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OPINION
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Parameter Identification for Solid Oxide Fuel Cell Models: Crucial Comments

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INTRODUCTION

Increasing global energy demand (Zhang et al., 2016; Shen et al., 2019), exhausted fossil fuel resources (Wei Yao et al., 2015; Yang et al., 2015), and deteriorating ecological environment have threatened the healthy development (Liu et al., 2016; Kalyan and Rao, 2021; Noman et al., 2021) of the world. Hence, numerous clean production technologies (Zhang et al., 2015; Bakeer et al., 2021; Iqbal et al., 2021) are conceived as candidates to alleviate energy depletion (Chen et al., 2019; Wang et al., 2020; Dzobo et al., 2021). Among them, hydrogen energy utilization (Yang et al., 2020a) plays a considerable role in alleviating environmental pressure and reconstructing energy structure because of its protruding characteristics of pollution-free and high energy conversion (Erdiwansyah et al., 2021). Besides, hydrogen (Zhang et al., 2021a) is used as an alternative renewable energy supplement, while solid oxide fuel cell (SOFC) techniques arouse extensive attention and research studies due to effective and dependable conversion of chemical energy into electrical energy. It is particularly noteworthy that accurate and reliable SOFC system models are hindered owing to the inherent nonlinearity, strong coupling, and diversification. Therefore, to address the aforementioned obstacles, advanced SOFC modeling approaches (Yang et al., 2020b) with flexible parameter identification technologies should be proposed for better behavior prediction and performance research. At present, the practical application of SOFC modeling and parameter identification is confronted with many challenges. First of all, the current research articles lack the description of overall accurate models about cell stack because the influence of electrical coupling is ignored. Second, after selecting an appropriate model, current parameter identification strategies also have potential defects, while advanced methods are worthy of further consideration and research. This study gives a clarification of the abovementioned problems and puts forward some perspectives on various SOFC modeling and parameter identification technologies.

SOFC MODELING

Accurate and reliable SOFC system models have a crucial part in maximum power point tracking (MPPT), behavior prediction, performance simulation, and research. For the sake of conducting a specific study on SOFCs from multiple perspectives, numerous modeling methods have been devised, which mainly comprise electrochemical model (Yang et al., 2021a), steady-state model (Jiang et al., 2014), and transient model (Wu et al., 2020). Particularly, the identification parameters of various SOFC models are demonstrated in **Table 1**, while the specific meaning of each parameter is detailed in reference (Yang et al., 2020b). Among them, the electrochemical model has the most extensive application in parameter identification, while it is considered to be a vigorous and deep description of electrochemical reaction phenomena of SOFC without involving complex situations such as concentration gradient (Xiong et al., 2018; Yang et al., 2021b). **Figure 1** shows the overall

TABLE 1 | Summarization of identification parameters on various models.

SOFC model	Identified parameters
Electrochemical model	E_o, A, R, B, $I_{0,a}$, $I_{0,c}$, I_L
Steady-state model 1	k_E, k_I, k_1, k_2, γ, and δ
Steady-state model 2	E_o, A, R, B, J_0, J_{max}
Transient model	E_o, A, R, B, J_0, J_{max}

generation process based on the electrochemical mechanism of the SOFC. It is clearly described in the study by Wang et al., (2022) that SOFC output voltage is lower than ideal voltage due to the existence of activation loss, ohmic loss, and concentration loss, which is extremely profitable for understanding and designing SOFC structure. Furthermore, the datasets from cylindrical cells (Pierre, 2010) and tubular cell stacks (Caisheng Wang and Nehrir, 2007) in literature (Xiong et al., 2021) are used for parameter identification of electrochemical models, where simulation research is specific to the type of the SOFC and possesses a certain promotion effect on the refinement of the model. In addition, steady-state models can be subdivided into two types (Yang et al., 2020b) as for easy differentiation to name them steady-state model 1 (Jiang et al., 2014) and steady-state model 2 (El-Hay et al., 2018). Since two steady-state models of the SOFC can be tracked and optimized, several unknown parameters under different operation conditions, that is, model 1 has six parameters and model 2 has seven parameters, upon which more trustworthy and efficient online control and performance study of SOFC systems can be achieved (Jiang et al., 2014; Huang and Turan, 2019). Yang et al., (2020b) describe in detail the voltage and load current (*V-I*) polarization characteristic of steady-state models 1 and 2, where it is necessary to cover a more in-depth and comprehensive introduction to difference comparison, advantages/disadvantages, and specific applications. It is worthwhile that neither model can display the response under transient disturbances and lack the capability of dynamic response during load changes. Besides, the transient response mainly depends on the reactant flow and the changes of external environment, such as the change rate of hydrogen, steam, and oxygen; the response time of fuel processors; and load variations, while these factors will cause chemical reaction parameter variation and a certain time delay in practical engineering (Xu et al., 2016; El-Hay et al., 2019). Therefore, it is an exceptional and practical discussion trend to investigate both steady-state models and transient models, such as in the study by Wu et al., (2019; Fathy and Rezk, (2022).

Especially, based on the abovementioned three modeling methods (Yahya et al., 2018), the output voltage of the whole cell stack is the number of cells multiplied by the output voltage of a single cell, which is assuming that *V–I* characteristics of all single SOFCs in the cell stack are same or similar. Nevertheless, due to the existence of electrical coupling, the characteristics (Cao et al., 2011; Chaudhary et al., 2019) of each SOFC make a distinction in practical engineering applications leading to inaccurate parameter identification results or poor model practicability. Under various references, the value range of each parameter to be identified is different in the same model, while there is no literature to emphasize the most scientific and universal value range. Besides, because the range of some unknown parameters is too large, the unreasonable search space results in a long optimization time and low accuracy. As a consequence, it plays an essential role to explore a scientific, precise, and accurate parameter value range in all SOFC models in future research.

METHOD OF PARAMETER IDENTIFICATION

With the rapid progress of computer technology and artificial intelligence (AI), a great number of meta-heuristic algorithms

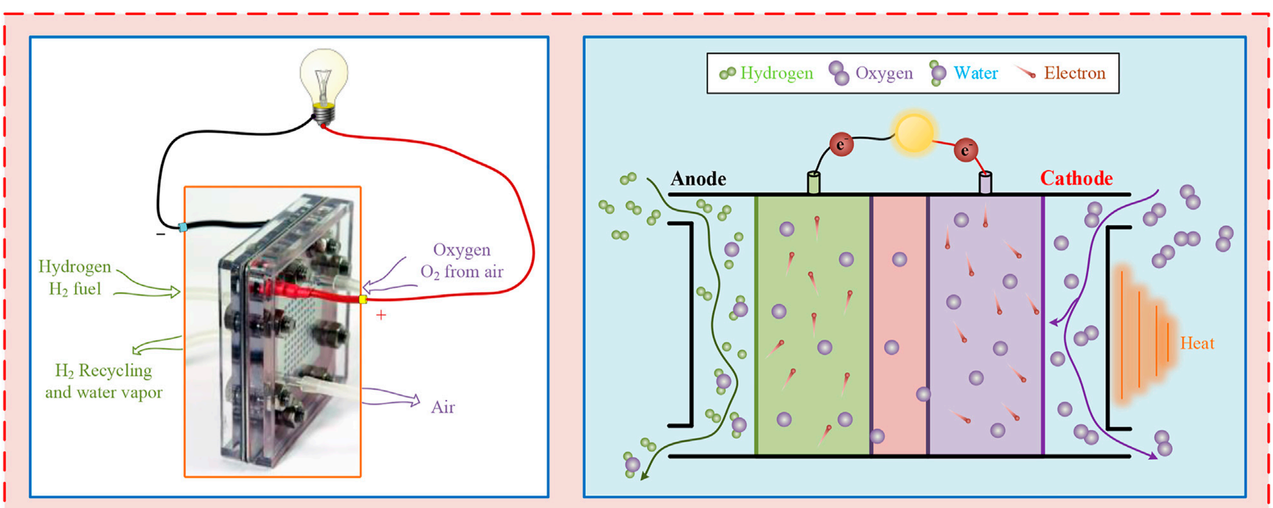

FIGURE 1 | Electrochemical mechanism of the SOFC.

and artificial neural network (ANN) technologies have been proposed for high nonlinear optimization problems. Meanwhile, these techniques have been supposed to solve a series of parameter identification of the SOFC with high flexibility and low computational pressure due to lack of gradient and complex computational processing. Until now, multitudinous advanced meta-heuristic algorithms have been developed astonishingly to identify unknown parameters in precise SOFC systems. The converged grass fibrous root optimization algorithm (CGROA) (Shi et al., 2020) is a novel optimized technique that is utilized to select unknown parameters in the electrochemical model of the SOFC, where the convergence speed and statistical analysis are applied to present a clearer contrast result. In the study by Wei and Stanford, (2019), an optimized algorithm based on the chaotic binary shark smell optimization (CBSSO) algorithm is recommended, which alleviates the limitations of the optimization process and obtains satisfactory unknown parameter results, upon which superior performance in global search is fully verified. Furthermore, there are other meta-heuristic algorithms with excellent performance, such as interior search optimizer (ISO) (), differential evolution (DE) (Sarmah et al., 2017), co-evolution RNA genetic algorithm (coRNA-GA) (Wang et al., 2019), and simplified variant of competitive swarm optimizer (SCSO) (Xiong et al., 2020).

Although the pure single-algorithm portfolios can acquire satisfactory solutions through multiple iterations, these algorithms also contain certain imperfections (Ghadimi et al., 2018), that is, weak balance ability of local exploitation and global exploration, premature convergence, long calculation time, and insufficient accuracy. In order to amplify the superiorities and partly ameliorate these deficiencies of pure single meta-heuristic algorithms, many scholars have begun to engender more outstanding methods, mainly mixing a variety of meta-heuristic algorithms to realize the parameter identification of the SOFC. Bai and Li, (2021) propose a remarkable and accurate method, that is, the combination of cuckoo search (CS) and gray wolf optimization (GWO) algorithm, where using CS changes the static control parameters in GWO to improve precision by reducing the probability of falling into local optimal points. In the study by Xiong et al., (2021), a novel optimization-based hybridization of differential evolution (DE) with the Jaya algorithm is implemented, which makes full use of the exploration character of DE and exploitation character of Jaya to achieve superb performance in a cylindrical cell and a tubular stack. These methods combine two or more meta-heuristic algorithms to improve search accuracy, shorten calculation time, and enhance robustness by complementing the disadvantages of one from the advantages of the other. It is a key direction of meta-heuristic algorithm research and design in the future, especially the number of hybrid meta-heuristic algorithms used to identify unknown parameters of the SOFC is still not enough.

In addition, the integration of meta-heuristic algorithms and ANN models is an alternative research direction extensively discussed at present. Zhang et al., (2021b) propose a novel optimal model of extreme learning machines (ELM) network based on the improved red fox optimization (CRFO) algorithm, upon which parameter identification under nonlinear dynamic behavior of the SOFC stack can be perceived by comparing with the other two methods. Based on the minimizing mean squared error (MSE) between empirical and modeled data, a new hybrid Elman neural network (ENN) method is designed to track unknown parameters of the SOFC efficiently and accurately, which is combined with the quantum pathfinder (QPF) algorithm, called QPF base ENN (QPF-ENN) (Jia and Taheri, 2021). There is no doubt that the use of various meta-heuristic algorithms to optimize the control parameters of ANN models can take into account the advantages of both, so as to significantly reduce fitting errors and improve accuracy.

However, few scholars pay attention to the shortage of experimental data and noise data, which exists objectively and cannot be ignored in practical engineering. Yang et al., (2021c) provide a perfect research idea, that is, paying attention to the insufficient experimental datasets and random noised datasets in the process of identifying SOFC parameters upon which ELM is applied to predict additional data and update noised data with outstanding stability, great robustness, and high efficiency. At present, several deficiencies need further follow-up research to solve and improve. First of all, more attention should be concentrated on noise data caused by complex operation conditions in order to increase the anti-interference ability of algorithms to identify parameters. In addition, in terms of expanding insufficient data, no standard is elaborated on what is the minimum amount of experimental data to accurately identify unknown parameters.

CONCLUSION

The precise modeling technology of the SOFC is a crucial step for its performance evaluation, simulation analysis, and subsequent fault diagnosis, while there is still much space to ameliorate in research and development. In particular, various thorny obstacles of present techniques exist in engineering practicability, stability, and efficiency, whose main conclusions are stated as follows:

- Standardized and realistic cell stack models owning perfect practicability for parameter identification have not been devised due to their electrical coupling phenomenon upon which the accuracy and authenticity of models are limited to a great extent. With consideration of various practical factors, the influence of electrical coupling on accurate models can weaken/ avoid.
- Models have the problems of too large parameter boundaries and inconsistency. Thus, it is necessary to formulate a unified standard for the unknown parameter range of each model, while the specific considerations should be combined with different types of cells.
- Multiple hybrid algorithms can make effective use of their advantages simultaneously, which can greatly tackle defects of a single meta-heuristic algorithm and balance the ability

of local exploitation and global exploration, such as CS-GWO, DE-Jaya, and QPF-ENN.

- Noise datasets exist in engineering applications with various complicated conditions, while the current research studies pay little attention. It is worthwhile to focus on noise datasets and find reasonable strategies to remarkably reduce or even eliminate their interferences.
- Another important aspect of this technology is the expansion of insufficient data. The amount of experimental data is a considerable research subject, while no research points out the minimum amount of data for parameter identification.

AUTHOR CONTRIBUTIONS

CZ: writing the original draft and editing. BY: conceptualization. YH: visualization and contributed to the discussion of the topic.

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