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Design of Efficient and Safe Wind-P2G-SOFC-GT Hybrid Systems through Machine Learning Enhanced Optimisation

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ABSTRACT

The Solid Oxide Fuel Cell (SOFC) will play a crucial role in the future energy sector for green and efficient H2-fueled applications. However, the complex thermal dynamic characteristics and safety performances of SOFC/GT systems introduce significant computational challenges to design systems utilising SOFCs. A wind/P2G/SOFC/GT multi-energy system structure is presented in the paper to demonstrate integrated energy systems that achieve optimal technical and economic performance. To address the design challenge, artificial intelligence technology offers the promise of constructing an accurate SOFC model using a minimal amount of experimental data, thereby alleviating computational demands and accelerating calculation times. In this study, we have developed an ensemble learning model designed to capture the thermodynamic and safety performances of SOFC/GT systems. This approach can accelerate calculations while ensuring the validity of optimisation results.

Keywords: renewable energy resources, machine learning, multi energy system, SOFC, power to gas, hydro energy

NONMENCLATURE

Abbreviations	
SOFC	solid oxide fuel cell
GT	gas turbine
GA	genetic algorithm
CR	curtailment rate
LCC	life-cycle cost
RMSE	root mean square error
MAPE	mean absolute percentage error

1. INTRODUCTION

Decarbonisation of energy generation has become a significant issue for environmental and economic development persistence.

A fuel cell-based system is considered one of the most important H2-fueled applications in future energy markets. Combined with a micro gas turbine and power to gas, the wind/P2G/SOFC/GT hybrid system provides a promising method of renewable energy utilisation with zero carbon involved.

The complicated and thermodynamical coupled feature of SOFC/GT results in a narrow operation window and strict safety boundary [1]. Optimising such a system, with fluctuations in wind power and user demands considered simultaneously, appears to be a difficult task. In our previous work [2], a multi-objective optimisation was carried out using a genetic algorithm (GA). However, the algorithm requires a large number of samples, resulting in heavy computing pressure and unsatisfying calculating time.

Machine learning methods offer a viable solution to overcome the limitations of mechanistic models, eliminating the necessity for intricate mathematical models involving partial differential equations. Instead, these methods directly gather insights from extensive experimental data to facilitate predictions. Despite the inherent non-linearity and the involvement of various physical and chemical processes in SOFC systems, previous research endeavours have adopted machine learning to forecast a range of operational parameters for fuel cells. For instance, Arriagada et al. [3] developed an artificial neural network-driven simulator to predict diverse operational parameters of SOFCs. Similarly, Song et al. [4] utilised a back propagation neural network, support vector machine, and random forest to forecast SOFC stack performance. Consequently, when subjected

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to appropriate training procedures, machine learning models can rapidly predict system performance based on input parameters [5].

Based on our previous works [1,2], this study presented a wind-powered P2G integrated with a full-detailed model of SOFC/GT was studied. The thermodynamic characteristic of the complete SOFC/GT system was captured via the ensemble learning technique. The algorithm simulated the critical safety performances of the hybrid system, as well as the available output power range and economic performance with the variation of multiple design parameters. The generated model was then cognised with wind power and P2G module, with the short-term operation and long-term planning performance optimisations carried out.

enters the micro gas turbine to generate power. The full-detail thermodynamic model of the wind/P2G/SOFC/GT system is established on the MATLAB/Simulink platform.

Several studies have been carried out on the energy system involving SOFC and gas turbines in our previous work [1][2][6], where experimental data have verified the modelling methodology.

2.2 Modelling

The anode-supported solid oxide fuel cell is selected in this study for modelling. The SOFC model [7] mainly includes electrochemical and thermodynamic models based on mass and energy balance equations. The micro gas turbine was modelled based on experimental data from an existing 30 kw-class turbine [8]. According to experiment results, the isentropic turbine efficiency presents a maximum close to 83%.

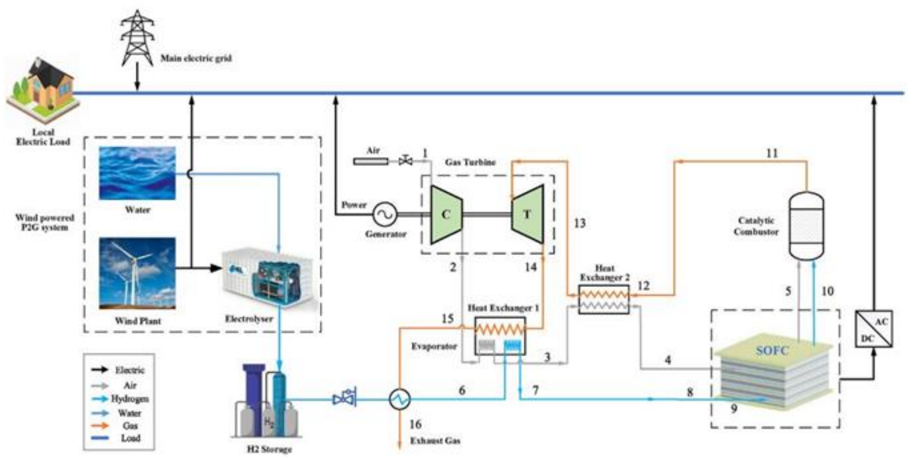

Fig. 1. Wind/P2G/SOFC/GT structure

2. SYSTEM STRUCTURE

2.1 Wind/P2G/SOFC/GT introduction

The structure of the wind/P2G/SOFC/GT multi-energy system is shown in Fig. 1. Electricity generated from the wind turbine is used to support local demand. Due to the randomness of wind sources, when the wind power exceeds local demand, the excess power will be consumed by electrolysers to generate H2 from water. The H2 acquired is kept in a storage tank.

When the wind power is insufficient to meet peak local demand, SOFC/GT will fill the gap as a backup power source using H2 from the storage tank. Both fuel and air are preheated in heat exchangers before entering the anode and cathode side of SOFC, respectively, where the electrochemical reaction happens. During this process, SOFC generates heat and electricity at the same time. The outlet's remaining H2 is entirely burned in the catalytic combustor. The exhaust gas of the combustor

Specific modelling equations and model validation could be found in our previous work [2, 6].

$$H_2 + O^{2-} \rightarrow H_2O + 2e^- \tag{1}$$

$$\frac{1}{2}O_2 + 2e^- \rightarrow O^{2-} \tag{2}$$

Local electricity and wind resource datasets from Scotland are used in this case [9]. Electrolysers produce H2 with the electrolysis of water powered by wind-source electricity. Operating efficiency of 75% and 0~100% operation load are assumed [1].

$$\eta_{HHV} = \frac{M_{fuel} \cdot HHV_{H_2}}{P_{el}} \tag{3}$$

2.2.1 Objectives

The wind/P2G/SOFC/GT system aims to efficiently supply the electrical demands with high local renewable energy consumed at low system cost. Therefore, the optimisation objectives should include short-term power management and long-term economic costs. Here, wind

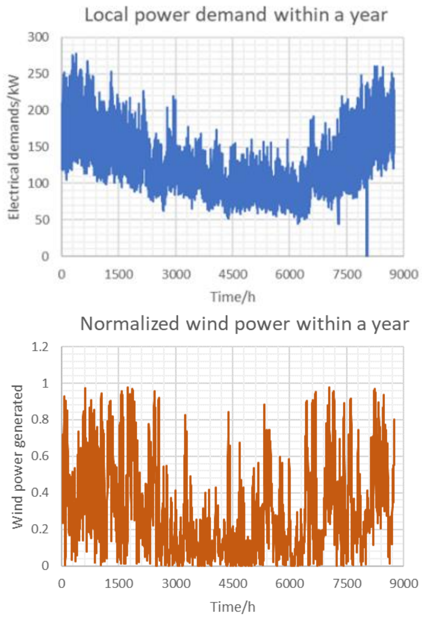

Fig. 2. Wind source and local demand data

power's curtailment rate (CR) and life-cycle cost (LCC) were used as optimisation objectives：

$$LCC = \sum_{i=1}^{j} CAPEX_{\mathrm{i}} + \sum_{i=1}^{j} OPEX_{\mathrm{i}} / \frac{\mathrm{r}(1+\mathrm{r})^{\mathrm{n}}}{(1+\mathrm{r})^{\mathrm{n}}-1} \tag{4}$$

$$CR = \frac{\sum_t Wind_{\mathrm{wasted,P2G}} + \sum_t Wind_{\mathrm{wasted,storage}}}{\sum_t Wind_{\mathrm{total}}} \tag{5}$$

where n represents an operating lifetime of 20 years, and r represents the discount rate, which is set as 8.9% in this study [1]. The curtailment rate of wind power includes the abandonment of wind power due to the operation limits of P2G and H2 storage.

During the extreme operation conditions where both the wind plant and SOFC/GT could not support load peak, electricity power from the main grid would be used, and the price of grid electric power was included in the LCC calculation. To achieve a high renewable energy penetration rate, the total share of wind power sources during all-time operation should be above 90%:

$$s.t. \frac{\sum_t W_{wind,t}}{\sum_t (W_{wind,t} + W_{grid,t})} \geq 90\% \tag{6}$$

Design parameters and ranges for multi-objective optimisation were given below:

Design parameters	Variation range for optimisation
Wind plant rated power	100 ~ 1000 kW
Electrolyser power capacity	100 ~ 2000 kW
Storage mass capacity	100 ~ 2000 kg
SOFC cell number	900 ~ 1200
SOFC utilisation ratio	0.7 ~ 0.85
Gas turbine modelling factor	1.3 ~ 1.5

Table.1. Optimisation ranges of parameters

2.2.2 Basic framework

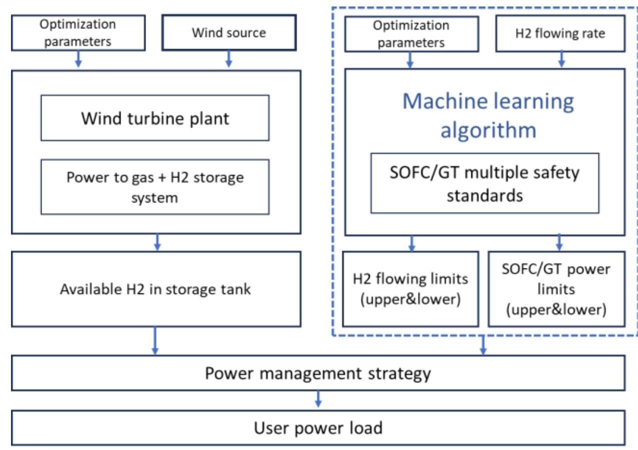

Fig. 3. Framework of wind/P2G/SOFC/GT system

The framework of this study includes two parts: the wind/P2G model simulates the access H2 amount at any given time; the machine learning algorithm will capture the thermodynamic and economic characteristics of the SOFC/GT system, generating maximum and minimum limits of the H2 flowing rate and output power. Then, these statistics of subcomponents will be given to a power management module for operation determination. The multi-objective optimisation is carried out using GA.

As can be seen, the most time-consuming part of the whole process is the determination of the maximum and minimum operation limits of SOFC/GT. This is due to the complicated mass and energy flows of the system. Critical safety standards must be met during every sample generated by GA, as well as total life-cycle operation. These requirements include SOFC operating temperature, SOFC temperature gradient, GT operating temperature, surge margin of compressor, and GT relative output power [1,2].

2.2.3 Machin learning algorithm

We leverage an ensemble learning algorithm [10] that utilises multiple decision trees as base learners, rooted in the principles of gradient boosting. This approach enhances the model's performance by adapting to negative gradients, commonly called residuals, and the final prediction result is calculated by summing the results from all base learners.

The algorithm's objective function consists of a loss function and a regularisation term, which are defined as follows:

$$min\ O = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{7}$$

where L is the loss function, and Ω represents the complexity of each weak learner, and can be expressed as:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{8}$$

where γ signifies the L1 norm penalty parameter, T represents the number of leaves, λ denotes the L2 norm penalty parameter, and w_j represents the weight of each leaf node.

We adopted the second-order Taylor series of the loss function; the loss function can be derived as

$$L\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) \simeq L\left(y_i, \hat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \tag{9}$$

where $\mathrm{g_i}$ and $\mathrm{h_i}$ denote the first and second derivatives of the loss function, respectively.

By integrating the above second-order expansion into the objective function. The objective function can be expressed as:

$$O^{(t)} \simeq \sum_{j=1}^{T}\left[\left(\sum_{i \in I_j} g_i\right) w_j + \frac{1}{2}\left(\sum_{i \in I_j} h_i + \lambda\right) w_j^2\right] + \gamma T \tag{10}$$

where I_j denotes as the collection of samples in leaf node j and eliminate the constant terms.

Finally, the optimisation of the objective function in this form can be converted into the problem of finding the minimum of a quadratic function.

We conducted uniform sampling across the valid range of three variables for system and fuel variables within each system, as shown in Fig. 3. These four input variables correspond to eight feature values used to assess safety conditions. We divided the data into training and test sets to create our datasets, adhering to an 8:2 split ratio. Additionally, we conducted hyperparameter optimisation for the ensemble learning model using the tree-structured Parzen estimator algorithm [11] before the training process.

3. RESULTS

3.1 Machin learning algorithm results

We employed two metrics to evaluate model performance: RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error). They are defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_t\right)^2} \tag{11}$$

$$\mathrm{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{y_t} \tag{12}$$

where $\mathrm{y_t}$ represents the actual value, $\hat{\mathrm{y}}_\mathrm{t}$ is the forecasted value for the t-th observation, and T is the total number of observations. The former are more sensitive to large errors, while the MAPE is more sensitive to small errors and outliers. The distribution of the mean absolute percent error is shown in Fig. 4.

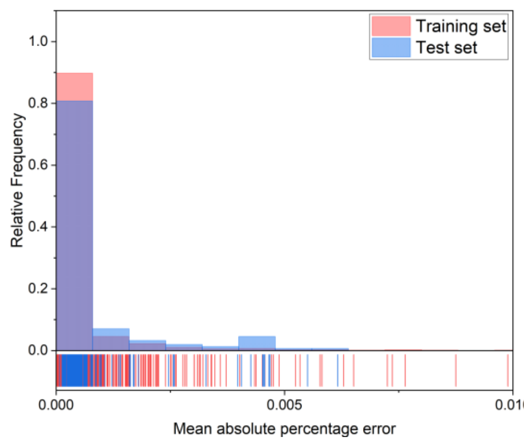

Fig. 4. MAPE of training set and test set

Algorithms	RMSE	MAPE
Polynomial Regression	324.21	0.0555
Lasso Regression	1158.64	0.1071
Xgboost	78.859	0.0048
Feedforward NN (50*2)	1270.59	0.0910
Random Forest	197.04	0.0061
(This work)	42.73	0.0016

Table.2. Prediction results of each algorithm

We can make several observations from this table. Firstly, the algorithm we employed demonstrates superior performance on both metrics, with Xgboost following, which is close in terms of algorithmic properties. Conversely, the performance of neural networks, frequently used in other studies, falls short of expectations. This discrepancy may be attributed to the fact that we trained our models with a limited amount of data, and neural network models typically demand more extensive datasets compared to ensemble learning models [12].

3.2 System multi-objective optimisation results

As shown in Fig. 3, after effectively building a ML surrogate model to replace the original thermodynamic explicit SOFC/GT simulation, the Pareto front of optimisation can be found rapidly and is given in Fig. 5. It can be seen that the rate of wind curtailment is decreasing with the increase of LCC cost, which indicates a trade-off between renewable sources utilisation and economic performance. According to the results, the total wind curtailment rate is expected to be lower than 4.8% when the LCC is higher than 2,796,630 £.

In this specific case, Fig. 6 shows the distribution of wind power generated in typical winter and summer scenes (two-week operation in both seasons). Results show that abandoning of wind power occurs in the minority of the timeline due to the power limit of the electrolyser.

Table 3 compares the optimisation time in our previous work [1] and this study. It is clear that based on machine learning methods, the simulation and optimisation time is much lower than before. This is because the algorithm successfully captures the thermodynamic and safety performances of SOFC/GT, resulting in the model free of time-costing simulation for every sample generated during GA optimisation. These results above indicate the benefit of the paper's framework. More detailed research on the characteristics of complicated energy systems could be carried out in future work.

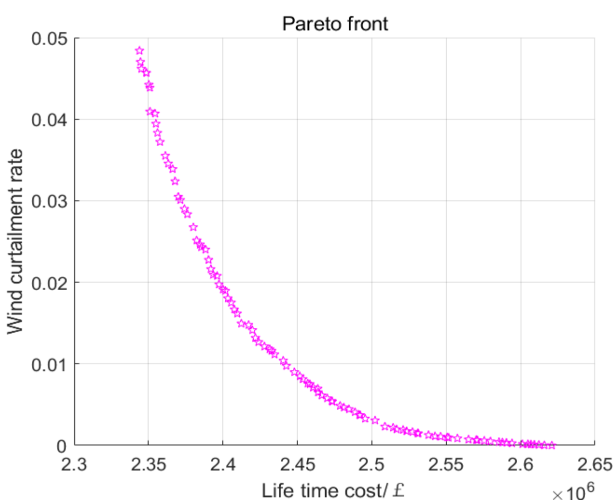

Fig. 5. Pareto front of multi-objective optimisation

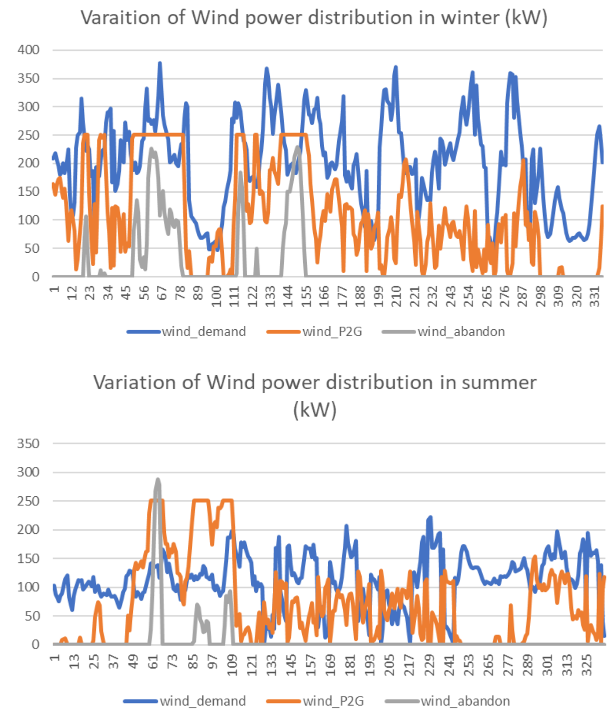

Fig. 6. Distribution of wind power generated in typical winter and summer scenes

Simulation patterns	Total optimisation time(s)
Thermodynamic wind/P2G/SOFC/GT model [1]	165,860
Machine learning based model (This work)	4,413

Table.3. Comparison of optimisation time

4. CONCLUSIONS

This work introduces a machine learning-based, data-driven surrogate simulation framework to capture the complex thermodynamic and economic characteristics of the SOFC/GT system. A wind/P2G/SOFC/GT multi-energy system structure is presented in the paper to illustrate the potential H2-fueled applications to facilitate renewable development. The prediction performance indicates that the RMSE and MAPE values for the test sets are 42.73 and 0.0016, respectively. This suggests that our ensemble learning model has comparable accuracy to the physical model while demonstrating a 37-time increase in computation-resource efficiency.

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