Simple Temperature Modeling of Proton Exchange Membrane Fuel Cell Using Load Current and Ambient Temperature Variations

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Abstract:

This paper proposes a simplified proton-exchange membrane fuel cell (PEMFC) temperature model for the purposes estimating PEMFC temperatures with high accuracy with air-cooling systems. Besides knowing that most of the existing models were designed for specific systems, the proposed model also focuses on generalizing the conventional temperature model for easy adoption by other PEMFCs. The proposed model is developed based on the first-order exponential equation to avoid the limitations of complex mechanistic temperature models. The model uses only the information available from typical commercial PEMFCs, the main inputs of which are the current, elapsed time, and ambient temperature. In addition, the PEMFC area, number of cells in the stack, and high/low operating currents were incorporated in the proposed model for ensuring its generalizability and applicability to different PEMFC technologies with air-cooling systems under various ambient conditions. The required model parameters were optimized using the Harris hawks optimization method. The proposed model was validated using experiments conducted on the Horizon-500 W and NEXA-1.2 kW PEMFC systems equipped with air-cooled mechanisms under different ambient temperatures and load currents. The root mean square error of all the examined cases was less than 0.5. The proposed model is helpful for simulations, dynamic real-time controllers, and emulators because of its fast response and high accuracy.

Keywords: Current-based model; Dynamic temperature model; Harris hawks' optimization; PEMFC, Algorithm.

1. Introduction

Proton exchange membrane fuel cells (PEMFCs) have been utilized in many stationary and portable applications, such as transportation electrification and back-up power supplies (Khan et al. 2019a). PEMFCs are energy conversion devices that transform hydrogen into electricity and some byproducts (e.g., water and heat) through chemical reactions between hydrogen and oxygen. The heat produced in this exothermic reaction increases the temperature of a PEMFC and has a substantial role in thermodynamic reactions, transport, and water distribution (Khan et al. 2019b). These processes determine the efficiency and long-term durability of PEMFC systems. Therefore, thermal management is crucial for the enhancement in the PEMFC performance. Different cooling mechanisms, including water and air cooling, have been employed for the thermal management of PEMFC systems (Muller et al. 2006; Ma et al. 2019). Forced air-cooled systems are commonly used in low- to medium-power PEMFC systems (Sohn et al. 2005; Khan et al. 2019c). The development of an accurate thermal model that influences the output voltage and power of PEMFC stacks is the main challenge in the design of efficient thermal management schemes (Alzeyoudi et at. 2015; Khan et al. 2019d).

The challenges in PEMFC temperature modeling can be summarized as follows:

- Requirement for detailed insight data about the PEMFC, which is not commonly available for commercial PEMFC systems.
- Necessity of a fast and dynamic temperature model to model the PEMFC voltage accurately. Currently, most PEMFC temperature and voltage models are interdependent of each other, so the model performance is not high enough for quickly varying dynamic applications.
- For application in online monitoring, a temperature model should be simple.
- The model should be applicable to different types of PEMFC systems. Conventional PEMFC temperature models are system specific, so they cannot be applied to different PEMFC systems.

To address these issues, different thermal modeling techniques have been developed, including mechanistic, semiempirical, and purely empirical models (Khan et al. 2019a), which are discussed in detail in the next section. To our knowledge, simple and generic PEMFC models suitable for effective and accurate online monitoring have not been proposed. The so-called Saad's temperature model proposed by Khan et al. (2019b) is effective but lacks generality and adaptability to different types of PEMFC systems.

In this study, we aim to propose a temperature model based on the Saad's model. The proposed method is developed by attempting to reduce the complexity, the requirement of extensive and detailed information, and system-specificity of previous models. To achieve this, we introduce a new exponential equation that considers the PEMFC area, number of cells in a stack, and high and low operating currents as dependent parameters. The state variables of the model are the load current, elapsed time, and ambient temperature.

The key contributions of the proposed study are as follows:

- We improved the Saad's PEMFC temperature model proposed by Khan et al. (2019b) by introducing the number of cells in a stack and the area of the PEMFC, which directly affect the heat loss of the PEMFC, into the model equations.
- We generalized the model for various PEMFC systems by introducing a separate set of parameters for low and high current levels (based on the rated power).
- We applied the Harris hawks optimization (HHO) method for model parameter identification for the first time.
- The proposed temperature model is tested and experimentally validated for commercial NEXA 1200 W and Horizon 500 W PEMFCs.

The proposed temperature model is initiated by testing the performance of the Saad's temperature model with different PEMFC systems and noting that the model parameters are not suitable for different PEMFC systems. Next, additional parameters (number of cells in a stack and area of PEMFC) are introduced in the model and the model parameters are reoptimized through HHO. Finally, two sets of equations are introduced to minimize the difference between the model prediction and experimental results obtained with NEXA 1200 W and Horizon 500 W PEMFCs for high and low current load variations.

The remainder of this paper is organized as follows. In Section 2, we report a literature review of the theoretical thermal modelling and thermodynamics of PEMFCs. In Section 3, we describe the Saad's temperature modelling and its limitations. In Section 4, we describe the proposed modifications to the Saad's temperature model. In Section 5, we discuss the HHO algorithm and the objective function used to evaluate the model parameters. In Section 6, we outline the experiments performed on the PEMFCs. Finally, Sections 7 and 8 outline the experimental results and conclusions, respectively.

2. State of the art PEMFC temperature modelling

The existing thermal models for PEMFC systems can be categorized as mechanistic, semiempirical, and purely empirical. The mechanistic models are normally based on complex algebraic equations to analyze different phenomena, such as mass inflows and outflows, which require a large amount of information about different physical parameters (Khan et al. 2019a). The models proposed by Jung et al. (2011), Zhang and Kandilkar (2012), Real et al. (2007) consider several parameters, such as the coolant channel, anode gasket, and flow field plate of the anode. However, for commercial PEMFC systems, these parameters are difficult to obtain. Theoretically, the temperature of PEMFCs can be extracted by solving the energy balance equations for the entire stack (Salva et al. 2016). The generalized heat balance equation for the membrane is expressed as follows:

$$\frac{T_{Mem}-T_{CL,c}}{R_{Mem-CL}}+\frac{T_{Mem}-T_{CL,a}}{R_{Mem-CL}}+A_{lat,Mem}\times h_{conv}\times(T_{Mem}-T_{amb})=0 \quad (1)$$

where T_{Mem} is the membrane temperature, $T_{CL,a}$ and $T_{CL,c}$ are the temperature of catalyst layer at anode and cathode respectively. R_{Mem-CL} is the thermal resistance in m^2 /kW between membrane and catalyst layer, h_{conv} is convective heat transfer coefficient in m^2 /kW, $A_{lat,Mem}$ is the lateral area of membrane and T_{amb} is the ambient temperature.

Similar equations can be extracted for the anode, cathode, gas diffusion layers, and bipolar plates. However, these heat equations are very complex and requires a lot of information in order to extract the exact temperature of PEMFCs at the given segment of the fuel cell stack. The temperature of different PEMFCs and different sections of a cell vary during operation. Generally, the average temperature is estimated through temperature modelling. Recently, Yuan et al. (2019), Berning and Kaer (2020), and Zhang et al. (2020) attempted to describe the thermodynamics of PEMFC stacks and to estimate the average temperature of PEMFCs.

Yuan et al. (2019) analyzed the temperature characteristics of a PEMFC system and employed a 3D numerical model to predict the temperature of PEMFCs. They also proposed a new thermal management system that controls the direction and speed of the air flow. This system is based on the following theoretical thermal equations for three nodes according to the direction of coolant channel:

$$m_{fc,1}C_{fc}\frac{dT_{fc,1}}{dt}=H_{reac,1}-\frac{P_{st,1}}{3}-Q_{rad,1}-Q_{cool,1}+Q_{i+1} \quad (2)$$

$$m_{fc,2}C_{fc}\frac{dT_{fc,2}}{dt}=H_{reac,2}-\frac{P_{st,2}}{3}-Q_{rad,2}-Q_{cool,2}+Q_{i+1}-Q_{i-1} \quad (3)$$

$$m_{fc,3}C_{fc}\frac{dT_{fc,3}}{dt}=H_{reac,3}-\frac{P_{st,3}}{3}-Q_{rad,3}-Q_{cool,3}-Q_{i-1} \quad (4)$$

where m_{fc} , C_{fc} , P_{st} are the mass, specific heat capacity, and power of a PEMFC, respectively, which remain the same in all cases. H_{reac} is the total energy released by the chemical reaction between hydrogen and oxygen in order to produce water and energy. This energy depends on the mass flow rate of reactants and the generated byproducts, as well as on the temperature of the three nodes and the ambient temperature (T_{amb}). The energies released at the three nodes are different because mass flow rate and temperature are different. In Equations (2)–(4), Q_{rad} is the energy rate released due to radiation; Q_{cool} is the heat rate removed by the coolant, which depends on the area (A) of the PEMFC, density of air (in case of air as coolant), fan speed, and specific heat capacity of air; and Q_{i+1} and Q_{i-1} are heat transfer rate between the three nodes.

Zhang et al. (2020) proposed a semiempirical model, which is relatively simple. In this model, the heat flow equation is used to calculate the temperature of open-cathode air-cooled PEMFC systems, and no nodes or components of PEMFCs are considered explicitly. Instead, a single thermodynamic equation is considered to explain the complete PEMFC stack assembly:

$$\frac{m_{fc}C_{fc}dT_{fc}}{dt} = H_{reac} - N_c I V_{st} - Q_{rad} - Q_{conv} \tag{5}$$

where V_{st} is the stack voltage, N_c is the number of cells in the stack, and Q_{conv} is the heat loss rate due to convection. In Equation (5), Q_{rad} and Q_{conv} mainly depend on the temperature of the PEMFC and the ambient temperature.

Berning and Kaer (2020) proposed a simplified model that considered the PEMFC thermodynamics in detail at different ambient conditions, including normal, hot and dry, and cold and dry conditions. In this model, the thermodynamics of the PEMFC are modeled using the first law of thermodynamics by considering the adiabatic condition of gases as follows:

$$P_{st} = \sum n_{prod}\, h_{prod} - \sum n_{react}\, h_{react} \tag{6}$$

where n_{prod} and n_{react} are the molar flow of product and reactant gases, respectively, and h_{prod} and h_{react} are the specific enthalpy (J/mol) of products and reactant, respectively. Salim et al. (2015) proposed an analytical model wherein the parameters are optimized using a particle swarm optimization algorithm. However, these parameters cannot be applied to other types of PEMFCs. Ariza et al. (2018) developed a simplified version of the model proposed by Salim et al. (2015) and tuned the parameters using a genetic algorithm. However, because this model was validated experimentally on cells rather than a stack, the model parameters cannot be applied to different types of PEMFCs. Apart from the issue of the dependency of the mechanistic models on several inaccessible physical parameters, the aforementioned studies considered voltage as an input for the thermal models. However, the voltage is directly dependent on the stack and ambient temperature, causing inaccuracy in the stack temperature estimation of the thermal models.

Purely empirical approaches involve the use of artificial intelligence and various other prediction techniques. Belmokhtar et al. (2014), Panos et al. (2012), Tao et al. (2005), and Qun et al. (2014) performed temperature modeling using artificial intelligence and predictive control techniques without considering voltage as an input. Panos et al. (2012) used the MATLAB Identification Toolbox to develop a reduced-order temperature model by considering the mass flow rate, coolant temperature, and compressor voltage. Subsequently, this model was integrated into a model predictive control framework. Akbari and Dahari (2019) proposed a temperature model dependent only on the inlet gas flow rate using an adaptive neuro-fuzzy inference system. This model was also integrated into the control loop to regulate the stack temperature. However, these data-driven models are specific and require extensive training data.

The empirical approach is not limited to above mentioned techniques. Soltani and Bathaee (2008), Restrepo et al. (2014), and Li et al. (2012) proposed generic models based on first-order semiempirical equations that utilize the current and ambient temperature as inputs. Li et al. (2012)

used a polynomial function based on the PEMFC current to estimate the stack temperature and time constants of the first-order equation. This approach results in poor performance and abrupt temperature changes. Restrepo et al. (2014) used sinusoidal functions, instead of a polynomial function, of the current to estimate the time constants and reduce the sensitivity of the model to sudden fluctuations. The simplest model of the PEMFC temperature was proposed by Bharath et al. (2020). In this model, the temperature equation is developed based on two exponentials as follows:

$$T_{fc} = a \times exp^{b \times I} + c \times exp^{d \times I} \tag{7}$$

This model is very simple but does not consider the ambient temperature change. The exponential equation is very useful in the simple modelling of PEMFC systems because the temperature curves of PEMFCs with load current variation closely follow these exponential curves, as mentioned by Soltani and Bathaee (2008). However, this model had many deficiencies, which were corrected by Khan et al. (2019b).

Furthermore, the model also requires parameter optimization for different PEMFC systems. Khan et al. (2019b) considered a new mechanism based on first-order empirical equations by optimizing the parameters using a lightning search algorithm (LSA). In Saad's model, the main concept is to detect the load changes and calculate instantaneous PEMFC temperature variations. This mechanism further improves the performance of the model proposed by Khan (2019c). However, the performance of this model in different ambient conditions and different fuel cell systems is still uncertain. Table 1 summaries the literature review of the thermal/temperature models of PEMFCs.

Table 1 Summary of PEMFC thermal/temperature models

3. Details of Saad's PEMFC temperature model

The Saad's temperature model in (Khan et al. 2019b) uses the following first-order discrete equation:

$$T_{mod}(k) = L_1 I_{t(k)} + L_2\left(I_{t(q)} - I_{t(k)}\right)e^{-L_3(t_k - t_q)} + T_{amb}(t_k) - L_4 \quad k=1,2,3,\ldots, \tag{8}$$

where $I_{t(q)}$ is the current value at sample q, which is recorded before the last significant change in current; $I_{t(k)}$ is the current value at the present sample k; and Tamb is the ambient temperature.

The following expressions are used to account for the air-cooling system of PEMFC:

$$T_{mod1}(t_k) = T_{mod}(t_k) - L_5 \frac{\{T_{mod}(t_k) - T_{mod}(t_q)\}}{(t_k - t_q)}, \tag{9}$$

$$T_{mod2}(t_k) = T_{mod1}(t_k) + L_6\{T_{mod1}(t_k) - T_{mod1}(t_q)\}, \tag{10}$$

where T_{mod2} is the final modeled temperature, and L_1 to L_6 are optimized using LSA. Table 2 shows the values of parameters L_1 to L_6 used in the model equations.

Table 2 Saad's model parameters

Parameters L_1 and L_2 are used to convert the current and difference of current into temperature, respectively; L_3 is a factor that controls the decay and increases the temperature time; L_4 is an offset from the temperature model in Equation (8); and L_5 and L_6 are the constant parameters in the differential equations (9) and (10), respectively.

Saad's model has the following limitations:

- The model output has fluctuations. To overcome this issue, in this study, the complex online filtering technique proposed by Junyan and Shudan (2015) is used.
- The model has only been validated experimentally for the NEXA 1200 W PEMFC system. However, to verify its generic performance, the model needs to be tested on other PEMFC systems.
- The temperature variation with the current level is a nonlinear process (Restrepo et al. 2014), whereas in Saad's model, this variation is simplified into a linear equation. Therefore, the model is not precise when large variations in the current, which also affect the temperature evolution, occur.

To address these issues, we proposed a modification to Saad's temperature model by introducing the number of cells in a stack and the area of the PEMFC into the model equations. Further improvements are suggested to adapt the linear equations to represent the relation between the system temperature and load current using two different set of equations for low and high load currents determined from the power rating of the system.

4. Suggested modifications in the Saad's temperature model

Two substantial modifications are considered in this section to further improve the performance of the Saad's model. The first modification deals with the extraction of a function to relate each L_i (i = 1 to 6) parameter to the number of cells (N_c) and membrane-active area (A). These parameters have an essential role in the generation and dissipation of heat in the PEMFC stack, and their values vary in each PEMFC system. Therefore, utilizing the function to relate each parameter (L_i) to Nc and A can compensate for the errors introduced by the application to different systems. In this study, these parameters of Horizon 500 W and NEXA 1200 W PEMFC systems are optimized using the HHO method.

After optimizing the parameters in both PEMFC systems, the equations of the parameters based on the number of cells in the stack and the active area of the membrane are extracted using first-order polynomial curve fitting in MATLAB®.

$$L_i = f(A \times N_c) \tag{11}$$

The second modification in the temperature model is related to the classification based on the current drawn from a PEMFC into the low and high levels to improve the estimation of the temperature evolution under different conditions. Furthermore, the thermal dynamics of the PEMFCs may differ at low and high currents. According to Ariza et al. (2018), the produced electrical energy is the main contributor to the generated net energy. Moreover, the electrical energy is directly related to the produced current. In this study, the parameters optimized at high and low currents may lead to good results in both PEMFC systems. The threshold current (I_t), which separates the high and low currents, is calculated using the function of electrical power (P) through the first-order polynomial fitting in MATLAB®. The parameters in Equation (12) are modified by considering It. In this study, f_1 and f_2 are two separate functions with different constants.

$$L_i = \begin{Bmatrix} f_1(A \times N_c) \text{ for } I \geq I_t = f(P) \text{ for high current} \\ f_2(A \times N_c) \text{ for } I < I_t = f(P) \text{ for low current} \end{Bmatrix}. \tag{12}$$

Table 3 presents the complete pseudocode of the proposed model, including a simple filtering technique. The equations used are the same as those in the Saad's model (Equations (8)–(10)), whereas the parameter values are modified using HHO for high and low currents based on the number of cells and membrane-active area. The filtering technique uses ten samples and filters any spikes in the final temperature model curve to reduce the fluctuations.

Table 3 Pseudocode of the proposed model and simple filtering technique

5. Application of HHO Algorithm for model parameter extraction

The successful application of metaheuristic optimization algorithms in PEMFC modeling has been verified in several studies (Khan et al. 2018; Kandidayeni 2019). The HHO algorithm was inspired by the natural behavior of Harris hawks (Asghar et al. 2019). This technique can be applied to all optimization problems and has different phases: the exploration, transition, and exploitation phases.

5.1 Exploration Phase

The exploration phase of Harris hawks deals with the search of prey with the help of their powerful eyes. They usually wait and monitor the site to detect their prey, and the waiting period can last several hours. In this optimization technique, Harris hawks are the candidate solutions, and the best candidate solution at every step is considered the prey, which is intended or referred to as the optimum solution. Harris hawks usually sit at random locations and look for their prey based on two major strategies. An equal chance (c) exists in each location based on the other locations, whereas the prey is modeled with the following equation under two conditions, i.e., $c < 0.5$ (small tree locations) and $c \geq 0.5$ (high tree locations):

$$X(t+1) = \begin{Bmatrix} X_{rand}(t) - r_1(X_{rand}(t) - 2r_2X(t) \quad c \geq 0.5 \\ (X_{prey}(t) - X_m(t)) - r_3(LB + r_4(UB - LB)) \quad c < 0.5 \end{Bmatrix}, \tag{13}$$

where $X(t+1)$ is the position in the next iteration; t is the iteration number; X_{prey} is the position of the prey; $X(t)$ is the position of the hawk at the current iteration; r_1, r_2, r_3, r_4, and c are random numbers ranging from 0 to 1; LB and UB are the lower and upper bounds of parameters, respectively; X_{rand} is the randomly selected hawk in the current population, and X_m is the mean position of the current population.

5.2 Transition phase

Exploitation occurs after exploration, but this phase depends on the escaping energy of the prey. The energy of the prey decreases considerably during the escape. The energy of the prey is expressed as follows:

$$E = 2E_o(1 - \frac{t}{Z}), \tag{14}$$

where E is the escaping energy of the prey, Z is the maximum iteration, and E_o is the initial energy of the prey, which E_o changes between −1 and 1. If E_o decreases from 0 to −1, then the prey is flagging; if E_o increases from 0 to 1, then the prey is strengthening. The dynamic trend of the energy decreases after successive iterations. However, when the energy is higher than unity, the hawk searches the prey in another region; when the energy is lower than unity, the hawk searches in the neighborhood of the present solutions.

5.3 Exploitation phase

In this phase, the hawk performs a surprise pounce by attacking the desired prey aggressively, while the prey attempts to escape. On the basis of the escaping and chasing behavior, the following strategies are proposed in the HHO algorithm to model the attack: (i) soft besiege, (ii) hard besiege, (iii) soft besiege with progressive rapid dives, and (iv) hard besiege with progressive rapid dives.

The prey always tries to save its life by running away. Suppose that r is the prey's chance to escape, and $r < 0.5$ and $r \geq 0.5$ indicate a successful or unsuccessful escape, respectively.

In soft besiege, $r \geq 0.5$ and $E \geq 0.5$, so the prey has enough energy to try to escape through misleading jumps but fails in the end. In this process, the hawk encircles the prey to exhaust it and finally pounces.

In hard besiege, $r \geq 0.5$ and $E < 0.5$, so the prey has low escaping energy. The hawk hardly encircles the prey and rapidly pounces in a sudden move.

In soft besiege with progressive rapid dives, $E \geq 0.5$ and $r < 0.5$. Thus, the prey has high energy to escape successfully, but a soft besiege is still created by the hawk before it surprises the prey with a pounce. This process is more complex than the soft besiege process because it considers the intelligent moves of the hawk and the prey.

In hard besiege with progressive rapid dives, $E < 0.5$ and $r < 0.5$. Thus, the prey has no energy to escape, and a hard besiege is created to catch and kill the prey. Although the situation is similar to that of soft besiege, in this case, the hawk tries to decrease the distance of the average location from the prey. The four cases are explained briefly in Figure 1.

The four strategies, including the optimization code with the corresponding equations, was described in detail by Asghar et al. (2019).

Figure 1 Summary of the prey-catching strategies of Harris hawks

The complete details of the four strategies, including the optimization code with the corresponding equations, are given in (Asghar et. al., 2019).

5.4 Objective function for model parameter extraction

The optimization process involves the minimization or maximization of an objective function. For PEMFC temperature modelling, the difference between the experimental measurement and the model output value, i.e., the error in the model output, is minimized; however, small errors may be difficult to obtain. The error e_t of sample t is calculated as follows:

$$e_t = optimized\ value - actual\ value \tag{15}$$

The bias is the average error for all samples obtained during the experiment for different input currents and ambient temperatures:

$$Bias = \frac{1}{n}\sum e_t \tag{16}$$

where n is the number of independent samples, which is set to 22000 in this study. The mean square error (MSE) can also be used as an objective function to evaluate the error. However, the MSE is not scaled to the original error because the error is squared (Equation (17)). The root mean square error (RMSE) is defined as the square root of the MSE (Equation (18)). Therefore, the RMSE avoids the scaling problem associated with the MSE and allows easy estimation of the error value. The RMSE does not treat each error in the same way.

$$MSE = \frac{1}{n}\sum e_t^2 \tag{17}$$

$$RMSE = \sqrt{\frac{1}{n}\sum e_t^2} \tag{18}$$

The major fitness is accessed on the basis of the RMSE of the modeled and experimental temperature values using HHO. In implementing HHO, the maximum iteration and initial population are set to 400 and 50, respectively.

6. Experiments performed on PEMFC

The experiments are performed on Horizon 500 W and NEXA 1.2 kW PEMFC systems. The specifications of these systems are listed in Table 4. The Horizon 500 W PEMFC is the main equipment under consideration. In this system, data was collected at different ambient temperatures, while in the NEXA 1.2 kW PEMFC system, data were collected at only one ambient temperature.

Table 4 PEMFC Horizon and NEXA system specifications

Figure 2 shows the experimental setups. Both the Horizon 500 W and NEXA 1.2 kW PEMFC systems were placed in a closed room with controllable temperature.

(a)

(b)

(c)

Figure 2 Experimental setup of PEMFC: (a) Horizon 500 W PEMFC system; (b) NEXA 1.2 kW PEMFC system (c) demonstration of complete experimental setup

6.1. Experiment 1

The first experiment was performed using the Horizon 500 W PEMFC system with abruptly changing load and ambient temperature of 25 °C. The voltage, current, and temperatures of the PEMFC obtained in Experiment 1 are shown in Figure 3.

(a)

(b)

(c)

Figure 3 Experimental results of the Horizon 500 W system at an ambient temperature of 25 °C: (a) current, (b) voltage, and (c) temperature

6.2. Experiment 2

Experiment 2 was performed using the Horizon 500 W PEMFC system with linearly varying current and ambient temperature of 28 °C. The voltage, current, and temperatures of the PEMFC obtained in Experiment 2 are shown in Figure 4.

(a)

(b)

(c)

Figure 4 Experimental results of the Horizon 500 W system at the ambient temperature of 28 °C for (a) temperature, (b) current, and (c) voltage

6.3. Experiment 3

Experiment 3 was performed using the Horizon 500 W PEMFC system with linearly varying current and ambient temperature of 18 °C. The voltage, current, and temperatures of the PEMFC obtained in Experiment 3 are shown in Figure 5.

(a)

(b)

(c)

Figure 5 Experimental results of the Horizon 500 W system at the ambient temperature of 28 °C for (a) voltage, (b) current, and(c) temperature

6.4. Experiment 4

Experiment 4 was performed using the Horizon 500 W PEMFC system with linearly varying current and ambient temperature of 22 °C. The voltage, current, and temperatures of the PEMFC obtained in Experiment 4 are shown in Figure 6.

(a)

(b)

(c)

Figure 6 Experimental results of the NEXA 1.2 k W system at the ambient temperature of 22 °C for (a) current, (b) voltage, and (c) temperature

7. Results and Discussion

7.1. Performance of Saad's Model

We compared the output of the modified Saad's temperature model proposed in this study with the experimental results of the Horizon 500 PEMFC system. Figure 7 shows the comparison of experimental and model output temperatures for Experiment 1. From the figure, it can be seen that the RMSE is very high even after filtering. Thus, the parameters must be updated using HHO and the objective function in Equation (18). The upper and lower bounds of the parameters were obtained from Khan et al. (2019b).

Figure 7 Comparison of model and experimental temperature in Experiment 1

7.2. Parameter Tuning with HHO

Table 5 Model parameter limits for HHO

The newly optimized parameters were extracted using HHO. The RMSE is approximately 1.26 and reduces to 1 after filtering the signal. The updated and original parameters are presented in Table 6. Figure 8 shows the comparison of the model output and experimental temperatures after filtering with a scaling factor of 1.

The results of Experiments 2 and 3 were verified using the same model parameters, and the results are shown in Figures 9 and 10, respectively. The results are unsatisfactory because the RMSE is significantly greater than 1. Hence, the parameters should be further optimized.

Table 6 Saad's model parameters optimized through HHO

Figure 8 Comparison of proposed model and experimental temperatures in Experiment 1 after optimization and filtering

Figure 9 Comparison of model and experimental temperatures in Experiment 2 after optimization and filtering

Figure 10 Comparison of model and experimental temperatures in Experiment 3 after optimization and filtering

7.3. Results after introducing the threshold current

The error analysis in Experiments 2 and 3 between the modeled and experimental temperatures reveal that the error from high to low currents varied largely from a negative value to positive value. Notably, a threshold current existed when the model temperature characteristics varied. After careful consideration of all the factors that affect the parameters, two separate sets of parameters were used at high and low currents. The threshold current was set to 25.2 A, which was almost 60% of the rated current. Then, the two sets of parameters were optimized using HHO. One set was optimized at low currents, and the other was optimized at high currents, i.e.,, above 60% of the rated current.

The parameters optimized at low and high currents are listed in Table 7. Figures 11, 12, and 13 show the temperature evolution after optimization in Experiments 1, 2, and 3, respectively. Form the figures, it can be seen that the RMSE is lower than 0.5 in all experiments.

Table 7 New parameters of HHO in the low and high currents (Horizon PEMFC)

Figure 11 Comparison of model and experimental temperatures in Experiment 1 after modifications

Figure 12 Comparison of model and experimental temperatures in Experiment 2 after modifications

Figure 13 Comparison of model and experimental temperatures in Experiment 3 after modifications

Similar parameters were used in the NEXA 1.2 kW system with the data of Experiment 4; 60% of the rated current in the NEXA 1.2 kW system corresponds to 43.2 A. Figure 14 shows the temperature evolution after optimization in Experiment 4. The results reported in the figure are satisfactory, but improvements can still be made by reoptimizing the parameters in NEXA 1.2 kW. The analysis reveals that the threshold current is 18 A (25% of the rated current) in this case. The parameters are optimized at high and low currents using HHO, and the results are shown in Table 8.

Figure 14 Comparison of model and experimental temperatures in Experiment 4 after modifications

Table 8 New parameters of HHO in the low and high currents (NEXA PEMFC)

The main difference in the parameters of the Horizon and NEXA systems is due to the changes in the number of cells (N_c) in the stack and the active area of the membrane (A). In theoretical temperature model described by Salim et al. (2015) and Ariza et al. (2018), the heat loss mainly depends on the product of N_c and A. In Salim et al. (2015) it is explained that heat loss mainly depends on the product of N_c and A. The equation (19) explains the heat loss (q_{loss}) in the PEMFC system, here h_{cell} is the convective heat transfer coefficient (W. m^{-2}.K^{-1}).

$$q_{loss} = h_{cell}(T - T_{amb})N_c A \qquad (19)$$

Therefore, this variation in parameters primarily relies on the product of N_c and A of the PEMFC stack. Figure 15 shows the final results in the NEXA PEMFC system. From the figure, it can be seen that in all cases, the RMSE is lower than 0.5 in both systems.

Figure 15 Comparison of model and experimental temperatures in Experiment 4 using the NEXA parameters

In summary, a first-degree polynomial for a single variable (product of A and N_c) was used to extract the parameters L_i. The threshold current could be extracted from the rated current of the output power of the PEMFC, and the rated power P was used to extract the function in the threshold current I_t. The functions of L_i and I_t in NEXA and Horizon PEMFCs are presented in Table 9. The threshold current is also calculated using the output power, which determines whether the current in the present sample is low or high. The output electric power is mainly responsible for energy used for electricity in thermal model as mention in Salim et al. (2015), hence the ouput electric power is selected to predict the threshold current for temperature model.

Table 9 Generic functions in the parameters and threshold current

8. Conclusion

We introduced a generic approach for modeling the temperature behavior in the PEMFC stack based on the Saad's model. Two considerable modifications were made to this model to make it suitable for different conditions and different PEMFC systems. First, six Li parameters were defined on the basis of a function that relates the parameters to the cell number and membrane-active area. This modification allows the variation in thermal evolution of different PEMFC systems, such as cell number and active area, depending on the PEMFC model. Second, the parameters were tuned once at a low-level current and once at a high-level current by defining the threshold current based on the rated power of the stack. This classification improves the performance of the model, particularly during sudden changes in the current drawn from the PEMFC, which in turn affects the temperature evolution. Finally, the performance of the proposed model was verified in two air-cooled PEMFC systems, namely the NEXA 1.2 kW and Horizon 500 W PEMFCs, in different conditions. The performance of the model is validated by a comparison with experimental results; the model outputs had an RMSE of less than 0.5 in all the considered cases. This study will help researchers in the development of simple, generic, and effective temperature models in the accurate estimation of the temperature of PEMFCs with air cooling system. The model can also be extended to various types of PEMFCs with other cooling mechanisms, such as liquid cooling. The parameters will vary accordingly and will be optimized again through the modern HHO algorithm. In future studies, the temperature variations of PEMFCs should be examined under air pressure variations. Also this model can be very helpful in future for thermal control of PEMFC in case of limiting temperature of PEMFC through loading.

9. Acknowledgment

This research was co-founded by the United Arab Emirates University (Fund code no. 31R067) and the Natural Sciences and Engineering Research Council of Canada (Grant no. 2018-06527).

References

Akbari, A.K.E., and Dahari, M.N.M. 2019. Using ANFIS technique for PEM fuel cell electric bicycle prediction model. Int. J. Environ. Sci. Technol. 16(1):7319–7326.

Alzeyoudi, H., Sasmito, A.P., and Shamim, T. 2015. Performance evaluation of an open-cathode PEM fuel cell stack under ambient conditions: Case study of United Arab Emirates. Energy Convers. Manag. 105(1):798–809.

Ariza, H., Correcher, A., Sánchez, C., Pérez-Navarro, Á., and García, E. 2018. Thermal and Electrical Parameter Identification of a Proton Exchange Membrane Fuel Cell Using Genetic Algorithm. Energies 11(8):2099.

Asghar, A., Mirjalili, S., Faris, H., and Aljarah, I. 2019. Harris hawks optimization: Algorithm and applications. Futur. Gener. Comput. Syst. 97(1):849–872.

Belmokhtar, K., Doumbia, M.L., and Agboussou, K. 2014. PEM fuel cell modelling using artificial neural networks (ANN). Int. J. Renew. Energy Res. 4(3):725–730.

Berning, T., and Kaer, S.K. 2020. A Thermodynamic Analysis of an Air-Cooled ProtonExchange Membrane Fuel Cell Operated in Different Climate Regions. Energies. 13(10): 2611.

Bharath, K., Blaabjerg, F., Haque, A., Khan, M. 2020. Model-Based Data Driven Approach for Fault Identification in Proton Exchange Membrane Fuel Cell. Energies. 13 (12): 3144.

Ghasemi, M., Ramiar, A., Ranjbar, A.A., Rahgoshay, S.M. 2017. A numerical study on thermal analysis and cooling flow fields effect on PEMFC performance. Int. J. Hydrogen Energy. 42(38) : 24319-24337

Jung, J.H., Ahmed, S., and Enjeti, P. 2011. PEM fuel cell stack model development for real-time simulation applications. IEEE Trans. Ind. Electron. 58(9):4217–4231.

Junyan, S., and Shudan, L. 2015. Dynamic Window-based Adaptive Median Filter Alogorithm. Open Cybern. Syst. J. 9(1):1502–1506.

Kandidayeni, M., Macias, A., Khalatbarisoltani, A., Boulon, L., and Kelouwani, S. 2019. Benchmark of proton exchange membrane fuel cell parameters extraction with metaheuristic optimization algorithms. Energy 183(1):912–925.

Khan, S.S., Shareef, H., and Mutlag, A.H. 2019b. Dynamic temperature model for proton exchange membrane fuel cell using online variations in load current and ambient temperature. Int. J. Green Energy 1(1):1–10.

Khan, S.S., Shareef, H., Bouhaddioui, C., and Errouissi., R. 2019c. Membrane-hydration-state detection in proton exchange membrane fuel cells using improved ambient-condition-based dynamic model. Interational J. energy Res. 44(2):869–889.

Khan, S.S., Shareef, H., Khan, I.A., Bhattacharjee, V., and Sultan, K.W. 2019a. Effect of ambient conditions on water management and faults in PEMFC systems: A Review. 2019 IEEE Can. Conf. Electr. Comput. Eng. pp. 1–5.

Khan, S.S., Shareef, H., Wahyudie, A., and Khalid, S.N. 2018. Novel dynamic semiempirical proton exchange membrane fuel cell model incorporating component voltages. Int. J. Energy Res. 42(8):2615–2630.

Khan, S.S., Shareef, H., Wahyudie, A., Khalid, S.N., Sirjani, R. 2019d. Influences of ambient conditions on the performance of proton exchange membrane fuel cell using various models. Energy & Environment 30(6):1–24.

Li, Q., Chen, W., Liu, S., Gao, Z., and Yang, S. 2012. Temperature optimization and control of optimal performance for a 300W open cathode proton exchange membrane fuel cell.

Procedia Eng. 29:179–183.

Liu, D., Chen, T., and Xie, Y. 2020. A two-dimensional analytical model of PEMFC with dead-ended anode. Int. J. Green Energy 17(4): 255–273.

Ma, T., Lin, W., Yang, Y., Cong, M., Yu, Z., and Zhou, Q. 2019. Research on control algorithm of proton exchange membrane fuel cell cooling system. Energies 12(3692):1–15.

Muller, E.A., and Stefanopoulou, A.G. 2006. Analysis, modeling, and validation for the thermal dynamics of a polymer electrolyte membrane fuel cell system. J. Fuel Cell Sci. Technol. 3(2):99–110.

Pandiyan, S., Jayakumar, K., Rajalakshmi, N., and Dhathathreyan, K.S. 2008. Thermal and electrical energy management in a PEMFC stack–An analytical approach. Int. J. Heat Mass Transf. 51: 469-473.

Panos, C., Kouramas, K.I., Georgiadis, M.C., and Pistikopoulos, E.N. 2012. Modelling and explicit model predictive control for PEM fuel cell systems. Chem. Eng. Sci. 67(1):15–25.

Qun, Y., Qing, L., Peichang, Z., and Datai., Y. 2014. Temperature modeling of PEM fuel cell based on fuzzy strategy. 26th Chinese Cont.l and Decis. Conf., pp. 2383–2387.

Real, A.J., Arce, A., and Bordons, C. 2007. Development and experimental validation of a PEM fuel cell dynamic model. J. Power Sources 173(1):310–324.

Restrepo, C., Konjedic, T., Garces, A., Calvente, J., and Giral, R. 2014. Identification of a Proton-Exchange Membrane Fuel Cell ' s Model Parameters by Means of an Evolution Strategy. IEEE Trans Industr Inform. 11(2):548–559.

Salim, R., Nabag, M., Noura, H., and Fardoun, A. 2015. The parameter identification of the NEXA 1.2kW PEMFC's model using particle swarm optimization. Renew. Energy 82(1):26–34.

Salva, J., Iranzo, A., Roza, F., and Tapia, E. 2016. Experimental validation of the polarization curve and the temperature distribution in a PEMFC stack using a one dimensional analytical model. Int. J. Hydrogen Energy. 41 (45) : 20615-201632.

Sohn, Y.J., Park, G.G, Yang, T.H., Won, Y.G., Sung, Y.L., Chang, D.Y., and Kim, S. 2005. Operating characteristics of an air-cooling PEMFC for portable applications. J. Power Sources 145(2):604–609.

Soltani, M., and Bathaee, S.M.T. 2008. A new dynamic model considering effects of temperature, pressure and internal resistance for PEM fuel cell power modules. 3rd Int. Conf. Deregul. Restruct. Power Technol. 1(1):2757–2762.

Tao, S.U.N., Si-jia, Y.A.N., Guang-yi, C.A.O., and Xin-jian, Z.H.U. 2005. Modelling and control PEMFC using fuzzy neural networks. J. Zheijang Univ.-Sci. A 6(1):1084–1089.

Yuan, W.W., Ou, K., and Kim, Y.B. 2020. Thermal management for an air coolant system of a proton exchange membrane fuel cell using heat distribution optimization. Appl. Thermal Eng. 25: 114715.

Zhang, B., Lin, F., Zhang, C., Laio, R., Wang, Y. 2020. Design and implementation of model predictive control for an opencathode fuel cell thermal management system. Renewable Energy. 154: 1014-1024.

Zhang, G., and Kandlikar, S.G. 2012. A critical review of cooling techniques in proton exchange membrane fuel cell stacks. Int. J. Hydrogen Energy 37(3):2412–2429

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