



Optimal Scheduling of Electricity- Hydrogen -Ammonia System Based on Information Gap Decision Theory

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Abstract. As the installed capacity of renewable energy continues to expand, its volatility and uncertainty pose challenges to power system operation. Utilizing surplus wind and solar power for electrolytic hydrogen production and subsequent ammonia synthesis can further enhance the integration of renewable energy. This paper establishes an Electricity-Hydrogen-Ammonia Integrated Energy System (EHA-IES) model and aims to minimize total operational cost. Information Gap Decision Theory (IGDT) is employed to analyze the impact of wind and solar uncertainty on scheduling outcomes under different risk preferences, offering comprehensive strategy references for decision-makers.

Keywords: Optimal Scheduling, Power to Hydrogen, Ammonia.

1 Introduction

Utilizing surplus renewable electricity for water electrolysis to produce hydrogen, and subsequently synthesizing green ammonia, is regarded as a highly promising technological pathway[1].

Current research on optimal scheduling of such complex integrated energy systems predominantly relies on deterministic forecast models. For instance, reference [2] applied the Sparrow Search Algorithm for day-ahead scheduling of electricity-hydrogen-ammonia systems, reducing curtailment rates. Reference [3] utilized chance-constrained programming to manage virtual power plant dispatch, reducing network losses. Reference [4] constructed an interval optimization model for power-to-gas systems and discussed the cost of various equipment. The aforementioned studies do not consider optimization from different decision-making perspectives.

In this paper, we construct an optimal scheduling model for EHA-IES. IGDT is introduced. The impact of wind and solar uncertainty on scheduling results and operational costs under different risk preferences is thoroughly analyzed. Finally, case studies validate the effectiveness of the proposed models and strategies.

2 EHA-IES Model Description

The structure of the proposed EHA-IES is presented in Fig. 1. renewable power is

converted into hydrogen and then ammonia for long-duration storage, while the thermal unit converts ammonia back to electricity to meet power demands.

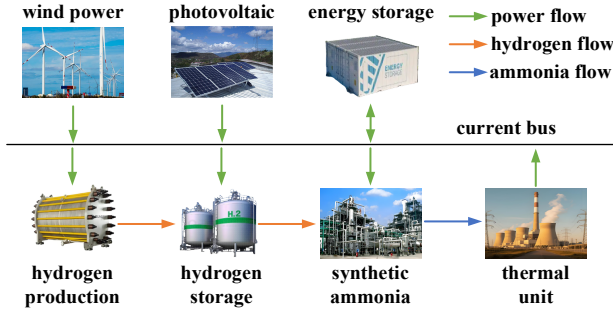


Fig. 1. EHA-IES structure diagram

2.1 Electrolytic Hydrogen Production Model

Based on the process operating characteristics of the electrolyzer and the system's scheduling flexibility requirements, the following model is established:

$$0.2P_{el,N} \leq P_{el}(t) \leq 1.1P_{el,N} \quad (1)$$

$$P_{el}(t) - P_{el}(t-1) \leq r_c P_{el,N} \Delta t \quad (2)$$

where: $P_{el,N}$ is the rated power of the electrolyzer; $P_{el}(t)$ is the operating power of the electrolyzer at time t , r_c is the ramping rate of the electrolyzer.

Considering the nonlinear characteristic of electrolyzer efficiency varying with the load factor, hydrogen production rate $m_{H_2}(t)$ is expressed as:

$$m_{H_2}(t) = \eta_{el} \frac{P_{el}(t)}{HHV_{H_2}} \quad (3)$$

where: HHV_{H_2} is the higher heating value of hydrogen; η_{el} is the efficiency.

2.2 Ammonia Synthesis Unit Model

Hydrogen produced from water electrolysis passes through a buffer tank and then enters the Haber–Bosch synthesis loop. Within this loop, the reaction takes place under high temperature (400–500 °C), high pressure (15–25 MPa) [5].

$$F_{nh3}(t) = \beta_{H_2} m_{H_2out}(t) \quad (4)$$

where: $F_{nh3}(t)$ is the ammonia production rate at time t ; β_{H_2} is the conversion coefficient of hydrogen to ammonia. $m_{H_2out}(t)$ is the hydrogen consumption at time t .

To prevent load changes from destabilizing the unit, characterize the dynamic load variation of the ammonia synthesis unit:

$$F_{nh3}(t) = F_{nh3}(t-1) + hr_{nh3}(t) \quad (5)$$

where: $r_{nh3}(t)$ is the climbing rate of synthetic ammonia load.

The coupling relationship between power consumption and ammonia production is established to quantify the power demand of the ammonia synthesis unit:

$$P_{nh3}(t) = P_{nh3,0} + c_{nh3}F_{nh3}(t) \quad (6)$$

where: $P_{nh3,0}$ is the base power; c_{nh3} is the constant coefficient for ammonia synthesis. The energy consumption per ton of ammonia is 1.4 MW.

The model for the ammonia storage tank is established as follows.

$$S_{NH3}(t) = S_{NH3}(t-1) + (F_{nh3}(t) - F_{nh3}^{out}(t))\Delta t \quad (7)$$

where: $S_{NH3}(t)$ is the ammonia inventory in the storage tank at time t ; $F_{nh3}^{out}(t)$ is the ammonia outflow rate from the tank at time t .

2.3 Ammonia Co-firing Model for Thermal Power Units

Using the ammonia produced by the system for co-firing with coal in thermal power units can reduce system costs:

$$m_{EM}(t) = \mu_{EM}P_{EM}(t) - m_{nh3}(t)L_{nh3} / L_{coal} \quad (8)$$

$$0 \leq \frac{m_{nh3}(t)L_{nh3}}{m_{coal}(t)L_{coal} + m_{nh3}(t)L_{nh3}} \leq \lambda_{max} \quad (9)$$

where: μ_{EM} is the unit coal consumption; L_{nh3} 、 L_{coal} are the calorific values of ammonia and coal, respectively; $m_{EM}(t)$ 、 $m_{nh3}(t)$ are the coal consumption and ammonia co-firing amount at time t , in sequence; $P_{EM}(t)$ denotes the generating power of the unit at time t . λ_{max} is the maximum ammonia co-firing ratio.

3 EHA-IES Optimization Model

3.1 Objective Function

The objective is to minimize the total operational cost of the EHA-IES, encompassing start-up/shut-down costs of coal-fired units F_{QT} , coal consumption costs F_{EM} , and power-to-ammonia operational costs F_{P2A} :

$$\min F = F_{QT} + F_{EM} + F_{P2A} \quad (10)$$

$$\begin{cases} F_{EM} = c_{mei} \sum_{t=1}^T (U_t m_{EM}(t)) \\ F_{QT} = c_{qt} \sum_{t=2}^T U_t (1 - U_{t-1}) \end{cases} \quad (11)$$

where: U_t is the binary start-up/shutdown variable; c_{mei} is the coal price; c_{qt} is the start-up and shut-down cost coefficient of the coal-fired unit.

3.2 Constraints

(1) Electrical Power Balance Constraint:

$$P_{load}(t) + P_{p2h}(t) + P_{nh3}(t) + P_{bat}(t) = P_{WT}(t) + P_{PV}(t) + P_{EM}(t) \quad (12)$$

where: $P_{load}(t)$ is the electric load; $P_{p2h}(t)$ is the power-to-hydrogen power; $P_{nh3}(t)$ is the ammonia synthesis power; $P_{bat}(t)$ is the energy storage power; $P_{WT}(t)$ is the wind turbine power; $P_{PV}(t)$ is the photovoltaic power; $P_{EM}(t)$ is the ammonia-blended thermal power.

(2) energy storage Constraint:

$$-P_{EN} \leq P_E(t) \leq P_{EN} \quad (13)$$

where: $P_E(t)$ is the energy storage power at time t , P_{EN} denotes the upper and lower limits of the energy storage power

4 Uncertainty Scheduling Model Based on IGDT

Table 1 compares stochastic programming(SP), robust optimization(RO) and IGDT. IGDT, requiring no probability distribution and offering adjustable risk-return trade-off, is adopted for the uncertain scheduling model.

Table 1. Characteristics of Uncertainty Scheduling Methods

Characteristic	SP	RO	IGDT
Probability Distribution	Required	Not Required	Not Required
Risk-Return Mechanism	Implicit	None	Explicit
Decision Perspective	Risk-neutral	Extremely Conservative	Adjustable

Considering the fluctuation characteristics of wind and solar power, an envelope bound model is selected for modeling:

$$U(\varphi_w, \tilde{d}_w) = \{d_w : (1 - \varphi_w)\tilde{d}_w \leq d_w \leq (1 + \varphi_w)\tilde{d}_w\} \quad (14)$$

$$U(\varphi_p, \tilde{d}_p) = \{d_p : (1 - \varphi_p)\tilde{d}_p \leq d_p \leq (1 + \varphi_p)\tilde{d}_p\} \quad (15)$$

where: d_w 、 d_p are the actual output powers of wind and PV power, respectively; $\tilde{d}_w$ 、 $\tilde{d}_p$ are the predicted values of wind and PV power, respectively; φ_w 、 φ_p are the fluctuation amplitudes of wind and PV power, respectively.

4.1 Risk-Averse (Robust) IGDT Scheduling Model

The risk-averse strategy aims to maximize immunity against uncertainty while ensuring that the total operational cost does not exceed a pre-specified threshold. The robust optimization formulation is:

$$\begin{cases} \max \varphi = \varphi_w + \varphi_p \\ \text{s.t.} \begin{cases} \max F \leq F_{\max} = (1 + \delta)f_0 \\ h(X, d) = 0 \\ g(X, d) \geq 0 \end{cases} \end{cases} \quad (16)$$

where: φ is the uncertainty index; $F_{\max}$ is the maximum acceptable system cost; δ is the robust deviation factor; f_0 is the optimal solution under the deterministic model.

4.2 Risk-Seeking (Opportunistic) IGDT Scheduling Model

The risk-seeking strategy aims to minimize the required uncertainty horizon to achieve a desired lower operational cost. The opportunistic optimization formulation is:

$$\begin{cases} \min \varphi = \varphi_w + \varphi_p \\ \text{s.t.} \begin{cases} \min F \leq F_{\max} = (1 - \varepsilon)f_0 \\ h(X, d) = 0 \\ g(X, d) \geq 0 \end{cases} \end{cases} \quad (17)$$

where: ε is the opportunity deviation factor.

The specific steps of the IGDT scheduling strategy are as follows:

(1)First, input the forecasted wind and PV power values to solve the deterministic model and obtain the benchmark cost f_0 .

(2)Then, the decision-maker sets a deviation factor according to the risk preference to calculate the maximum acceptable cost $F_{\max}$. Under the risk-averse strategy, a stronger aversion to risk corresponds to a larger deviation factor; under the risk-seeking strategy, a stronger appetite for risk corresponds to a larger deviation factor.

(3)Finally, $F_{\max}$ is introduced as a constraint into the IGDT robust model or opportunistic model for optimization.

5 Case Study and Results Analysis

5.1 System Parameters

The case comprises 50 MW installed capacity for both wind and PV generation, along with fourteen 5 MW electrolyzers. The coal-fired unit has a power limit of 75 MW. The electrical energy storage capacity is 150 MWh. The model is solved using CPLEX.

5.2 Scheduling Results and Discussion

Table 2. Scheduling Results Under Different Scenarios ($\delta/\epsilon=0.03$)

Indicator	Deterministic Optimization	Risk-Averse	Risk-Seeking
Total Cost (CNY)	314600	322900	306300
power discard rate(%)	7.4	3.7	10.2

As shown in Table 2, the risk-averse strategy increases the total system cost by 2.6% but reduces the renewable curtailment rate from 7.4% to 3.7%, demonstrating its effectiveness in trading minor economic loss for higher reliability. Meanwhile, the risk-seeking strategy cuts the total cost at the expense of a higher curtailment rate of 10.2%. These results verify that IGDT enables flexible cost-reliability trade-offs.

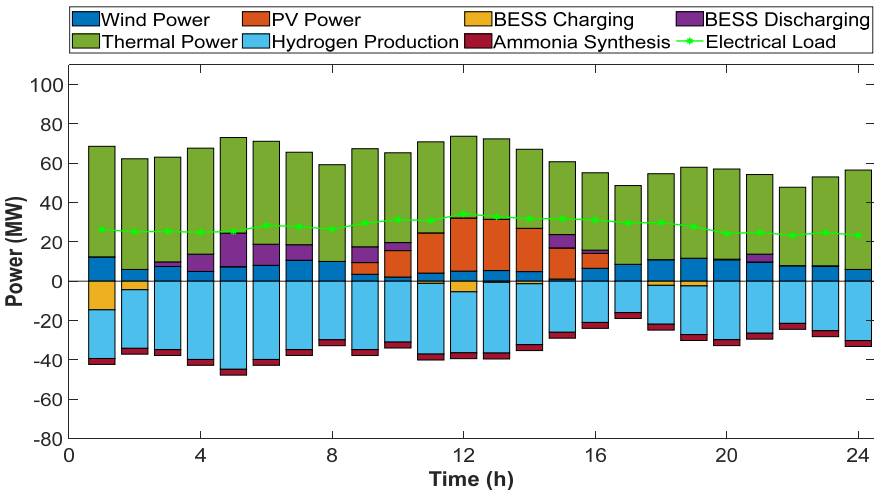


Fig. 2. Power Optimization Results under Risk-Averse Strategy

As illustrated in Fig. 2, the risk-averse strategy prioritizes conservative scheduling to ensure supply reliability. When wind and PV output fall to the lower bound of the uncertainty set, generation from coal-fired units increases significantly to compensate for the deficit. Concurrently, electrolyzer power is reduced to avoid competition with the electrical load, thereby mitigating system dependence on renewable generation.

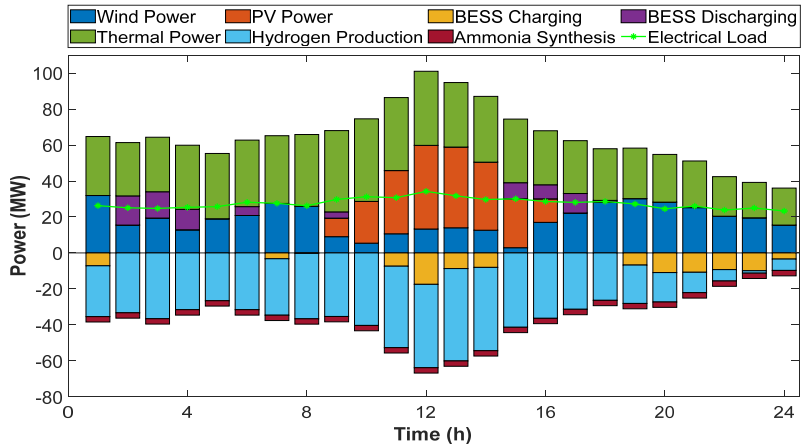


Fig. 3. Power Optimization Results under Risk-Seeking Strategy

As shown in Fig. 3, the risk-seeking strategy leverages uncertainty to reduce operational costs. When wind and PV output approach the upper bound of the uncertainty set, electrolyzer power increases to absorb excess generation and convert it into hydrogen. Compared to the risk-averse strategy, power allocation exhibits greater volatility, reflecting a preference for high-risk, high-reward scenarios. The opportunistic model maximizes potential benefits through flexible energy distribution.

Table 3. Calculation Results

Strategy	δ/ε	Φ	Cost/ 10^4 CNY
Risk-Averse	0	0	31.46
	0.03	0.3426	32.29
	0.07	0.6255	33.41
	0.1	0.7079	34.23
Risk-Seeking	0	0	31.46
	0.03	0.2349	30.63
	0.07	0.5482	29.52
	0.1	0.7832	28.69

Table 3 presents the uncertainty index and total system cost for various deviation factors under both risk-averse and risk-seeking strategies. For a deviation factor of 0.03 under the risk-averse strategy, the uncertainty index is 0.3426 and the total cost is 322900 CNY. This implies that as long as real-time wind/PV output remains within 57.91% to 100% of the forecast value, the total scheduling cost will not exceed 322900 CNY. Conversely, under the risk-seeking strategy with the same deviation factor, the uncertainty index is 0.2349 and the total cost is 306300 CNY, indicating that if real-time output exceeds the forecast by up to 31.21%, the total scheduling cost can be reduced to at most 306300 CNY.

6 Conclusion

This paper proposes an optimal scheduling model for an Electricity-Hydrogen-Ammonia Integrated Energy System (EHA-IES), incorporating electrolytic hydrogen production, ammonia synthesis, ammonia co-firing, and energy storage. By applying Information Gap Decision Theory, the model effectively addresses the operational challenges posed by wind and solar uncertainty. The comparative analysis of risk-averse and risk-seeking strategies provides valuable insights for system operators to balance operational costs and reliability under renewable forecast uncertainty.

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Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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