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LSTM-Driven Predictive Scheduling for Green Energy-Hydrogen-Methanol Integrated System

Rui Bian[a], Renchu He[a,*], Xinyu Yan[a], Xinglin Tong[b]

[a]Department of Automation, College of Artificial Intelligence, China University of Petroleum, Beijing, 102249, China
[b]Wuhan University of Technology, Wuhan, 430070, China
rche@cup.edu.cn

This study proposes an optimization scheduling model for the Green Energy-Hydrogen-Methanol Integrated System (GEHMIS) based on the Long Short-Term Memory (LSTM) network, aimed at achieving efficient, stable, and economical operation of renewable energy systems. In response to the fluctuations and uncertainties in the output of wind and solar energy, this paper introduces the LSTM network to accurately predict wind speed and temperature using historical data. The integrated system model developed in this study covers key processes such as wind and solar power generation, water electrolysis for hydrogen production, hydrogen storage and transportation, and methanol synthesis. The objective of this research is to maximize the overall system profit by developing a multi-constraint mathematical optimization model that takes into account multiple factors, including hydrogen and methanol production efficiencies, hydrogen consumption, operation and maintenance costs, electricity price fluctuations, grid interactions, and carbon dioxide costs. Compared to traditional random resource allocation strategies, the proposed optimization model demonstrates significant advantages in terms of economic benefits and energy utilization efficiency: the overall system profit increased by approximately 68.3 %, and the hydrogen utilization rate improved by 30 %. This provides important technical support and a practical pathway for the large-scale application of green energy and the global transition to sustainable energy.

1. Introduction

Amid growing global energy crisis and environmental challenges, the over-reliance on traditional energy sources has created pressing issues, necessitating urgent development of clean and sustainable energy solutions (Wang et al., 2023). While renewable energies like wind and solar power face integration and storage challenges in large-scale applications, hydrogen and methanol have emerged as promising clean energy carriers (Mazzeo et al., 2022). The wind-solar hydrogen-to-methanol technology not only enhances renewable energy utilization but also contributes to CO_2 reduction, offering significant environmental advantages.

However, the intermittent nature of wind and solar power complicates accurate forecasting and scheduling using conventional methods. Long Short-Term Memory (LSTM) networks, a specialized Recurrent Neural Network (RNN) architecture introduced by Hochreiter and Schmidhuber (1997) in 1997, demonstrated exceptional capability in capturing long-term dependencies and have been widely adopted for renewable energy forecasting (Sherstinsky, 2020). Al-qaness et al. (2024) achieved improved wind power prediction accuracy by integrating LSTM with optimization algorithms. In the context of energy economic efficiency, the concept of the methanol economy proposed by Prakash et al. (2011) regarded the hydrogenation of CO_2 to methanol as one of the most attractive and potentially profitable technological pathways. To realize the systematic application of this pathway, Macedo and Peyerl (2022) conducted an economic analysis of hydrogen production from wind-solar power plants in Brazil, demonstrating that selling hydrogen is more economically beneficial than converting it into electricity. Zheng et al. (2022) constructed a model of the production system and quantitatively evaluated the influence of key operational parameters on methanol cost structures.

Currently, most wind and solar power generation methods still rely on static or low-accuracy weather forecasting models, which struggle to capture the dynamic nature of renewable energy. Although some studies have explored green electricity-based hydrogen production pathways, few have addressed specific strategies for equipment scheduling and hydrogen processing. Moreover, existing research mainly focuses on hydrogen itself,

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lacking comprehensive analysis of co-production with downstream products, such as methanol, and related market revenues, resulting in limited model practicality and incomplete assessment of system-level economic performance.
To address these issues, this paper proposes an LSTM-based optimization method for scheduling in GEHMIS. The LSTM network, trained on historical data, is used to predict wind speed and temperature, enabling dynamic, multi-constraint optimization of hydrogen production and methanol synthesis. The model aims to maximize overall profit by optimizing power allocation and ensuring stable and efficient system operation. This approach offers the potential for cost reduction, emission mitigation, and improved economic performance, providing both theoretical and practical value.

2. Modeling methodology for the GEHMIS

The GEHMIS primarily comprises the wind-solar power generation system, hydrogen production by electrolyzer, grid interaction, and methanol production and sales. Hydrogen is partly sold and partly used with CO_2 to produce methanol. Renewable power is prioritized for electrolyzer, with surplus sold; when insufficient, grid electricity is purchased to maintain stable operation. The specific schematic diagram is shown in Figure 1.

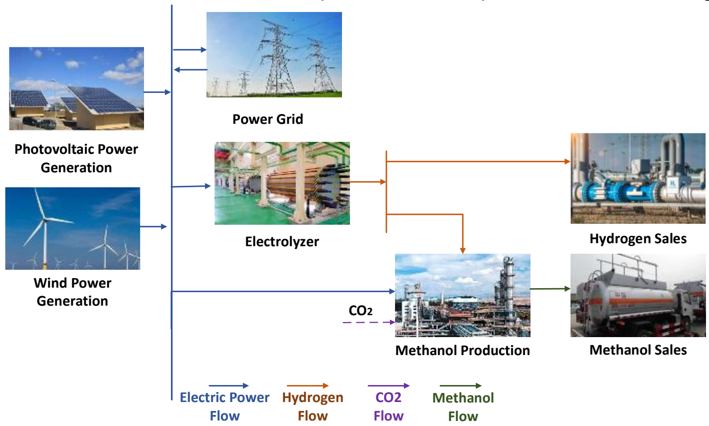

Figure 1: The structural diagram of the GEHMIS

2.1 System mathematical models

The study establishes a a wind–solar–hydrogen–methanol model and enables interaction with the power grid.
(1) Wind power model

$$P_{WD,t} = \begin{cases} 0 & v < v_1 \text{ or } v > v_3 \\ \frac{1}{2}\pi\rho R^2 C_P v^3 & v_1 \le v < v_2 \\ P_0 & v_2 \le v \le v_3 \end{cases} \tag{1}$$

Eq(1) represents the wind power model based on the works of Wang et al. (2024). The output power of the wind turbine $P_{WD,t}$ over a time period t is jointly determined by the radius of the turbine blades R, wind energy utilization coefficient C_P, wind speed v, and the rated power P_0. v_1, v_2, v_3 represent the cut-in wind speed, rated wind speed and cut-out wind speed of the wind turbine, respectively.
(2) Photovoltaic power model

$$P_{PV,t} = P_{STC} \cdot [1 + k(T_t - 25)] \cdot \eta_{PV} \cdot S_{PV} \tag{2}$$

The photovoltaic power model in Eq(2) is derived from the methodology proposed by Yousefi et al. (2017), where, $P_{PV,t}$ denotes the photovoltaic power output and T_t represents surface temperature. P_{STC} represents the light intensity coefficient, k is the power temperature coefficient, η_{PV} is the conversion efficiency of the photovoltaic array, and S_{PV} is the area of the photovoltaic array.
(3) Electrolyzer and methanol synthesis section models
Eq(3) and Eq(4) formulate the electrolyzer and methanol synthesis section models based on the works of Buttler and Spliethoff (2018).

$$q_t^{H_2} = \eta^E \cdot P_t^{PEM} \cdot L_{H_2}, q_t^{CH_4} = \lambda^{CH_4} \cdot P_t^{CH_4} \cdot L_{CH_4} \tag{3}$$

$$q_t^{CHH} = \varphi^{CH_4} \cdot q_t^{CH_4}, q_t^{CO_2} = V_t^{CH_4} / \kappa^{CO_2} \tag{4}$$

where, $q_t^{H_2}, q_t^{CH_4}$ represent the hydrogen and methanol production, η^E, λ^{CH_4} represent the production efficiency of hydrogen and methanol, $P_t^{PEM}, P_t^{CH_4}$ represent the power consumption of the electrolyzer and the methanol production equipment, and L_{H_2}, L_{CH_4} represent the electricity-to-hydrogen and electricity-to-methanol factor. q_t^{CHH} refers to the hydrogen required for methanol production, while φ^{CH_4} refers to the hydrogen consumption per kg of methanol produced. $q_t^{CO_2}$ is the required production of CO_2, and κ^{CO_2} refers to the carbon dioxide utilization rate.

2.2 System optimization models

This study focuses on short-term scheduling issues. Since the initial investment cost is a fixed expenditure, it is not considered. This study also disregards system start-up/shutdown costs and separate transportation costs.

$$\max C = C_{revenue} - C_{inv} - C_M - C_{CO_2} \tag{5}$$

where, Eq(5) is the objective function of the model. C represents the total revenue, $C_{revenue}$ includes the sales of hydrogen and methanol, while C_{inv} represents the operating costs, C_M is the grid interaction costs, and C_{CO_2} represents the cost of CO_2.

(1) Revenue calculation

$$C_{revenue} = \sum_{t=1}^{T} (c^{H_2} \cdot q_t^{H_2\_sell} + c^{CH_4} \cdot V_t^{CH_4}) \tag{6}$$

where, c^{H_2} and c^{CH_4} represent the market selling prices of hydrogen and methanol, and $q_t^{H_2-sell}$ represents the quantity sold of hydrogen.

(2) Cost calculation

$$C_{inv} = \sum_{t=1}^{T} (\sum_{i=1}^{4} (c_i \cdot \zeta_i^t)) \tag{7}$$

$$C_M = \sum_{t=1}^{T} (\omega_{buy} \cdot P_t^{buy} - \omega_{sell} \cdot P_t^{sell}) \tag{8}$$

$$C_{CO_2} = \sum_{t=1}^{T} (\omega_{CO_2} \cdot q_t^{CO_2}) \tag{9}$$

where, i represents the various system equipment, including wind power generation, photovoltaic generation, electrolyzer, and methanol production units. c_i represent the operating costs of each type of equipment, and ζ_i^t represent the consumption of each equipment. $\omega_{buy}, \omega_{sell}$ and ω_{CO_2} represent purchasing, selling price of the electricity, and carbon dioxide purchasing price. P_t^{buy}, P_t^{sell} represent the power associated with buying and selling electricity, respectively.

The model constraint equations are as follows:

(1) Power constraint

$$P_{WD,t} + P_{PV,t} + P_t^{buy} = P_t^{sell} + P_t^{PEM} + P_t^{CH_4} \tag{10}$$

The total of generated and purchased electricity equals the sum of electricity consumption and electricity sold.

(2) Hydrogen balance constraint

$$q_t^{H_2-sell} + q_t^{H_2,CH_4} = q_t^{H_2} \tag{11}$$

The hydrogen produced by the electrolyzer $q_t^{H_2}$ is supplied for methanol production $q_t^{H_2,CH_4}$ and sold for hydrogen use $q_t^{H_2-sell}$.

(3) Interaction and power constraints

$$P_{PEM}^{\min} \le P_t^{PEM} \le P_{PEM}^{\max} \tag{12}$$

$$P_{CH_4}^{\min} \le P_t^{CH_4} \le P_{CH_4}^{\max} \tag{13}$$

$$\begin{cases} P_M^{\min} \le P_t^{buy} \le \mu_{M,t} \cdot P_M^{\max} \\ P_M^{\min} \le P_t^{sell} \le (1-\mu_{M,t}) \cdot P_M^{\max} \end{cases} \tag{14}$$

where, $P_{PEM}^{\min}, P_{PEM}^{\max}, P_{CH_4}^{\min}, P_{CH_4}^{\max}, P_M^{\min}, P_M^{\max}$ are the minimum and maximum power of the electrolyzer, methanol production equipment, and grid interaction. $\mu_{M,t}$ represents the state of purchasing and selling electricity from the superior power grid, where a value of 1 indicates purchase mode and 0 indicates sale mode.

3. Case study and system parameters

This case study selects Cangzhou, Hebei Province, China, as the target region. Based on wind speed and temperature data predicted by the LSTM neural network model, a dynamic optimization scheduling analysis of the GEHMIS was conducted over a two-month period, using a one-day time step. The key components involved in the system include wind turbine, photovoltaic module, electrolyzer, and methanol synthesis unit, with their core unit costs in Table 1 (Wiser et al., 2019). In terms of economic parameters, the selling price of methanol is set at 2.6 CNY/kg, the cost of CO_2 capture is 0.40 CNY/kg, and the hydrogen selling price is 20 CNY/kg (Liu et al., 2023). Meanwhile, the system is connected to the main power grid, with average electricity purchase price of 0.3 CNY/kWh and selling price of 0.15 CNY/kWh (Yang et al., 2023).

Table 1: Costs of each equipment

Equipment	Operating cost
Wind turbine	0.04 CNY/kWh
Photovoltaic	0.05 CNY/kWh
Electrolytic cell	0.2 CNY/kWh
Methanol production equipment	0.528 CNY/kg

4. Analysis of system results

This section primarily focuses on conducting an in-depth analysis of the LSTM prediction results and the system optimization scheduling results obtained by using the CPLEX optimizer based on the parameter settings.

4.1 LSTM-based prediction results

To evaluate the forecasting accuracy of the LSTM model, the prediction performance and error trends are analyzed to evaluate the method's reliability. The results are shown in Figure 2. Figure 2(a) presents a comparison between the actual and LSTM-predicted wind speed values, with the prediction errors ranging from -0.036 to 0.020. Figure 2(b) depicts temperature prediction results, where the errors between predicted and actual values range from -0.094 to 0.131.

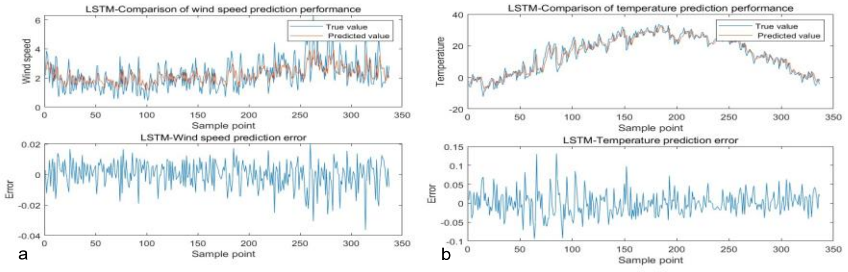

Figure 2: Prediction results of (a) LSTM wind speed, (b) temperature

These error values denote the point-wise deviation between predicted and actual values, expressed in the same units as the target variables. The mean absolute percentage error (MAPE) was introduced to systematically evaluate overall model performance, where lower values indicate higher predictive accuracy. It is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{15}$$

where, y_i denotes the actual observed value, $\hat{y}_i$ represents the predicted value, and n is the total number of samples. Both MAPE value of wind speed and temperature predictions are below 0.3 %, demonstrating the model's exceptionally strong forecasting accuracy.

4.2 Optimized scheduling results of the GEHMIS

The optimized system operation is analyzed, including equipment scheduling and power transactions, in accordance with energy and hydrogen balance principles. Figure 3(a) illustrates the overall power balance scheduling, where wind and photovoltaic systems generate a total of 1.423×10^5 kWh during the cycle. Figure 3(b) presents the hydrogen scheduling balance, where the electrolyzer produces 5.877×10^4 kg of hydrogen, of which 3.996×10^4 kg is sold. The remaining hydrogen is used for methanol synthesis, yielding 1.8076×10^4 kg of methanol. The overall hydrogen utilization rate is approximately 32 %.

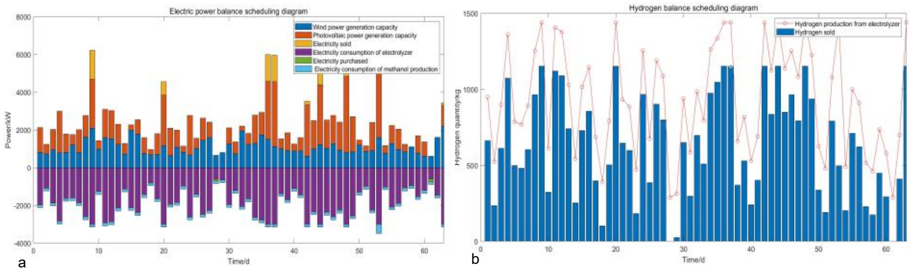

Figure 3: (a) Electrical power, (b) hydrogen balance scheduling diagram of the optimized model

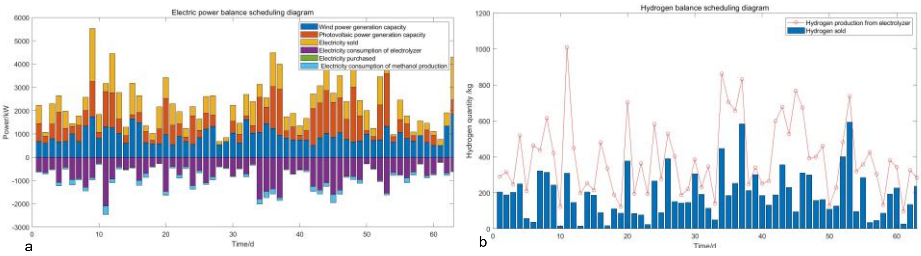

Figure 4: (a) Electrical power, (b) hydrogen balance scheduling diagram of the stochastic model

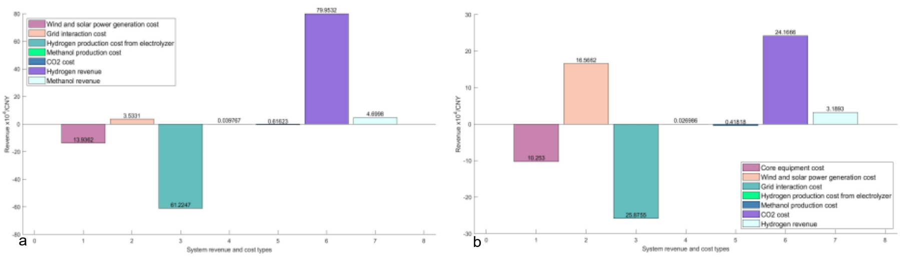

Figure 5: The revenue and cost of the (a) optimized model, (b) stochastic model

According to Figure 5(a), the total system revenue amounts to 9.86×10^5 CNY. Among this, hydrogen sales are the primary source of income, generating 7.995×10^5 CNY, which accounts for approximately 81 % of the total revenue. The final system profit is 1.237×10^5 CNY. To further validate the advantages of the optimized scheduling model, a comparative analysis was conducted against a stochastic model under the same cost parameters. As shown in Figure 4(b), the electrolyzer produces a total of 9.936×10^4 kg of hydrogen, of which only 2 % is used for methanol synthesis. Figure 5(b) shows that the stochastic model yields a final profit of 7.348×10^4 CNY, while the optimized model achieves a 68.3 % increase in profit. In addition, the hydrogen utilization rate rises from 2 % to 32 %, indicating a higher share of hydrogen being used for methanol production. These results demonstrate that, under all operational constraints, the optimized scheduling model significantly enhances the economic performance and energy conversion efficiency.

5. Conclusions

Experimental research on the GEHMIS based on LSTM prediction demonstrates excellent performance in wind speed and temperature prediction, with MAPE below 0.3 %. Compared to the random allocation model, the optimized scheduling model boosts economic benefits by 68.3 %, increases hydrogen utilization rate by 30 %. These results demonstrate that the optimized model significantly improves system operational efficiency and economic performance, providing strong support for stable operation and efficient energy conversion. Future research should focus on integrating multi-objective optimization algorithms and improving real-time scheduling to enhance system performance. These advances will support large-scale green energy deployment and aid the global energy transition toward sustainable development goals.

Acknowledgments

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