Employing Direct Methanol Fuel Cell Yielded In Situ Methanol Concentrations under Varying Operating Conditions: A Comparative Optimal Search Study

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In the literature there are hundreds of research papers for the synthesis of featured membrane to deal with the methanol crossover. Parallel to these experiments, studies focusing on working methanol concentration are continued to obtain the best results in the existing obstacles. Conducted studies reveal that an optimal concentration exists for each current density depending on operating conditions and operating a system near these points provides benefit to the fuel and energy efficiencies. In this study an approach is presented to minimize the crossover effects and operate the fuel cell at existing optimal concentration values depending on current density and methanol fuel rate. Firstly the performance of Golden Section algorithm (GS) while searching the optimal concentration is explored. Then prediction power of Adaptive Neuro Fuzzy Inference System (ANFIS), training at various operating conditions, is evaluated. Subsequently, ANFIS is evaluated in the control algorithm to determine the optimal concentration and the corresponding voltage. In this way it is aimed to operate the fuel cell yielded in situ concentration control depending on operating conditions.

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Direct methanol fuel cells (DMFCs) are potential energy sources considered especially for portable electronic devices.1 But there are many obstacles to be overcome. Methanol crossover problem is one of the challenges in the commercialization of DMFCs. There are substantial impacts on electrical efficiency and fuel economy.2 Studies with several aspects are encountered in the literature to reduce the methanol crossover.3–5 Ahmet and Dincer2 released a review on the featured membranes and operating conditions conducted to reduce the methanol crossover and to increase the efficiency, they extracted from the results that increasing the methanol concentration causes increasing in the methanol crossover for all modified membranes. Recently, Arico et al.6 explored various membranes alternative to Nafion by investigating their methanol permeation characteristics and proton conductivity; they found that the power density of the SPEEK-based MEA was favorable because of the lower methanol crossover and the suitable area specific resistance. On the other hand, it is possible to see the studies conducted in the presence of this obstacle to get the higher efficiency. In this regard, the trend is focusing on methanol working concentration. Working on low methanol concentration to prevent the methanol crossover causes lower cell output voltage especially because of diffusion constraints (Fick law) and less in terms of Nernst potential.7 However, increasing the methanol concentration leads to increase of cell voltage to a point, because after that point methanol crossover effect becomes felt. Besides, the water discharging is one of the slow steps of the entire anodic reactions. Thus, an excess of water concentration play a favorable role on the cell voltage.8 Fuel and electrical utilization of DMFC is tightly linked two cases.9 Numerous compromises are required to maintain both energy and power efficiencies simultaneously. Low methanol flow rates and concentrations provide high fuel efficiencies. On the contrary, mass transport limitations restrict the achievement of high power densities under relevant conditions.10 In this regard, a multi-objective aim arises and the weights of these aims should be determined e.g. priorities must be assigned. These conditions reveal the necessity of properly controlling the methanol concentration. Methanol sensors can be used in order to control methanol concentration accurately, but it brings many disadvantages and burdens.10 Methanol concentration control studies carried out on DMFC in the last decade are reviewed below.

Chiu and Lien11 obtained constant concentration surfaces under various operating conditions (voltage, current, temperature), then they used an interpolation algorithm to predict the methanol feed concentration depending on in situ operating conditions. Shen et al.12 reported an algorithm by improving the Chiu and Lien’s algorithm which is insufficient for the MEA degradation problem. In their algorithm, additionally operation time, consumption rates of water and methanol were accounted to estimate the MEA decay. Ha et al.13 built a database to predict the methanol consumption rate by measuring the CO2 concentration at the cathode under various operating conditions such as concentration, temperature and loading. Then they used algorithm to keep the concentration at a predetermined value. In their first study, Lian et al.14 used an empirical equation to determine the ideal output voltage; their algorithm feeds a specific amount of methanol into the mixing tank, system voltage and loading response is monitored, then the algorithm takes action in the case of whether the concentration is sufficient or not. In their later study, instead of ideal output voltage, Lian et al.15 used reference voltage which was identified during the experiment upon the operating conditions; the algorithm takes a new step according to voltage response by analyzing the voltage and loading characteristics. Cheng et al.16 conducted a series of works on methanol concentration control. In their first study, they suggested ‘IR-DTFI’ algorithm that works at steady load conditions; the algorithm feeds needed amount of methanol to the methanol reservoir by using system characteristics such as voltage and current during a monitoring period. They also tested their algorithm over a 40 W electronic device.17 Chang et al.18 published another study that works under dynamic load conditions by modifying IR-DTFI algorithm. After that, an advanced version of the algorithm ‘IR-CDTFI’ was published which shortens the monitoring period and makes the algorithm more effective.19 Finally Chang et al.20 by using ‘IR-DTFI’ and ‘IR-CDTFI’ algorithm explored the effect of various operation characteristics on DMFC system. In the study of An et al.,21 authors stated that there is close relationship between the methanol concentration and stack temperature. Therefore, they suggested an algorithm which provides benefit from that feature. Firstly, methanol consumption rate is determined by using database which was published in a previous study,21 then this amount of methanol is fed into mixing tank in a controlled manner (PID control) to keep the stack temperature at a set value. In this manner methanol concentration is controlled indirectly. After that, Author conducted their studies by varying the ambient temperature.22 Arissetty et al.23 showed in their study that an optimal methanol concentration was required for each working current density in point of view of electrical and fuel efficiencies. Also they demonstrated the abnormal fuel loss caused by crossover due to inconsistent working concentration by measuring the CO2 concentration at the cathode. Based on this truth, authors reported an algorithm to explore the optimal concentration depends on loading; the algorithm, which is based on bisection optimization method, searches the

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needed concentration by starting a predetermined concentration value and after a monitoring period, it determines whether it is required to increase or decrease the methanol concentration.

Consequently, almost all of the studies conducted on the working concentration control broach the issue whether concentration is sufficient or not at the working conditions. Furthermore, a great part of the studies are based on the voltage and/or current density response to concentration changes. In this comparative study, two methanol concentration control algorithm is proposed to deal with the problems caused by methanol crossover. Firstly Golden Section algorithm is used to find the optimal methanol concentration at various current densities and methanol flow rates. Then, an ANFIS model is established with the data collected at various concentrations, current densities and flow rates. This ANFIS model is used to determine the optimal concentration and corresponding maximal cell voltage depending on working conditions. The system is not allowed to work in these conditions in an uncontrolled manner, the mean cell voltage is measured and compared continuously in a predetermined monitoring period by considering the MEA decay and calibration problems may cause trouble later. Thus, a new approach is presented which directly aims to maintain the high power performance of the cell, preventing excess methanol consumption while providing this goal, by controlling the methanol concentration depending on operating conditions.

Operating at Appropriate Methanol Concentrations

Compared the other operating characteristics such as flow rates and temperature, effect of methanol concentration on the performance of direct methanol fuel cell is distinguished. As known, to overcome the anode over potential issue, it is required to work at high methanol concentration level. But unfortunately, high concentration level is also the driving force for the methanol crossover. Basically three transport mechanisms are effective in the crossover throughout the membrane: Electro-osmotic drag, diffusion and convection.2 The main problems caused by the methanol crossover are as follows:23–26

- Fuel inefficiencies by wasting permeated methanol
- Occupation of the active catalyst cites at the cathode side
- Poisoning of the cathode catalyst
- Reduced electrical efficiency due to mixed potential

Methanol crossover depends on concentration on the membrane surface which in turn depends on current density and bulk methanol concentration. Besides, operating DMFC at high methanol concentration causes a decrease of the cell voltage not only due to crossover effects but there is also an effect on the anode reaction kinetics. In fact, the anode reaction is affected by the optimal combination of adsorbed methanolic species and OH species from water discharging. The water discharging is one of the slow steps of the entire process.5 Thus an excess of water concentration play a favorable role. Therefore, an optimal methanol concentration level exists for each current density that can be drawn from the cell. Fig. 1 shows the expected voltage - concentration curve for a constant current density. In addition working near the optimal concentration reduces the fuel loss i.e. working higher concentration increases fuel loss many times.7 The above implications bring the requirement of accurately and locally control the methanol concentration for each current density (in situ optimal concentration control). As an approach, methanol concentration sensor can be used to control the methanol concentration adequately and locally depending on operating conditions. However, below statements should be taken into consideration for both chemical and physical phenomena based sensors:

- Electrochemical principles based sensors may lead to degradation of MEA.
- Sound speed, density etc. based physical sensors may be sensitive to carbon dioxide bubbles and pulse signal sending from the pumps.
- Temperature dependence and calibration issue of this sensor should be considered.

ANFIS Structure

Artificial neural network and Fuzzy logic are commonly used techniques in modeling of complex, multi input-output and nonlinear systems. Neural networks have capabilities of generalizing from given samples so that it can produce solution for unknown samples. Fuzzy logic is a knowledge based system, which has human reasoning capabilities that can produce inference in a case. However, there are some challenges working with fuzzy logic.27

Rule base, membership function of both input and output variables and membership function numbers should be identified. To handle this, previously gained experience on related subject or an expert knowledge is referred to. But unfortunately, these are time consuming and boring tasks that possibly various problems are to be encountered. To benefit from the outstanding features and overcome the weakness of fuzzy logic adaptive capability is gained namely; Artificial neuro fuzzy inference system.

ANFIS is a kind of Takagi - Sugeno type fuzzy logic inference systems. Artificial neural network is used to determine the optimal rule base and the membership functions parameters of fuzzy inference system by using data sets. Fuzzy inference system is gained an adaptive feature by using data sets for training the artificial neural network. In training the neural network, generally a hybrid algorithm, containing back-propagation gradient descent method and the least squares method is used.25

Adaptive neuro fuzzy inference systems (ANFIS).—Artificial neural networks provide adaptive feature to ANFIS, which is consisting of nodes, so that relationships between inputs and outputs are learned by means of samples by identifying the relationship between nodes.

Basic ANFIS structure is illustrated in Fig. 2 consists of two input and one output variables. The general expression of rules in Sugeno type ANFIS system with two inputs is below and visualized in Fig. 3.

\[ f_1 = a_1 x + b_1 y + c_1 \]

\[ f_2 = a_2 x + b_2 y + c_2 \]
Figure 2. Structures of Sugeno type ANFIS system with two inputs and one output.

Training purpose calculation of each layer in the network structure is given below step by step.28

Layer 1.—The calculation of output of each node in the layers is given with the Eqs. 1–7.

\[ O_{1,i} = \mu_{A_i}(x) \quad \text{for } i = 1, 2 \]  
\[ O_{1,i} = \mu_{B_i-2}(y) \quad \text{for } i = 3, 4 \]

Here, \( O_{1,i}(x) \) indicates the membership degree of input variable ‘x’ belonging to ‘\( A_i \)’ membership function.

Gaussian, triangular, trapezoidal, etc. functions can be chosen as a membership function, but here ‘gaussian’ is used for demonstration purposes. The general expression of ‘gaussian’ function is below.

\[ \mu_{A_i}(x) = \frac{1}{1 + \left( \frac{x - m_i}{k_i} \right)^2} \]

Here, \( k_i, l_i, m_i \) are the antecedents of the rule and all them must be identified.

Layer 2.—In this layer determination of firing strength of the rule is carried out, usually ‘AND’ norm is used.

\[ O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2 \]  

Layer 3.—Determination of average weight of each rule;

\[ O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \]

Layer 4.—Weighted rule outputs are obtained in this layer by multiplying consequent part of the rules with the weighted average.

\[ O_{4,i} = \overline{w}_i f_i = \overline{w}_j(a_i x + b_i y + c_i) \]

Consequently, it appears that each output parameter \( (a_i, b_i, c_i) \) should be identified.

Layer 5.—In this last layer, corresponding output is obtained.

\[ O_{5,j} = \sum_i w_i f_i = \sum_i \frac{w_i f_i}{\sum_i w_i} \]

After basic calculation steps, antecedent and consequent parameters of the rules need to be determined. As mentioned before, ANFIS

Figure 3. Sugeno type fuzzy sets with two inputs (membership functions).
Figure 4. Experimental setup prepared for the concentration control.

uses two learning algorithms, both forward and backward step. In the forward pass consequent parameters are calculated by keeping antecedent parameters constant according to least squares method and in the backward pass antecedent parameters are determined via the gradient descent method by keeping consequent parameters constant.

Experimental

An experimental system, which is shown in Fig. 4, was installed to handle methanol concentration control task. Two peristaltic pumps, an electronic load, a data acquisition board, an air feeding system, a reservoir, a cell and methanol concentration sensor (used for observation purposes) are the main parts of the system. Details of the system components are as follow.

DAQ card: National instrument PCI-6221 data acquisition card
Pump 1: Heidolph pumpdrive 5206 peristaltic pump
Pump 2: Heidolph pumpdrive 5201 peristaltic pump
Mass flow controller: Porter LB-366
Electronic load: Fideris methanol test station electronic load unit
Concentration sensor: ISSYS microMCS methanol sensor

The electronic load and the air feeding system are connected via serial port to communicate the personal computer. Also control signals are sent to the pumps via DAQ card in order to supply desired methanol flow rates and concentration. The temperature of the cell is controlled with a plc. Labview environment was used to create a user interface to send and acquire signals. Matlab scripts embedded in Labview environment also were used for running both ANFIS and Golden Section algorithms.

System description and preliminary studies.—The Membrane electrode assembly (MEA) purchased from Fuelcellstore was used in the conducted experiments. The MEA specifications are as follows.

Active electrode area: 25 cm$^{-2}$
Membrane type: Nafion 117
Anode catalyst: 4 mg cm$^{-2}$ 1:1 Pt-Ru
Cathode catalyst: 2 mg cm$^{-2}$ Pt black
Gas diffusion layer: Carbon cloth

All experiments in this study were conducted at 60°C and air flow rate of 1000 cc min$^{-1}$ (40 cc min$^{-1}$ cm$^{-2}$). Voltage values were collected at various flow rates i.e. 10, 15 and 20 cc min$^{-1}$ (e.g. 0.4, 0.6 and 0.8 cc min$^{-1}$ cm$^{-2}$), concentrations and current densities for the training process of ANFIS. When obtaining the voltage values, the system was allowed to come stable and the average voltage values were recorded by considering that the oscillations may occur during the experiments. Additionally, data collection had to be carried out at concentrations set precisely. Concentration was controlled by PID controller due to fact that calibration problem of the peristaltic pumps and precise solution preparation requirements which may cause trouble in operating at desired concentrations.

While flow rate of the concentrated methanol pump was controlled with the PID controller, the water flow rate was automatically adjusted according to the total flow rate.

As can be seen from Fig. 5, reaching the desired concentration was provided in a short time and healthy data collection was achieved in this manner.
Results and Discussion

Golden section search algorithm.—The concentration control in DMFC is actually a convex optimization problem. In the literature there are many conventional solution methods to solve convex optimization problem. The most preferred are bisection algorithm and Golden Section Search method which is an advanced version of bisection method. This algorithm delivers optimum results by re-determining the boundaries of the solution space.

The methanol flow rate and current density were changed in each trial and the algorithm was launched to make the cell working at optimal concentration and a maximal cell voltage for the specified flow rate and the current density.

In the first experiment, methanol flow rate was set to 13 cc min$^{-1}$ and system operated at open circuit voltage (OCV); Golden Section algorithm was launched to search the optimal concentration and the corresponding maximal open circuit voltage (OCV) value. As seen from Fig. 6, the algorithm firstly supplies the high concentration to the system measured as 1.3 M and corresponding cell output voltage is floating between 0.5–0.53 V. After an observation period of 200 seconds, the algorithm calculates the average cell voltage and takes a new step. The upper bound of the solution space is reduced continuously (gradually). This reduction causes an increase in the cell voltage. Eventually, the cell output voltage is handled as 0.57 V on average when the concentration reaches about 0.3 M.

Fig. 7 shows the result of experiment conducted following conditions; the total methanol flow rate was taken as 22 cc min$^{-1}$ and the system was operated at current density of 50 mA cm$^{-2}$. Again, the maximum optimal concentration value where the cell voltage value has a maximum is searched by Golden Section method. Eventually, the algorithm points to the concentration of 0.4 M as an optimal where the corresponding cell voltage is predicted as 0.353 V. In addition, excessive voltage drops occurring at inappropriate concentrations are clearly observed. Namely, the molar values close to zero (440–640 and 1240–1440s) cause great voltage drops and at these points the desired current (fixed), which could not be drawn from the cell, decreases too. When the concentration increases, voltage values begin to increase, thus the current rises and a voltage jumps occur when trying to adjust the current.

Training ANFIS.—The results of ANFIS training as a part of the control task are given in this section. Cell voltage values were collected at three different flow rates (10, 15 and 20 cc min$^{-1}$) various concentrations and current densities for training process. Ultimately, 60% of the 119 data was used for the training (71 data), 20% of it for the control (24 data) and remaining 20% for the test (24 data). In the training process, widely used membership function namely; ‘trimf’ and ‘gaussmf’ functions were selected. The number of membership function of each input variables was changed as 2 or 3. Each experiment was repeated 10 times with the randomly distributed data and the root mean squared error (RMSE) values were calculated for each of them. Then minimum, maximum and average values of the repeated experiments were determined so that algorithm dependence on the data was also investigated.

In Table I, the results are given for the case of ‘trimf’ membership function used for the inputs; the methanol flow rate, concentration and current density, the number of the membership function being 2 or 3. As it is seen, the best values on average (2-2-3) were handled in the case membership function number was taken as 3 for the current density. Remarkable results were obtained which are close to the
Table I. ANFIS training results with ‘trimf’ function for different membership function numbers.

| Membership Numbers | Min. val. | Max. val. | Mean val. |
|--------------------|-----------|-----------|-----------|
|                     | Training RMSE | Control RMSE | Test RMSE | Training RMSE | Control RMSE | Test RMSE |
| 2-2-2               | 0.014      | 0.012      | 0.011     | 0.006        | 0.004        | 0.004     |
| 3-2-2               | 0.010      | 0.008      | 0.007     | 0.004        | 0.002        | 0.002     |
| 2-3-2               | 0.011      | 0.009      | 0.008     | 0.003        | 0.002        | 0.002     |
| 2-2-3               | 0.013      | 0.011      | 0.010     | 0.005        | 0.003        | 0.003     |
| 3-3-2               | 0.008      | 0.006      | 0.005     | 0.002        | 0.001        | 0.001     |
| 3-2-3               | 0.014      | 0.012      | 0.011     | 0.006        | 0.004        | 0.004     |
| 2-3-3               | 0.012      | 0.010      | 0.009     | 0.005        | 0.003        | 0.003     |
| 3-3-3               | 0.010      | 0.008      | 0.007     | 0.003        | 0.002        | 0.002     |

best value, in the cases where membership function numbers were chosen as 2-2-2, 2-2-3, 3-2-2, and 3-2-2. Thus, the training process is not effected so much in the case that the membership function number of any input variable is bigger than 2. If it took a look to the worse results than priors, results of 3-3-2 and 3-2-3 appear. These results belong where the membership function number of the current density or concentration is lower than the other two. Therefore, it can be said that these results are handled due to incorrect training. Because the number of membership functions of the major variables were selected lower than the relatively minors. Finally, if looking at the worst results (2-3-3 and 3-3-3), a situation is experienced that, the training RMSE values are very low compared to other training results, but the algorithm is unsuccessful in the case of test and/or control steps. Here, these results can be explained by the excessive training and memorizing of ANFIS. Therefore, it could not produce appropriate solutions against to the new situation.

The same approach was implemented for ‘gaussmf’ membership function, but almost all of the results obtained were very bad so that they are not presented here. The best RMSE values in these conditions are given below and also corresponding regression graphs are illustrated in Fig. 9.

Training RMSE: 0.010, checking RMSE: 0.020, Test RMSE: 0.011
As a result, it can be said that ANFIS performs well for the all situations; training, test and control.

In the final stage of the training process, attempts were carried out by varying current density and methanol flow rate in order to show the prediction power of ANFIS. Experimental results are plotted with the ANFIS predictions in Fig. 10. As implied before, these curves also show the concentration dependence of the cell voltage. Convex structure of this relationship brings along an optimal concentration and corresponding cell maximum voltage. It is also observed that the change of methanol flow rate causes changes in the shape of curves.

**ANFIS control.**—Fig. 11 summarizes the proposed algorithm. Accordingly, after entering the methanol flow rate and current density information to be worked into the control algorithm, it uses ANFIS to determine the optimal concentration and corresponding maximal cell voltage. Concentrated methanol flow rate and pure water flow rate are adjusted according to the total flow rates to access the defined concentrations. Considering calibration problem of the peristaltic pump, the necessity of precise adjustment of concentrated methanol solution and MEA degradation, the algorithm measures the average cell voltage during a monitoring period. Then it compares the average value with the previous period. If improvement exists compared to the previous, algorithm increases the concentrated methanol flow rate otherwise decreases. In this way, continuously concentration control depending on cell voltage is carried out. When a change in the working flow rate and/or current density is made, the algorithm detects it and processes are re-applied according to new situation.

**Figure 9.** Regression graph for the training, checking and testing data.

**Figure 10.** Cell voltage-methanol concentration relations in various operating conditions, solid line: ANFIS prediction, discrete spots: experimental data.

**Figure 11.** ANFIS control algorithm.
In the first study, current density of 25 mA cm\(^{-2}\) was drawn at 13 cc min\(^{-1}\) methanol flow rate; ANFIS was asked to work at optimal conditions. As seen in Fig. 12, initial concentration is 1.3 M and corresponding cell voltage value is measured as 0.47 V. Then the controller is activated to determine the optimal feed concentration and the maximum cell voltage corresponding to this value (0.63 M-0.55 V). The signal is sent to the pump to bring the concentration to 0.63 M. But, due to the concentrated methanol solution or the pump calibration problems, concentration is handled as 0.56 M. After this point an increase is observed in the cell voltage value. But the controller continues checking the system and calculates the average cell voltage during the monitoring period. It increases or decreases the flow rates by comparing the previous values. Eventually, cell voltage of 0.53 V on average is obtained at feeding concentration of 0.621 M.

The second trial result is illustrated in Fig. 13; initially the cell produces 0.22 V at 1.5 M. Optimal conditions are determined as 0.375 M and 0.41 V when the controller is activated. After that the methanol concentration was handled as 0.33 M. Again, the pump flows are continuously manipulated in the specific monitoring period to control the concentration. As a result, the cell voltage of 0.38 V on average is achieved at 0.36 M.

The average cell voltage of 0.2 V is measured at about 0.3 M when the system is on startup as seen in Fig. 14. The controller determines the optimal conditions as 0.55 M and 0.27 V. Finally the average cell voltage of 0.28 V is obtained at 0.55 M.

As can be seen from Fig. 15, for the stated conditions system produces 0.208 V at concentration of 0.9 M. The controller determines the optimal values as 0.55 M-0.23 V. And consequently, a value of 0.22 V is measured when concentration comes close to 0.55 M.

It can be concluded from the studies demonstrated above that ANFIS exhibits good control performance in the determination of optimal working concentration. It does not give rise to excessive voltage drop as Golden Section method does. Furthermore it immediately adapts to new working conditions so it does not take long. Also it follows the continuously cell voltage by taking into account the possible calibration problems and loss of MEA performance, and manipulates the concentration depending on average voltage values. Also the increases in the cell voltages are outstanding. These increases no doubt depend on the initial selected concentrations but it should not be forgotten that the algorithm has a power to avoid the working inconsistent concentration. In this way, by keeping the concentration near the optimal values, it clearly contributes to both fuel and power efficiencies of the system.

Conclusions

In the study to prevent the losses caused by the methanol crossover, activities are carried out to determine the optimal methanol concentration at various current densities and methanol flow rates. Firstly the experimental system was established to collect data in a healthy way. To determine the optimal concentration at various operating conditions, Golden Section method was used. Then, in order to create a database, experiments were carried out by changing the current density, concentration and methanol flow rate. This database was used to create an ANFIS model. In the modelling studies, ‘trimf’ and ‘gaussmf’ were tried as membership functions and membership function numbers were changed for each input variables. The best result was obtained in the case of ‘trimf” function with membership function number equal to 3 for the current density. Then, this model was used to determine the optimal concentration and corresponding cell voltage in the control algorithm. Based on the experimental results, it can be said that...
ANFIS exhibits pretty good performance to predict the optimal values. Subsequently, system was kept controlled by closely monitoring against the possible calibration and MEA degradation problems. As a conclusion; ANFIS delivers the cell in a very short time to optimal conditions when compared to Golden Section, and it does not lead to excessive voltage drops during the search, adapting to new operating conditions immediately.

List of Symbols

\[ a, b, c \] parameters of consequent of the rules
\[ A, B \] linguistic variables
\[ C \] Methanol concentration
\[ f_1, f_2 \] consequents of the rules
\[ f \] rule output
\[ i_{\text{cell}} \] cell current density
\[ k, l, m \] membership function parameters
\[ lb, ub \] lower and upper bound for working concentration
\[ O \] output of the node
\[ q_t \] total flow rate
\[ V_{\text{act}} \] actual cell voltage
\[ V_{\text{acte}} \] prior actual cell voltage
\[ \text{Vanfis} \] ANFIS voltage predict
\[ w \] weight of the membership function
\[ \overline{w} \] average weight of the rule
\[ x, y \] input variables

Greek

\[ \mu \] membership degree

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