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A Gas Starvation Diagnosis Method of PEM Fuel Cells Based on Adaptive Network-Based Fuzzy Inference System (ANFIS)

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ABSTRACT

Compared with traditional power source vehicles, there is still a gap in the durability of fuel cell vehicles. On fuel cell vehicles, gas starvation caused by start-stop and frequent load changes is one of the significant factors that cause the fuel cell lifetime decay. Gas starvation refers to the state in which the reactant gas of the fuel cell works under substoichiometric numbers. However, due to the complexity of the fuel cell structure and reaction mechanism, the existing researches have not reached a unified and accurate diagnosis method. It is difficult to establish a clear relationship between the gas starvation state of fuel cell and its external characteristic parameters. Therefore, this paper innovatively uses the adaptive network-based fuzzy inference system (ANFIS) method in gas starvation diagnosis. In this study, a proton exchange membrane fuel cell (PEMFC) is modelled and analyzed by ANFIS. Meanwhile, CFD simulation is used as an auxiliary tool to obtain 102 samples' data. Experimental data are obtained to verify that the steady-state response of the PEMFC is consistent with the simulation data. This research finally achieves a 92% accuracy of gas starvation prediction, and the ANFIS model can predict the size of starvation area in PEMFC cells, providing a feasible technical route for the prediction of starvation in fuel cell systems and vehicles.

Keywords: Proton exchange membrane fuel cell; Gas starvation diagnosis; Artificial neural network; Adaptive network based on fuzzy interface system; Computational fluid dynamics

1. INTRODUCTION

Fuel cells allow the transformation of chemical energy into electrical energy. For this high-efficiency transformation method, fuel cells are regarded as a new generation clean vehicle power source. Polymer electrolyte membrane (PEM) fuel cell is an especially promising power source due to its high efficiency, zero-emission, quick response, and low noise [1]. Many studies have proved that gas starvation during operating condition changing is the main reason for PEM fuel cells' lifetime decay. A quick diagnosis and solution will help to prolong the lifetime of PEM fuel cells[2].

Since PEM fuel cell is a complicated non-linear multi-physics coupling system, it is still impossible to fully predict it using the traditional modeling method. A vital research trend in fuel cells is focusing on the use of data-driven methods. Li et al.[3] have proposed an effective informed adaptive particle swarm optimization (EIA-PSO) for a PEMFC mechanism model identification, which correctly predicted the performance of a PEM fuel cell. Zhou et al.[4] have compared fuzzy cluster method (FCM) and support vector machine (SVM) applying on PEM fuel cell classical faults diagnosis. Shao et al.[5] have presented an artificial neural network (ANN) ensemble method based fault diagnostic of PEM fuel cell. Liu et al.[6] have proposed a fast failure diagnosis of a PEM fuel cell system, which combines extreme learning machine (ELM) and Dempster–Shafer (D-S) evidence theory. Liu et al.[7] have presented a discrete hidden Markov model (DHMM) fault diagnosis strategy based on K-means clustering. Daeichian et al.[8] have proposed an online estimation method based on data fusion.

The heuristic algorithms used in the previous research on PEM fuel fault diagnose lacked an inference process. They obtained the results purely through data training. Fuzzy logic and neural networks have developed rapidly in recent years. Fuzzy reasoning systems are very suitable for expressing fuzzy experience and knowledge, but they lack an effective learning mechanism. Although regular neural networks have self-learning functions, they cannot express reasoning functions well. The adaptive network-based fuzzy inference system (ANFIS) combines these two methods, which exerts their advantages and makes up for their shortcomings. Therefore, this paper uses the ANFIS method to conduct the data-driven method modeling and fuzzy inference functions to study the diagnosis of gas starvation.

2. METHODOLOGY

2.1 Adaptive Network-based Fuzzy Inference System

The adaptive neuro-fuzzy inference system proposed by J. S. R. Jang is a novel fuzzy inference system structure that organically combines fuzzy logic and neuronal networks [9], which inherits the interpretability feature of the fuzzy inference system and the learning ability of the adaptive network in terms of functionality and can change the system parameters based on a priori knowledge so that the output of the system is closer to the actual output. An ANFIS structure is illustrated as follows[9]:

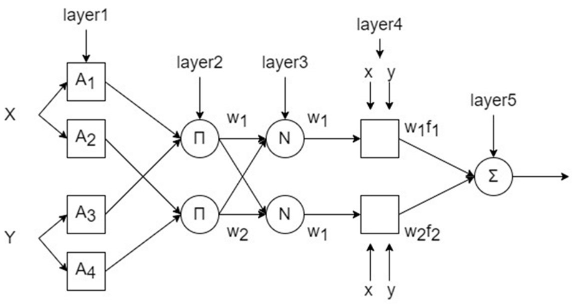


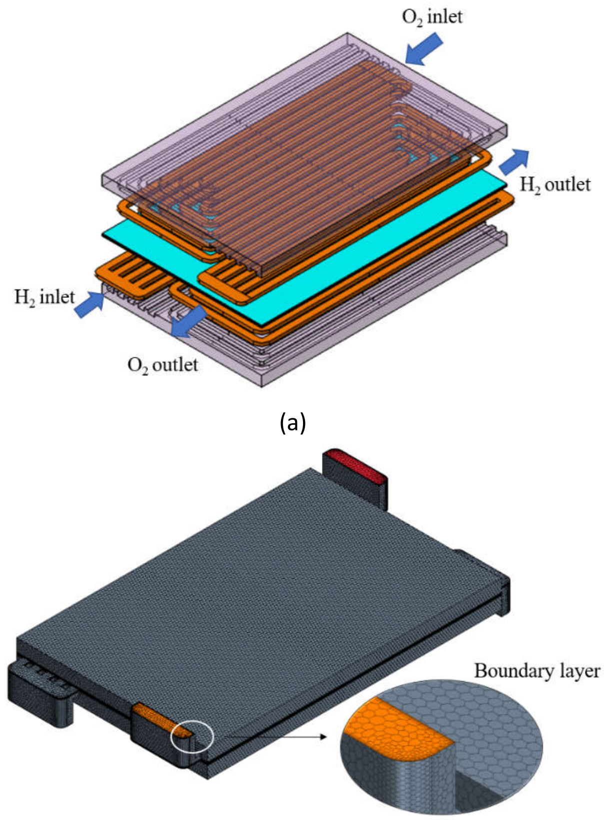
Fig.1. A typical ANFIS structure

The input x, y are fuzzified in the first layer. The fuzzification method: the input features x, y are fuzzified with the membership functions (MFs) to obtain a [0,1] membership grade. In the second layer, the membership grade of each feature is multiplied to obtain the firing strength of each rule. The third layer normalizes the firing strength of each rule obtained in the previous layer and characterizes the firing weight of the rule in the whole rule base, i.e., the extent to which the rule is used in the whole inference process. The fourth layer calculates the result of the rule, which is generally given by a linear combination of the input features. The fifth layer is defuzzified to get the exact output, and the final system output is a weighted average of the results of each rule.

2.2 Model development

2.2.1 Model geometry and meshing

This section determines the boundary conditions and model parameters by a three-dimensional single-phase flow model of a five-fluid serpentine flow field in a single cell of PEMFC. The fuel cell consists of cathode, anode, gas diffusion layer (GDL), catalytic layer (CL), and proton exchange membrane (PEM), as is shown in Fig.4. The grid was divided based on STAR-CCM+, which was prepared for ANSYS FLUENT, as is shown in Fig.2(b).



(b)

Fig. 2. Explosive and mesh view of PEMFC cell
(a) Explosive view (b)Mesh view

The area of MEA is 52×31mm, and the cross-section area of a single channel is 1.2×0.8mm. The specific thickness of the remaining parts is illustrated in Table1.

Table 1 Thickness of critical PEMFC parts

Component	Current collector	Flow channel	GDL	CL	Membrane
Thickness/mm	2	0.6	0.2	0.01	0.05

Table2 Model parameters

Plate		**Electrode**	
Density	2719 $kg\cdot m^{-3}$	H2 diffusion coefficient	9.15×10^{-5} $m^2\cdot s^{-1}$
Specific heat capacity	871 $J\cdot kg^{-1}\cdot K^{-1}$	O2 diffusion coefficient	2.2×10^{-5} $m^2\cdot s^{-1}$
Thermal Conductivity	100 $W\cdot m^{-1}\cdot K^{-1}$	H2O diffusion coefficient	2.56×10^{-5} $m^2\cdot s^{-1}$
Conductivity	500 $\Omega^{-1}\cdot m^{-1}$	Anode concentration index	0.5
Gas diffusion layer		Cathode Concentration Index	1
Density	2719 $kg\cdot m^{-3}$	Anode exchange coefficient	2
Porosity	0.5	Cathode exchange coefficient	3
Conductivity	80 $ohm^{-1}\cdot m^{-1}$	Open circuit voltage	0.92V
Viscous resistance	3.33×10^{12} m^{-2}	Anode reference current density	4615 $A\cdot m^{-2}$
Catalyst layer		Cathode reference current density	5.25 $A\cdot m^{-2}$
Porosity	0.3	Proton exchange membrane	
Viscous resistance	3.33×10^{12} m^{-2}	Thermal Conductivity	2 $W\cdot m^{-1}\cdot K^{-1}$
Surface-volume ratio	200000 m^{-1}	Proton conductivity	1

2.2.2 Model assumption

In this paper, the following assumptions are used to model the fuel cell:

- Incompressible and ideal gas
- homogeneous, isotropic material properties
- Laminar flow
- No liquid exists, water exists only in gaseous form
- Constant temperature(353K)

2.2.3 Simulation conditions and model parameters

Under-relaxation factors of hydrogen, oxygen, water content, and water saturation are set to 0.95 to ensure the stability of the solution. The under-relaxation factors for momentum and pressure were set to 0.3 and 0.7, respectively. Specific parameters are shown in Table 2.

2.2.4 orthogonal simulation

In order to make the simulation data more representative and to reduce the huge sample size of combining different levels of multiple variables, a five-factor, nine-level orthogonal test design was used for simulation sample collection in this paper, as shown in Table 3.

2.2.5 Basic equations of the model

The basic equations of CFD simulation are mass conservation equation, momentum conservation equation, and energy conservation equation. Besides, there are particularly hydrodynamic equations, electrochemical reaction equations, gas diffusion equations, and water transfer equations in fuel cells.

- Mass conservation equation:

$$\frac{\partial(\varepsilon\rho)}{\partial t}+\nabla\cdot(\varepsilon\rho\vec{u})=S_m \tag{1}$$

Table3 L81(9^5) orthogonal test boundary condition

Pressure	Humidity	Anode	Cathode	Current density
1atm	20%	0.4	0.5	0.05$A\cdot cm^2$
1.25atm	30%	0.6	0.8	0.05$A\cdot cm^2$
1.5atm	40%	0.8	1.1	0.05$A\cdot cm^2$
1.75atm	50%	1	1.4	0.05$A\cdot cm^2$
2atm	60%	1.2	1.7	0.05$A\cdot cm^2$
2.25atm	70%	1.4	2	0.05$A\cdot cm^2$
2.5atm	80%	1.6	2.3	0.05$A\cdot cm^2$
2.75atm	90%	1.8	2.6	0.05$A\cdot cm^2$
3.0atm	100%	2	2.9	0.05$A\cdot cm^2$

In Equation. (1), ε is porosity, ρ is fluid density, $\vec{u}$ is fluid velocity vector, S_m is the mass source term.

- Momentum conservation equation:

$$\frac{\partial(\varepsilon\rho\vec{u})}{\partial t}+\nabla\cdot(\varepsilon\rho\vec{u}\vec{u})=-\varepsilon\nabla P+\nabla\cdot(\varepsilon\mu\nabla\vec{u})+S_N \quad (2)$$

In which P is fluid pressure, μ is fluid viscosity, S_N is the momentum source term.

- Energy conservation equation:

$$\frac{\partial\left(\varepsilon\rho C_p T\right)}{\partial t}+\nabla\cdot\left(\varepsilon\rho c_p\vec{u}T\right)=\nabla\cdot\left(k^{eff}\nabla T\right)+S_Q \quad (3)$$

In Equation. (3), C_p is the fluid constant pressure specific heat capacity, T is the fuel cell temperature, k^{eff} is effective thermal conductivity, and S_Q is the energy source term.

- Species conservation equation:

$$\frac{\partial\left(\varepsilon c_k\right)}{\partial t}+\nabla\cdot\left(\varepsilon\vec{u}c_k\right)=\nabla\cdot\left(D_k^{eff}\nabla c_k\right)+S_k \quad (4)$$

in which subscript k represents species. c_k is the concentration of k, D_k^{eff} is the effective diffusion coefficient of k, S_k is the species source term.

2.2.6 Model validation

To verify the reliability of the PEMFC model, a common method is to compare the simulation polarization curve with the experimentally measured polarization curve. Simulation on different voltages is conducted to obtain the polarization curve. Meanwhile, the experimental data comes from fuel cell in the laboratory of the same size and structure as the established model[10]. The comparison between the simulation and experiment is shown in Fig.3, which shows high coincidence between them.

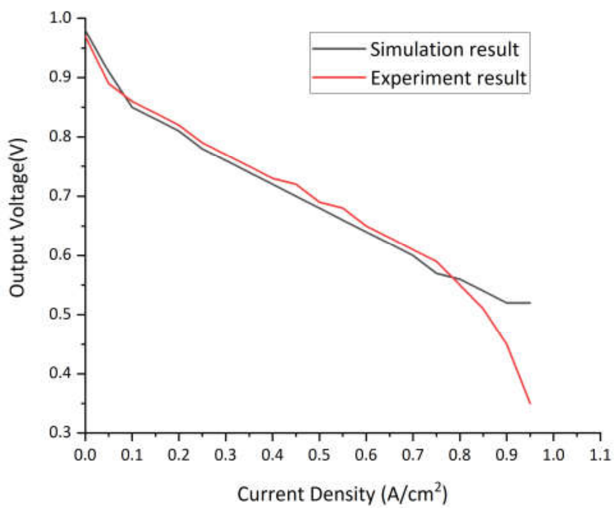


Fig. 3. Comparison between model polarization curve and test data

2.2.7 Selection of modeling parameters

This paper selects these may have a strong correlation with starvation and can be measured in practice as modeling parameters to establish an ANFIS prediction model for fuel cell starvation: concentration distribution of H_2 (CDH), concentration distribution of O_2 (CDO), current density distribution (CDD), voltage distribution (VD), water content distribution of the proton exchange membrane (WD), working pressure (WP), and relative humidity (RH). The evaluation index of the distribution parameters (CDD, VD, WD) are represented by the variance of the data of the four sampling points in the sample.

$$\sigma^2=\frac{1}{4}\sum_{i=1}^{4}(x_i-\bar{x}) \quad (5)$$

3. RESULT AND DISCUSSION

3.1 Evaluation of gas starvation degree

As is shown in Fig.4, three different states correspond to different current density distributions. In Fig.4(a), more than 80% of the membrane is unable to provide output current, and the cell is unable to work normally, which corresponds to the state of overall gas starvation. In Fig.4(b), about 30% of the area cannot provide output current. However, the other areas still have expected current output, and the cell will not significantly decrease in external characteristics, which corresponds to the state of local gas starvation. In Fig.4(c), a normally-working cell is shown. Low current only happens at some areas where the flow channel ridge contacts the membrane, which is normal.

Based on the above analysis, this paper adopts the percentage of the area where starvation happens as the criterion for evaluating starvation. Fig.5 shows the comparison of starvation area percentage between the gas starvation and normal samples. Normal samples only have slight starvation at flow channel ridge, so the starvation area percentage does not exceed 10%, while the percentage of starvation samples usually far exceeds that of normal samples. In this paper, cells with more than 50% starvation area are defined as overall starvation, 10%-50% are local starvation, 10% are defined as non-starvation.

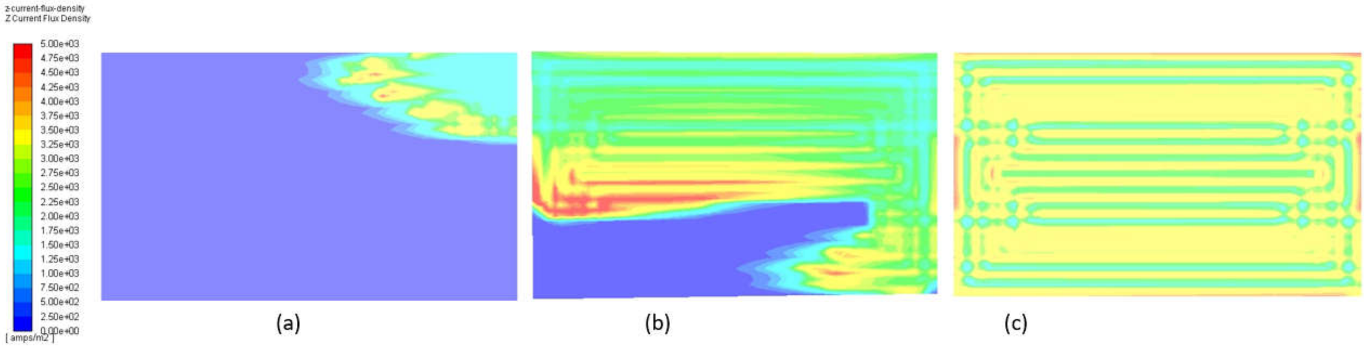


Fig. 4. Different status of gas starvation (a)Overall starvation (b)Local starvation (c) Normal case

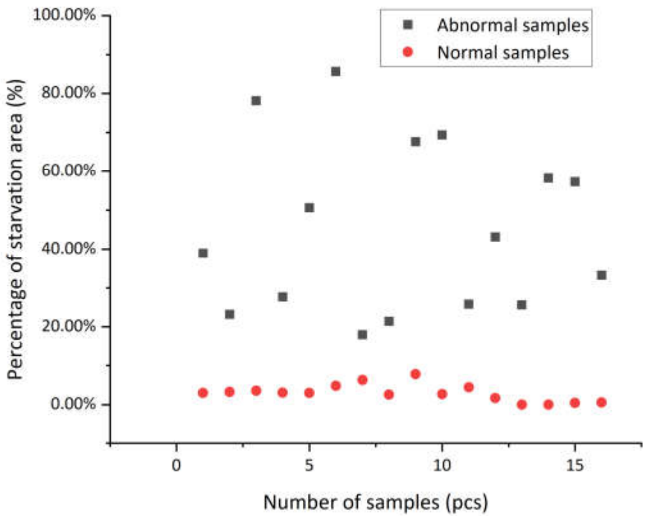


Fig. 5. Starvation area percentage of different status PEMFC

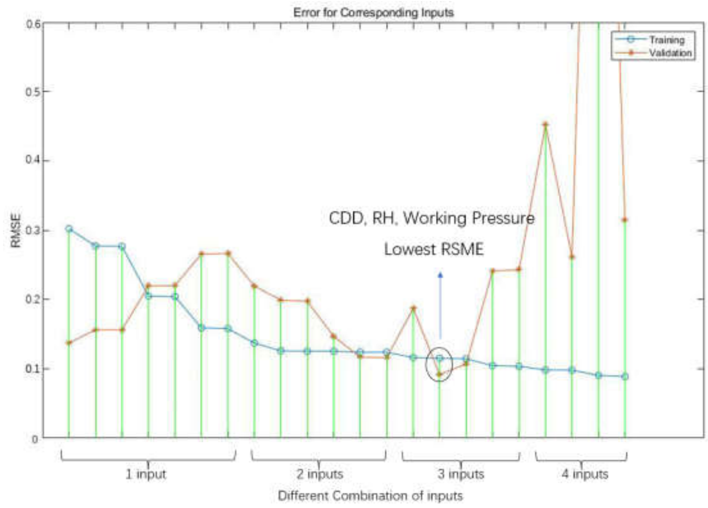


Fig. 6. Error for corresponding inputs

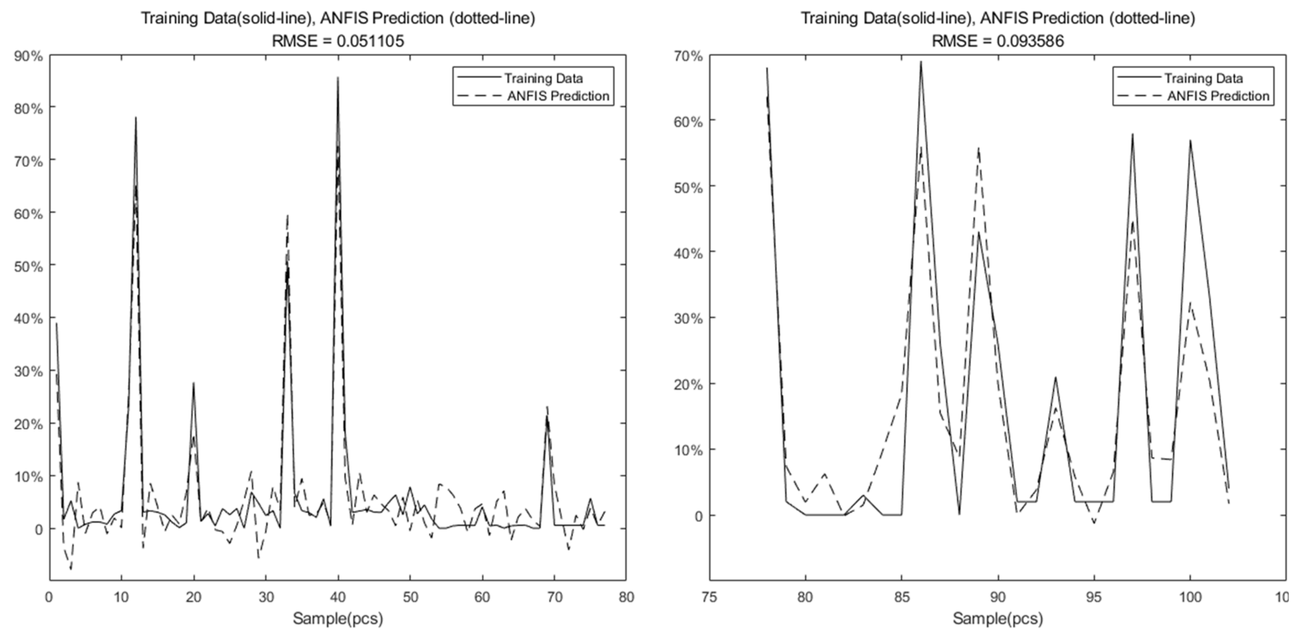


Fig. 7. ANFIS prediction result compared with actual value

3.2 ANFIS Model training result

A sequential forward search of the inputs is conducted, selecting each input variable sequentially for optimizing the root mean square error (RMSE), shown as Fig.6. The search has tried all combinations of input and selected three parameters (CDD, RH, WP) as inputs, as the model with these inputs has the lowest training RMSE (0.1251) and validation RMSE (0.1018). Because when the number of input parameters reaches to4, the validation RMSE shows a huge surge, though the training RMSE is low.

The training result is shown in Fig.7. The ANFIS model predictions fit the data very closely on both the training and validation sets. The RMSE between the validated and actual values on the training set is 0.051, and an RMSE of 0.093 is achieved on the validation set.

This paper distinguishes between non-starvation and local starvation samples with 10% of the gas starvation area and between local starvation and overall starvation with 50% of the gas starvation area. The model achieved correct prediction for 23 samples out of 25 data in the validation set. An accuracy of 92% is achieved.

One of the drawbacks of the current model is that when predicting for non-starvation samples, the predicted values are negative because their starvation areas are very close to zero, and the model does not filter the negative predicted data. However, the starvation area does not have negative values in practice, so the model is potential for improvement.

4. CONCLUSION

This paper presents a prediction model of gas starvation in proton exchange membrane fuel cells based on ANFIS. The variance of CDD, VD, WD, pressure, and RH are selected as prediction parameters for the gas starvation. The degree of gas starvation is evaluated by the percentage of the gas starvation area, which is also used in the ANFIS model as a predicted parameter. The ANFIS model tries different parameters combination for prediction and select the one that has the lowest RMSE (0.1251 training RMSE and 0.1018 validation RMSE). CDD, RH, WP are selected as the final input parameters for ANFIS. Simulation samples are divided into the training set and validation set. The trained ANFIS model shows great precision for predicting the gas starvation status in the validation set, as shown in Fig.7(b), which has an accuracy of 92%.

The modeling parameters selected by the model have practical significance in actual operating conditions and can be applied to the prediction of fuel cell gas starvation area and status, providing a feasible technical route for the prediction of starvation in fuel cell systems and vehicles. Future research shall focus more on the stack-level diagnosis and thus can be better applied to fuel cell systems.

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