant (C/mol)} \]
\[ p_t^L \text{ Electricity loads (MW)} \]
\[ \eta_{\text{con}} \text{ Converter efficiency} \]
\[ m^\text{Load}_t \text{ Hydrogen load (kg/h)} \]
\[ SoC_0 \text{ Initial state of charge of hydrogen tank} \]
\[ p_t^\text{con} \text{ Power of converter (MW)} \]
\[ m^\text{ele}_t \text{ Hydrogen from electrolyser (kg/h)} \]
\[ m^\text{by}_t \text{ Hydrogen through bypass (kg/h)} \]
\[ m^\text{in}_t, m^\text{out}_t \text{ Inlet and outlet hydrogen of tank (kg/h)} \]
\[ SoC_t \text{ State of charge of hydrogen tank} \]

1. INTRODUCTION

Renewable hydrogen is regarded as a promising energy carrier for sustainable energy transition. It could be produced by water splitting using electricity from various renewable resources. Such a production pathway makes the renewable hydrogen a womb-to-tomb green energy carrier. This carbon-free fuel contributes to the deep decarbonization of a range of sectors, especially hard-to-abate ones (iron, steel, intensive transport) [1]. It can also serve as a way to store renewable energy...
enabling a high renewable energy penetration and offering flexibility to power systems.

A grid-connected wind/hydrogen system is a typical configuration to produce hydrogen (see Fig. 1). In this way, hydrogen is mostly produced from wind power while electricity from utility grid could also be used as an alternative in the case of insufficient wind power generation. However, as reported in [2], the cost of the hydrogen is much higher than the conventional fuel-based hydrogen (one from steam methane reforming). It is also indicated that the electricity cost plays an important role in the levelized cost of hydrogen. Hence, electricity cost reduction becomes an effective way to enhance the cost-competitiveness of the renewable hydrogen.

Fig. 1. Schematic diagram of a typical grid-connected wind/hydrogen system

One way to reduce the electricity cost is to participate in the electricity spot market and perform energy arbitrage. This is possible thanks to the high flexibility provided by electrolyzers. Under a dynamic pricing scheme, an electrolyser could respond to price signals and alter its power consumption rapidly to achieve economical benefits [3]. However, the daily operation plan has to be submitted before the gate-closure of the day-ahead market, e.g., at 12:00 on the previous day (in Nordpool). Operators have to make decisions based on price prediction while such information is by no means perfect. They need to bear the risk of uncertainty in price prediction.

Stochastic and robust optimization (SO and RO) are widely used to cope with the uncertainty. The SO typically assumes a probability distribution for the uncertain parameters and then generates scenarios. For instance, reference [4] proposed a multi-stage stochastic optimization for the design of a hydrogen supply chain network under demand uncertainty. The authors extracted nine scenarios from a scenario tree. The RO, on the other hand, is focused on the performance of the decisions in the worst case. This is generally achieved by introducing an uncertainty set that limits the range of uncertain parameters. B. Li et al. studied the optimal component sizing of an isolated microgrid considering uncertainties from loads and power outputs [5]. Polyhedron uncertainty set was used to represent the uncertainties. Nevertheless, it is believed that the SO is biased because the real distribution is unknown while the RO is too conservative due to the risk aversion [6]. Data-driven methods bridge the gap between the SO and RO and are viewed as effective methods to cope with uncertainty. Instead of using an assumed distribution or an uncertainty set, a range of possible distributions (called ambiguity set) are applied [7]. The decision is assessed in light of the worst distribution, balancing the robustness and economical benefits.

This paper contributes to the state-of-the-art as follows:

1. A data-driven robust chance constrained (DDRCC) optimization method is proposed to handle the uncertainty from price prediction. The whole problem is successfully reformulated into a MILP form and thus can be easily solved.
2. We compare the proposed method with SO and RO to show its effectiveness and reliability.
3. An advanced operational model of an alkaline electrolyser is utilized for better description of system behaviors.

The remaining paper is organized as follows: Section II introduces the modeling of wind turbines and electrolyzers, along with the day-ahead optimization problem. Section III copes with the uncertainty and reformulates the proposed DDRCC method as a tractable MILP form. The main results are described in section IV and section V concludes this work.

2. PROBLEM DESCRIPTION

2.1 Electrolyser modeling

Alkaline electrolyzers are considered in this work. The key problem is to reveal the relationship between hydrogen production and the required electricity. Hydrogen production, according to Faraday's law of electrochemistry, is in proportion to the electrolyser current. Electrolysers exhibit higher efficiency at lower current density, i.e. at lower hydrogen production. For example, 48.1kWh is required to produce one kg hydrogen at full current load while only 42.7kWh at 25% load [8]. Therefore, we use a piece-wise linear function to represent the power demand at different currents.

On the other hand, the on/off properties of electrolyzers are also included in this model. Electrolysers could be typically operated at three states:
production, standby and off state [9]. In the production state, hydrogen is produced and the required electricity is determined by the aforementioned piece-wise linear function. The standby state prohibits hydrogen production and uses a small amount of electricity to maintain the temperature so that electrolysers could be started up (Hot start) very quickly. At the off state, no hydrogen is produced and no electricity is consumed. However, the next startup (Cold start) is much slower. Both the hot and cold start bring extra operational costs.

2.2 Optimal operation problem

2.2.1 Objective function

The objective is to reduce the operational costs of the system.

$$\min \sum_{t=1}^{T} (C^{Elec}_{t} + C^{BS}_{t} + C^{CS}_{t} Y^{b}_{t} + C^{ON}_{t} Z^{b}_{t})$$

(1)

where the first term is the cost derived from the electricity consumption. It is positive for the case of net import; negative for net export, which generally occurs in the presence of high wind power. The second term denotes the costs related to electrolyser hot and cold start. The decision variables are summarized as:

$$x = [p^{u}, p^{con}, p^{Ele}, Y^{b}, Z^{b}, m^{by}, m^{u}, m^{to}, m^{ele}]$$

(2)

2.2.2 Constraints

$$p^{u}_{t} = \sum_{b=1}^{N_{b}} w_{b,t} p^{Ele}_{t} + s^{P, ele}_{t}$$

(3)

$$I^{ele}_{t} = \sum_{b=1}^{N_{b}} w_{b,t} I^{Ele}_{t} + s^{I, ele}_{t}$$

(4)

$$-M(s^{b}_{t} + i^{b}_{t}) \leq s^{P, ele}_{t} \leq M(s^{b}_{t} + i^{b}_{t})$$

(5)

$$-M(s^{b}_{t} + i^{b}_{t}) \leq s^{I, ele}_{t} \leq M(s^{b}_{t} + i^{b}_{t})$$

(6)

$$\sum_{b=1}^{N_{b}} w_{b,t} = 1$$

(7)

$$w_{1,t} \leq z_{1,t}$$

(8)

$$w_{b,t} \leq z_{b-1,t} + z_{b,t} \quad \forall 2 \leq b < N_{b}$$

(9)

$$w_{N_{b},t} \leq z_{N_{b},t}$$

(10)

Constraints (3) to (10) are the mixed integer representation of the piece-wise linear function for electrolyser power at different currents. Inequalities (5) and (6) introduce two slack variables to decouple the linear relation between current and power at standby and off state, as this relation is only applicable at the production state. The remaining constraints are other necessary restrictions and more details are available in [10].

Equations (11) claims that the three states are incompatible. The next constraint is the safety range of electrolyser current, which is only activated in the production state, followed by restrictions on electrolyser power. Inequality (14) prevents the transition from the off state to the standby state. The Faraday’s law is described in Eq. (15), linking hydrogen production with current. The next two constraints are the definitions of hot start and cold start, which could be linearized by introducing more binary variables. The power balance and the converter efficiency are included in the next two constraints:

$$p^{u}_{t} + p^{w}_{t} = p^{con} + p^{I}_{t}$$

(18)

$$p^{con} \cdot \eta_{con} = 1000 n_{s}^{i} p_{t}^{ele}$$

(19)

Mass balances are described as:

$$\dot{m}_{t}^{ele} = \dot{m}_{t}^{by} + \dot{m}_{t}^{b}$$

(20)

$$\dot{m}_{t}^{by} + \dot{m}_{t}^{bo} = \dot{m}^{load}$$

(21)

Finally, we assume a continuous operation:

$$SoC_{0} = SoC_{T}$$

(23)

The whole optimization problem only incorporates linear function and could be solved by MILP solvers, such as Gurobi.

3. DDRCC REFORMULATION

To shed light upon the structure of the proposed day-ahead operation problem, we abbreviate its original form in a more compact way, as follows:

$$\min_{x} c^{T} x + \xi^{T} p^{u}$$

s.t. \quad x \in \chi$$

(24)

where \(\chi\) is the feasible region of decision variable \(x\). \(p^{u}\), the purchased electricity, is one element of \(x\) but is separated for clarity. Here, for notation convenience, \(\xi\) is referred to the uncertain price prediction errors. We can further move \(\xi\) to constraints by considering the equivalent epigraph form of the primal problem (24):

$$\min_{x \in \chi, d} c^{T} x + d$$

s.t. \quad \xi^{T} p^{u} - d \leq 0$$

(25)
Variable $d$ indeed links historical data with the decisions. As an example, a positive $\xi_t$ means that the real price is very likely to be higher than the predicted value at time $t$. Then it is suggested to reduce the power consumption at time $t$, from the perspective of math, to get a lower bound of $d$. The perfect solution is using the real distribution of $\xi$ to find the best decisions while it is not possible. A good approximation is to consider a series of possible distributions and a chance constraint using the data-driven method, as follows:

$$\mathbb{P}[\xi \in S(p^u, d)] \geq 1 - \epsilon, \quad \forall \mathbb{P} \in \Gamma(\theta)$$  \hspace{1cm} (26)

$$S(p^u, d) = \{\xi | \xi^T p^u - d \leq 0\}$$  \hspace{1cm} (27)

$$\Gamma(\theta) = \{\mathbb{P}|d_m(\mathbb{P}, \mathbb{P}^N) \leq \theta\}$$  \hspace{1cm} (28)

Inequality (26) states that the choice of $p^u$ and $d$ is required to ensure that $\xi$ falls within the safety set $S$ with a probability larger than $1 - \epsilon$. This inequality should be satisfied under every distribution $\mathbb{P} \in \mathbb{V}\Gamma(\theta)$ where $d_m$ is the distance based on Wasserstein metrics and $\theta$ is the radius. The original problem (24) becomes:

$$\min_{x \in X, d} \ c^T x + d$$  \hspace{1cm} s.t. \hspace{0.5cm} \mathbb{P}[\xi \in S(p^u, d)] \geq 1 - \epsilon, \quad \forall \mathbb{P} \in \Gamma(\theta)$$  \hspace{1cm} (29)

Chen et al. demonstrate that for such a problem with individual chance constraints, the problem is equivalent to a mixed integer conic program [11].

$$\min_{x \in X, d, q, s, t} \ c^T x + d$$  \hspace{1cm} s.t. \hspace{0.5cm} \mathbb{P}[\xi \in S(p^u, d)] \geq 1 - \epsilon, \quad \forall \mathbb{P} \in \Gamma(\theta)$$  \hspace{1cm} (30)

with the $\|p^u\|_*$ denoting the dual norm. In this paper, we choose infinite norm as the primal norm, of which the dual form is 1-norm. In this way, the first constraint becomes:

$$eNt - \mathbf{e}^T s \geq \theta N \sum_{t=1}^{T} |p^u_t|$$  \hspace{1cm} (31)

The absolute value of $p^u_t$ could be released by introducing extra variables. Let $|p^u_t| = p^{u,a}_t$, $U$ a constant that is larger than the upper bound of $p^{u}_t$ and $u^b_t$ a binary variable. Following equations are needed to ensure $|p^u_t|$ and $p^{u,a}_t$ are equivalent:

$$0 \leq p^{u,a}_t - p^u_t \leq 2Uu^b_t$$  \hspace{1cm} (32)

$$U(1 - u^b_t) \geq p^u_t$$  \hspace{1cm} (33)

$$0 \leq p^{u,a}_t + p^u_t \leq 2U(1 - u^b_t)$$  \hspace{1cm} (34)

$$-Uu^b_t \leq p^u_t$$  \hspace{1cm} (35)

$$-U \leq p^u_t \leq U$$  \hspace{1cm} (36)

Problem (30) is reformulated as:

$$\begin{align*}
\min_{x \in X, d, q, s, t, p^{u,a}, u^b} & \quad c^T x + d \\
\text{s.t.} & \quad eNt - \mathbf{e}^T s \geq \theta N \sum_{t=1}^{T} |p^u_t| - \xi_i^T p^u + d + Mq_i \geq t - s_i, \quad \forall i \in [N] \\
& \quad M(1 - q_i) \geq t - s_i, \quad \forall i \in [N] \\
& \quad q \in \{0, 1\}^N, s \geq 0 \\
& \quad 0 \leq p^{u,a}_t - p^u_t \leq 2Uu^b_t \\
& \quad U(1 - u^b_t) \geq p^u_t \\
& \quad 0 \leq p^{u,a}_t + p^u_t \leq 2U(1 - u^b_t) \\
& \quad -Uu^b_t \leq p^u_t \\
& \quad -U \leq p^u_t \leq U 
\end{align*}$$  \hspace{1cm} (37)

Although more constraints are included, the final problem could still be identified as a MILP problem, which is an advantage of using infinite norm in the first constraint of problem (30). For other norms, it will be a mixed integer conic programming.

4. RESULTS AND DISCUSSION

4.1 System parameters

The parameters regarding the wind turbines and electrolyser are available in [8, 9, 12, 13]. They are both obtained from commercial applications. Other important parameters are the predicted electricity price errors, which are the input data for the proposed DDRCC method. We build up a multi-layer perception neural network for prediction. The predicted price as well as the real observed price are displayed in Fig. 2a; the corresponding prediction errors are presented in Fig. 2b. It is clear that the spot price has strong volatility and the prediction has poor performance during the days with dramatic price changes. We use these data to build a dataset for prediction errors. For example, provided that we are considering the decisions for day $D$ that is made on day $D-1$, then we use the prediction errors obtained from day $D-2$, $D-3$, ..., $D-1-N$ as N samples.

4.2 DDRCC optimization
In such a wind/hydrogen system, the operators make decisions on the predicted spot price to minimize the operational costs at the same time of meeting the electricity and hydrogen loads. The decisions mainly incorporate the scheduling of electrolysers, hydrogen storage and material balance, i.e. whether using the produced hydrogen directly or storing it. The predicted price, as a key information for decision-making, highly influences the results. For better comparison, we examine the decisions based on imperfect prediction, perfect prediction and the data-driven method. Perfect prediction is of course not possible in the real world. The reason to introduce this scenario is to provide a benchmark for better comparison.

As shown in Fig. 3, we calculate the final daily cost using decisions from different methods. The results show that the minimal cost from adopting decisions based on the imperfect forecast is always inferior to the one based on perfect forecast. For some scenarios (day 6, 7, 8, 9), the difference between these two methods is very small, implying that the prediction is excellent these days. However, for other scenarios (day 1, 2, 3, 4, 5), it is clearly observed the daily costs are higher than those derived from the perfect forecast. Additionally, the results show that the proposed DDRCC method further reduces the daily cost compared to imperfect forecast. This is especially true on day 4, where the daily cost based on poor prediction is thousands of euros higher than the perfect solution. The cost is reduced from 4000€ to nearly 2000€ by using the DDRCC method. For other days, the daily costs decrease more or less. Nonetheless, we also observe that on day 7 more cost is brought by using the DDRCC method, implying that the DDRCC method does not always outperform the trivial method.

4.3 Discussion

As mentioned, there are three important parameters related to the DDRCC-method, i.e. the number of samples, the radius of Wasserstein ball and the probability by which the chance constraint is satisfied. Here we give a brief discussion on the influence of the samples and radius. Figure 4 presents the minimal daily cost (day 9) as a function of the number of samples with different radius \(\theta\). With more samples, the minimum cost firstly decreases and starts to increase when the number of samples reaches a certain point. This phenomenon implies that more samples are not always better. However, in this specific problem, as the spot price may differ by different years (e.g. affected by policy), the old samples are not likely to have the same distribution with the concerned uncertain parameters. The involvement of such samples in fact has a negative effect on the estimation of uncertainty. This phenomenon is also observed for the analysis of other days. Note that this conclusion is problem-specific and limited to this work and may not be true for other application of DDRCC. It is therefore recommended to carefully choose the sample set for other application.

The radius of the Wasserstein ball represents the range of the considered distribution \(\mathbb{P}\) in (28). The larger radius, the more possible distributions are included in the Wasserstein ball. It is shown in Fig. 4 that larger radius results in the higher cost. This result supports the idea that the DDRCC method achieves stronger robustness by sacrificing economical benefits. Further discussion is needed to explain this trade-off between robustness and economies while it is out of the scope of this paper and could be studied in the future.

5. CONCLUSIONS

This paper proposes a DDRCC method to improve the decision-making based on imperfect prediction for a wind/hydrogen system. A detailed electrolyser model is utilized to describe its varying efficiency and state.
transition properties. Using the proposed model, a day-ahead optimal operation problem is considered with the aim of minimizing daily cost. The spot price of electricity is predicted to provide necessary information for decision-making. However, the resulted operational strategies are inefficient due to prediction errors. To further improve the performance, a DDRCC method is proposed. The results show that by considering the uncertainty from price prediction, the daily cost is further reduced, which is caused by the extra information provided by historical prediction data. The results demonstrate the effectiveness of the proposed data-driven method.

REFERENCE


