Extended Load Flexibility of Industrial P2H Plants: A Process Constraint-Aware Scheduling Approach

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Abstract—The operational flexibility of industrial power-to-hydrogen (P2H) plants enables admittance of volatile renewable power and provides auxiliary regulatory services for the power grid. Aiming to extend the flexibility of the P2H plant further, this work presents a scheduling method by considering detailed process constraints of the alkaline electrolyzers. Unlike existing works that assume constant load range, the presented scheduling framework fully exploits the dynamic processes of the electrolyzer, including temperature and hydrogen-to-oxygen (HTO) crossover, to improve operational flexibility. Varying energy conversion efficiency under different load levels and temperature is also considered. The scheduling model is solved by proper mathematical transformation as a mixed-integer linear program (MILP), which determines the on-off-standby states and power levels of different electrolyzers in the P2H plant for daily operation. With experiment-verified constraints, a case study shows that compared to the existing scheduling approach, the improved flexibility leads to a 1.627% profit increase when the P2H plant is directly coupled to the photovoltaic power.

Index Terms—alkaline electrolysis, load management, hydrogen production, power-to-hydrogen (P2H), scheduling

I. INTRODUCTION

Industrial hydrogen production via water electrolysis has been recognized as promising for renewable electrical power admittance and decarbonization of the chemical engineering and transportation industry [1], [2]. As an electrical power load, the power-to-hydrogen (P2H) plant can adjust its load level flexibly to accommodate the fluctuating power generation of wind or solar energy [3], [4] or provide auxiliary regulatory services (peak shaving, frequency regulation, etc.) for the power systems [5], [6]. In order to better admit the volatile renewable power and provide auxiliary services, the flexibility of P2H load should be fully exploited.

Water electrolysis is the most common power-to-hydrogen (P2H) conversion method. Mainstream technical routes include alkaline water electrolysis (AEL), proton exchange membrane electrolysis (PEMEL), and solid oxide cell electrolysis (SO-CEL) [7]. Due to relatively high maturity, large capacity, and long lifespan, AEL is preferred for many industrial hydrogen production [7]-[9]. Hence, this work focuses on extending the flexibility of AEL P2H plants.

An alkaline electrolyzer can adjust its hydrogen production rate and power consumption, but its load flexibility is constrained by internal dynamic processes [10], [11]. For example, the electrolyzer cannot operate at full power unless warmed up [10] and cannot operate at low power for a long duration due to the accumulation of hydrogen-to-oxygen (HTO) crossover [10], [11]. Moreover, the energy conversion efficiency is significantly affected by the temperature and pressure [10].

In addition, an industrial P2H plant is usually composed of multiple electrolyzers [1], [7], [8]. When coupled with renewable power generation, in order to accommodate the intermittent and volatile power supply, the plant operator needs to determine the number of operational electrolyzers and their load levels at different times according to the renewable power forecast [8], [12]. Therefore, a plant-level daily scheduling program is also needed.

In traditional P2H plant scheduling methods, the operational constraints of the electrolyzer are set as constant [8], [12], [13]. However, this can be too conservative. For example, the electrolyzer can operate at low power for a short time without violating the HTO impurity constraint, as explained in Section II-E. Therefore, to fully extend the load flexibility of the P2H plants, this work aims to present a scheduling approach taking into account these dynamic process constraints that are not considered in existing research. The literature review and contributions of this work are briefly below.

A. Literature Review

The flexible operation ability of P2H load has been recognized by the community. However, many existing works only considered small-capacity integration of P2H in the renewable power systems or microgrids with only one electrolyzer, and the process constraints were omitted [14], [15].

Several latest works investigated the P2H plant scheduling with multiple electrolyzers. For example, rule-based plant scheduling strategies were proposed in [16], [17], which may not be optimal. Serna et al. [12] proposed a model predictive control (MPC) based scheduling framework for offshore electrolyzers coupled with wind and wave power. Varela et al.
[8] developed an MILP-based scheduling model for the P2H plant to consider the on-off operation state of each electrolyzer. Uchman et al. [13] used exhaustive search to determine the optimal production schedule of three electrolyzers, which can be hard to scale up. He et al. [18] considered the UC and capacity limits in P2H plant scheduling, but the process constraints of the electrolyzers were omitted. Instead, the operation of electrolyzer is constrained by constant constraints when the plant is shutdown and startup is required, formulated by

\[ b_{i,k}^{\text{shutdown}} + b_{i,k}^{\text{startup}} - b_{i,k}^{\text{idle}} = 1. \]

The indicators of startup and shutdown, i.e., switching from Idle to Production or Standby and reversely, are depicted by binary variables \( b_{i,k}^{\text{startup}} \) and \( b_{i,k}^{\text{shutdown}} \), subjected to

\[ b_{i,k}^{\text{startup}} + b_{i,k}^{\text{shutdown}} + b_{i,k}^{\text{idle}} = 1. \]

Meanwhile, a minimal gap of \( N^{(\text{min, idle})} \) time steps between shutdown and startup is required, formulated by

\[ t_{i,k}^{\text{idle}} + t_{i,k}^{\text{idle}} - \sum_{i=1}^{j-1} t_{i,k}^{\text{idle}} - j \leq 0, \quad \forall j = 2, \ldots, N^{(\text{min, idle})}. \]

The schematic of electrolyzer state switching is shown in Fig. 2 and details can be found in [8].

### B. State Switching of Electrolyzers

Following the idea of [8], three mutually exclusive binary variables \( b_{i,k}^{\text{on}} \), \( b_{i,k}^{\text{standby}} \), and \( b_{i,k}^{\text{idle}} \) are used to represent the three operational states for the \( i \)-th electrolyzer at time \( k \), as

\[ b_{i,k}^{\text{on}} + b_{i,k}^{\text{standby}} + b_{i,k}^{\text{idle}} = 1. \]

### C. Hydrogen Production and Power Constraints

Supposing the pressure is maintained constant, the hydrogen production rate of an electrolyzer is a concave function of electrolytic power and temperature [11], denoted by

\[ \dot{n}_{i,k}^{\text{H}_2, \text{prod}} = f(P_{i,k}^{\text{ele}}, T_{i,k}). \]

where \( \dot{n}_{i,k}^{\text{H}_2, \text{prod}} \) is the \( i \)-th electrolyzer’s hydrogen production rate at time \( k \); \( P_{i,k}^{\text{ele}} \) is the electrolytic power; and \( T_{i,k} \) is the temperature of the electrolyzer.

To facilitate modeling the plant scheduling problem as an MILP, the production function (3) is approximated by a polyhedron using the famous double description (DD) algorithm [21] and then relaxed as a group of inequality constrains, as

\[ \dot{n}_{i,k}^{\text{H}_2, \text{prod}} \leq A P_{i,k}^{\text{ele}} + b_{i,k}^{\text{on}} \leq C, \]

In Production, the electrolyzer breaks up water molecules into hydrogen and oxygen using electrical power, the pump keeps lye circulating, the cooler takes away excess heat, and the control system keeps the temperature and pressure in an appropriate interval. The total power consumption is the sum of electrolytic power and the power consumed by the auxiliary equipment. In Standby, the electrolytic power becomes zero, but the control system keeps working, and the heater keeps the system warm so that it can quickly switch to the Production state. In Idle, the whole system is turned off.

### B. Contributions of This Work

To extend the load flexibility of the industrial P2H plants, a scheduling method considering dynamic process constraints of the alkaline electrolyzer is proposed. The main contributions of this work include:

1) A novel scheduling framework for industry P2H plants considering process constraints in the alkaline electrolyzer is first presented.
2) The proposed P2H plant scheduling model with the nonlinear production function and dynamic temperature and HTO crossover constraints are reformulated and solved as an MILP problem.
3) Case studies show that the extended flexibility improves total hydrogen production compared to the traditional method with constant constraints when the plant is directly coupled with solar energy.

The remainder is organized as follows. Section II presents the dynamic process constraints of the alkaline electrolyzer; Section III presents the plant scheduling model and solution method, which is verified by case studies in Section IV.

### II. Modeling Dynamic Process Constraints of an Alkaline Electrolyzer

#### A. Overview

The process schematic of an alkaline electrolyzer is shown in Fig. 1. To accommodate fluctuating power supply, the electrolyzer switches between three different operational states, namely Production (P), Standby (S), and Idle (I).
Electrical Power (MW) 

Heat, in, out

H2 Production Rate (Nm³/h) 

Electrolytic Power (MW) 

Res, heat, cool

(b) Hydrogen-to-oxygen crossover dynamics model

Fig. 3. Piecewise linearized production function of the electrolyzer

where \( A, B \) and \( C \) are constant coefficient vectors.

According to (6), when the electrolyzer is in Standby or Idle, the hydrogen production is zero. When in Production, because the scheduling objective always maximizes hydrogen production, the operation point will be on the surface of the production function, as shown in Fig. 3.

Moreover, to avoid sudden changes in pressure, separator liquid level, or stack gas-liquid ratio that may cause excessive stress, the ramping rate of production is limited, as

\[
\Delta P_{\text{H}_2} = \Delta \dot{N}_{\text{H}_2} = \dot{N}_{\text{H}_2} - \dot{N}_{\text{H}_2} \leq \bar{\Delta} P_{\text{H}_2},
\]

where \( \Delta P_{\text{H}_2} \) and \( \bar{\Delta} P_{\text{H}_2} \) are the upper and lower bounds.

The power consumption of an electrolyzer is the sum of both electrolytic and the balance of plant (BoP) consumption:

\[
P_{\text{tot},i,k} = P_{\text{ele},i,k} + (b_{\text{on},i,k} + b_{\text{standby},i,k}) P_{\text{BoP},i,k}.
\]

The BoP consumption \( P_{\text{BoP},i,k} \) includes

\[
P_{\text{BoP},i,k} = P_{\text{heat},i,k}/\eta_{\text{heat}} + P_{\text{cool},i,k}/\eta_{\text{cool}} + P_{\text{aux}}
\]

where \( P_{\text{heat},i,k} \) and \( P_{\text{cool},i,k} \) are the active heating and cooling power; \( \eta_{\text{heat}} \) and \( \eta_{\text{cool}} \) are heating and cooling efficiencies; \( P_{\text{aux}} \) is the power of auxiliary equipments like the pumps and the control system, which is assumed to be constant here.

When directly coupled to renewable energy sources (RESs) such as photovoltaic power, the total power consumption cannot exceed the available RES power \( P_{\text{RES},k} \) at each moment:

\[
\sum_{i=1}^{N_{\text{ele}}} P_{i,k} \leq P_{\text{RES},k},
\]

where \( N_{\text{ele}} \) is the number of electrolyzers in the plant.

**D. Temperature Dynamic Model and Constraints**

Temperature has a big impact on the efficiency and loading range of the electrolyzer [7], [19], [20]. Therefore, different from previous works that omitted the temperature dynamics [8], [12], [13], this paper takes it into account in scheduling.

The first-order temperature model [19], [20] is adopted in this work, illustrated in Fig. 4(a) and expressed as

\[
T_{i,k+1} = T_{i,k} + h \frac{P_{\text{react},i,k} - \dot{e}_{\text{diss}} (T_{i,k} - T_{\text{am}}) - P_{\text{cool},i,k} + P_{\text{heat},i,k}}{C_{\text{temp},i,k}},
\]

where \( C_{\text{temp},i,k} \) is system heat capacity; \( \dot{e}_{\text{diss}} \) is the conductivity of heat dissipation; \( T_{\text{am}} \) is the ambient temperature; \( h \) is the step length of scheduling; \( P_{\text{heat},i,k} \) is the external heating

\[
0 \leq P_{\text{heat},i,k} \leq (b_{\text{on},i,k} + b_{\text{standby},i,k}) P_{\text{heat},i,k},
\]

where \( P_{\text{heat},i,k} \) is the upper limit of heating power; \( P_{\text{cool},i,k} \) is the active cooling power, which satisfies

\[
0 \leq P_{\text{cool},i,k} \leq (b_{\text{on},i,k} + b_{\text{standby},i,k}) C_{\text{cool}} (T_{i,k} - T_{\text{cool}}),
\]

where \( T_{\text{cool}} \) is the coolant temperature; and \( P_{\text{react},i,k} \) is the electrolytic heating power, approximated by a second-order function of stack current and temperature, as

\[
P_{\text{react},i,k} = N_{\text{cell}} I_{i,k} (U_{\text{cell}} - U_{\text{th}})
\approx N_{\text{cell}} (a_0 I_{i,k} + a_1 I_{i,k}^2 + a_2 I_{i,k}^2 - U_{\text{th}} I_{i,k}),
\]

where \( N_{\text{cell}} \) is the number of electrolysis cells in the stack; \( U_{\text{th}} = 1.48 \) V is the thermal neutral voltage; \( a_0, a_1 \) and \( a_2 \) are constant coefficients; \( I_{i,k} \) is the stack current, which satisfies

\[
i_{\text{H}_2} \leq N_{\text{cell}} I_{i,k} / (2 F),
\]

where \( F \) is the Faraday constant of the electrolyzer; and \( F = 96485.3 \) C/mol is the Faraday constant.

Although higher temperature means higher energy conversion efficiency, the stack temperature should stay below a limit to avoid damaging the diaphragm, as

\[
T_{i,k} \leq T_{\text{th}},
\]

where \( T_{\text{th}} \) is the upper limit of stack temperature, set as 373 K in this work; and the electrolytic voltage should not exceed a safety margin (2.1 V here) to avoid damaging electrode microstructure, especially when the temperature is low, as

\[
U_{i,k} \approx a_0 + a_1 I_{i,k} + a_2 I_{i,k} \leq 2.1 \text{V}.
\]
Due to the HTO impurity accumulation rate being higher at a low load level, the electrolyzers usually have a minimal steady-state load level between 10% and 40% \cite{22}. Existing works on P2H plant scheduling usually assume such a minimal loading constraint \cite{8, 12, 13, 18}.

However, because HTO accumulation is a dynamic process, operating at a lower power level temporarily without violating the 2% constraint is possible, which may improve the load flexibility of the electrolyzer. Therefore, this work takes the HTO crossover dynamics into account.

A simplified dynamic model of HTO accumulation is illustrated in Fig. 4(b) and can be represented \cite{11} by

\[ n_{i,k+1} = n_{i,k} + h \left( b_{i,k}^\text{in} n_{i,k} - \frac{\dot{n}_{i,k}^\text{prod}}{c_{\text{im, out}}} \right), \]  

where \( n_{i,k}^\text{im,in} \) is the impurity crossover flow rate, which can assumed to be constant at constant system pressure, and is non-zero in only Production state; \( n_{i,k}^\text{prod} \) is the production rate of oxygen, equal to \( n_{i,k}^\text{Hz, prod}/2 \); \( c_{\text{im, out}} \) is the impurity discharge constant, see details in \cite{11}.

The HTO impurity constraint is expressed as

\[ \frac{n_{i,k}^\text{Hz, im}}{n_{i,k}^\text{O2, prod}} \leq 2\% \]  

For easy understanding, Fig. 5 shows the results of HTO impurity crossover simulation under different steady-state loading levels, and different speeds under different load levels. The model for HTO crossover dynamics is transformed into a linear one.

The objective of P2H plant scheduling is as maximizing the profit, i.e., the revenue from the sale of hydrogen minus electricity and startup costs, formulated by

\[ J = \sum_{k=1}^{N^h} \sum_{i=1}^{N^\text{ele}} \left( c_{H^2} n_{i,k}^\text{Hz, prod} - c_k^\text{power} P_{i,k} + c_{\text{startup}} b_{i,k}^\text{startup} \right) \]  

where \( N^h \) is the scheduling horizon; \( c_{H^2} \) is the hydrogen price; \( c_k^\text{power} \) is the price of electric power at time \( k \); and \( c_{\text{startup}} \) is the startup cost, which is used to characterize the depreciation expense of the electrolyzer.

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B. Reformulation of Process Constraints

Some dynamic process constraints introduced in Section \ref{sec:dynamic_process} include bilinear terms. This causes nonlinear formulation of the plant scheduling problem and makes it hard to solve. Therefore, we reformulate them into linear ones.

The bilinear terms are categorized as two types, i.e., the product of a real variable and a binary variable in \cite{6, 8, 13, 18}, and the product of two real variables in \cite{12} and \cite{14}. For the first type, for example \( b_{i,k}^\text{in} T_{i,k} \) in \cite{6}, it is linearized by the standard big-M method.

For the second type, i.e., the product of two real variables, for example \( I_{i,k} T_{i,k} \) in \cite{14}, we can discretize it as \( I_{i,k} \approx \sum_{j=1}^{N^d} 2^j \beta_{i,k,j} \Delta I \), where \( \beta_{i,k,j} \) is a binary variable and \( \Delta I \) is the step length. Then, we can reformulate the product as

\[ I_{i,k} T_{i,k} = \sum_{j=1}^{N^d} 2^j \delta_{i,k,j} \Delta I, \]

where in the process constraints \cite{6, 8, 13, 14, 18} the bilinear terms are replaced by \cite{21, 22}.

The control variables \( u \) include the states indicators, i.e., \( b_{i,k}^\text{in}, b_{i,k}^\text{down} \), and heating and cooling powers \( P_{\text{ele}, i,k}, P_{\text{heat}, i,k} \), and \( P_{\text{cool}, i,k} \) for time \( k = 1, \ldots, N^h \). They are implemented to the electrolyzers in operation.

The plant scheduling problem \cite{23} is an MILP, which can be solved easily with commercial solvers. Further, notice that the renewable power supply may deviate from the forecast in online operation. In this case, we can implement it in a receding-horizon manner to alleviate the impact of the forecast error. Due to the space limit, we will not go further.

IV. CASE STUDY

A. Case Settings

We assume a P2H plant composed of 6 alkaline electrolyzers, each rated 5 MW, a total rating of 30 MW, connected to photovoltaic power. The parameters used in the case study are given in Table \ref{tab:parameters}. Moreover, we assume there is a bilateral contract with the photovoltaic plant. Therefore, the electricity price is set as constant. The platform for modeling the scheduling problem and simulation is Wolfram Mathematica 12.3, and the solver for MILP employed is Gurobi 9.5.0.

B. Result of the Proposed P2H Plant Scheduling

1) Basic case: Given the scenario of the power supply based on the data of a photovoltaic plant in Sichuan Province, China, as shown in Fig. 6, the proposed scheduling method calculates the optimal operational states and power commands for all electrolyzers, respectively shown in Figs. 7 and 8.
by simulation of the models from Section II, the temperature and HTO impurity of each electrolyzer are given in Fig. 8.

As seen from Fig. 7 following the sunrise around 7 am, the electrolyzers startup successively. Then, due to the temporary drop of the solar power, three of them switch to Standby for 15 to 30 minutes before all electrolyzers start production. The power of each electrolyzer increases gradually as the temperature increases to avoid the cell voltage becoming too high. Before reaching the full loading level, the HTO impurity first increases due to a temporarily low loading level and then decreases. After sunset, the electrolyzers switch off and cool down due to heat dissipation.

For the most time, the electrolyzers operate at the upper-temperature limit to maximize production. Meanwhile, the HTO impurity is relatively low due to the high loading, as explained in Fig. 5. Note that although the minimal steady-state loading is 34% and is set as the lower power limit in the literature [8], [12], [13], the proposed scheduling method enables the electrolyzers to operate at a lower power level, which extends the flexibility when the power supply is low.

Finally, we compare the proposed process constraint-aware scheduling approach to the existing one [8], with the result shown in Table I. We can see that the improved flexibility leads to a 0.825% increase of the total hydrogen production and a 1.627% profit increase.

2) Comparison to the existing P2H plant scheduling method under various scenarios: Moreover, we compared the proposed and the existing plant scheduling method using the photovoltaic power of 30 different days. The simulation result shows that the proposed method achieves a 0.839% hydrogen production increase and a 1.638% profit increase on average. This result further confirms the improvement of this work.

V. CONCLUSIONS

This paper first incorporates the dynamic process constraints of the electrolyzers into the P2H plant scheduling framework. Simulation shows that the proposed method extends the load-
We can see that the simulation fits the experimental data quite well. Therefore, these models are validated.

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