NEURO-FUZZY SYSTEM BASED ON GENETIC ALGORITHM FOR ISOTHERMAL CVI PROCESS FOR CARBON/CARBON COMPOSITES

Zhengbin Gu, Hejun Li, Hui Xue, Aijun Li, Kezhi Li

College of Materials Science and Engineering, Northwestern Polytechnical University, Xi'an 710072, China

Corresponding author e-mail address: lihejun@nwpu.edu.cn

Introduction

Soft computing [1] is a collection of methodologies that aims to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost, and it is a promising method to describe nonlinear systems. Its principal constituents are fuzzy logic, neural network and evolutional computing, such as genetic algorithm. In this present study, the neural fuzzy system (NFS) is selected as a method to model isothermal CVI processes.

Firstly, a numerical model by the finite element method (FEM) [2] for isothermal CVI was established based on the characteristics of mass transfer in the process; and the virtual samples for training NFSs were collected from the simulation results of the FEM numerical model. The data was processed with higher speed and efficiency owing to the parallel computing ability of neural networks. Consequently the relationship between pyrolysis conditions and deposition rate were studied in detail. Combining the numerical simulation with computing intelligence can help us to avoid the shortcoming of numerical simulation and decrease the cost of experiments as well as to ensure the veracity and reliability of the training samples. In order to improve the stability and precision of NFSs, genetic algorithm, a global search technique [3], was used to optimize the parameters of the membership functions and to identify the connection weights of the neural network.

2. FEM simulation model of isothermal CVI

Numerical simulation of the isothermal CVI for a 2D C/C composite by FEM was clearly described in Ref. [2]. This numerical model was established on the principle of mass transfer characteristics of the isothermal CVI. Experiments were conducted in a 50kW furnace and a carbon fiber preform was used (D = 165mm) to test the veracity of the said numerical model. Comparing the experiment and simulation results, it was noticed that the said numerical model possessed a high precision.

3. Neuro-fuzzy system

3.1. Structure of Neuro-fuzzy system

In the present study, a 4-layer feed forward network was used to implement the inference of the fuzzy system. The schematic diagram was shown in Fig. 1.

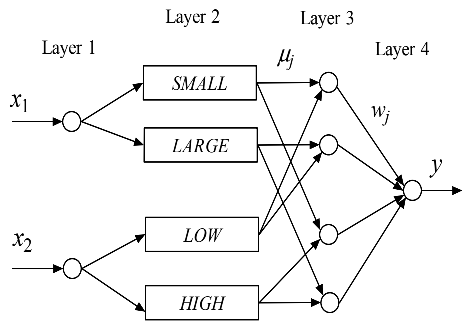

Fig. 1 Architecture of a neuro-fuzzy system

3.2. Optimization problem of NFSs

According to the fuzzy system theory, Takagi–Sugeno (T-S) rules have the following characteristics [4]:

$$R_j\text{: If } x_1 = X_{1j}, \text{ and } x_2 = X_{2j}, \text{ then } y = Y_j \qquad (1)$$

where R_j represents the j_{th} rule. X_{ij}, i = 1, 2, and Y_j are linguistic terms which are fuzzy sets defined by membership functions, while $X = (x_1, x_2)^T$ and y are the input and output linguistic variables respectively.

In this investigation, Gaussian functions were employed as the standard form of the membership functions. Their parameters can be represented by the parameter set $\{m_{ij}, \sigma_{ij}\}$.

$$\mu_{X_{ij}}(x_i) = \exp\left[-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^{\ 2}}\right] \qquad (2)$$

For a real-valued input vector $X = (x_1, \ldots, x_n)^T$, the overall output of the neuro-fuzzy system is a weighted average of the Y_js:

$$y = \frac{\sum_{j=1}^{m} w_j \mu_j}{\sum_{j=1}^{m} \mu_j} \qquad (3)$$

where w_j is the connection weight between the inference layer and the output layer, as shown in Fig. 1.

The optimization problem consists in tuning the parameters of m_{ij}, σ_{ij} and w_j, and all these parameters were optimized by genetic algorithm in this paper.

4. NFSs for Isothermal CVI

4.1. Virtual sample

The crucial parameters controlling the isothermal CVI processes, such as deposition time (t/hr), temperature (θ/°C), reactor pressure (P/kPa), preform thickness (h/mm), fiber volume fraction (V_f/%), precursor gas flow ratio (*r*), and rate (v/m^3·hr^{-1}), were selected as the input variables of NFSs. Their effects on isothermal CVI were also discussed in this paper. In order to solve this complicated problem, the 6 parameters were divided into 3 groups, as shown in Fig. 2. Therefore, 3 independent neuro-fuzzy systems were used to model isothermal CVI processes. The bulk densities (ρ/g·cm^{-3}) of C/C composites were the output variables of NFSs.

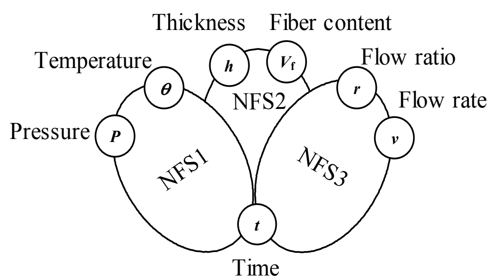

Fig. 2 NFS used to model isothermal CVI processes

Virtual samples were collected corresponding to Table 1 with the help of the FEM program. In order to keep the NFSs possessing excellent properties, a full-factorial design was adopted, i.e. there are 4^3 virtual data were sampled for the NFSs.

Table 1 Factors and levels used for experiment design

LEVEL	1	2	3	4
Time: *t* /hr	100	200	400	500
Temperature: *θ* /°C	900	1000	1100	1200
Pressure: *P* /kPa	2	4	6	7
Thickness: *h* /mm	10	15	20	25
Fiber content: V_f /%	35	50	60	70
Gas ratio: *r* (propylene/nitrogen)	0.3	0.5	0.8	1.0
Gas flow rate: v /m^3·hr^{-1}	0.2	0.3	0.4	0.6

4.2. Genetic algorithms for NFS

Genetic algorithm (GA) was used to tune and optimize the parameters, m_{ij}, σ_{ij} and w_j, and the first problem to be solved was how to encode and adjust chromosomes.

In this paper, the chromosomes were real-valued encoded and described as V = (m_{11}, σ_{11}, m_{12}, σ_{12}, …, m_{33}, σ_{33}, w_1, w_2, …, w_{27}). The quadratic error was defined by

$E=\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$, where i stood for the number of the training samples, (X_i, y_i) the ith training sample, and $\hat{y}_i$ the output of the NFSs corresponding to the input vector X_i. The optimization problem consisted in tuning the parameters m_{ij}, σ_{ij} and w_j, in order to minimize E, and the optimization objective was to obtain a chromosome with the smallest quadratic error E.

5. Results and Discussions

By the NFSs model of isothermal CVI, the influences of θ, P, h, V_f, r and v on C/C composites bulk density were studied, and the results were shown in Fig. 3~Fig. 9.

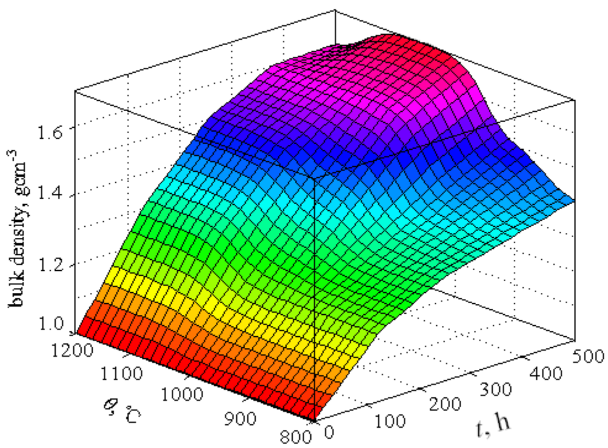

Fig. 3 Influence of deposition temperature on the bulk density
(P=4.5kPa, V_f=55%, h=20mm, r=0.6, v=0.3$m^3 \cdot h^{-1}$)

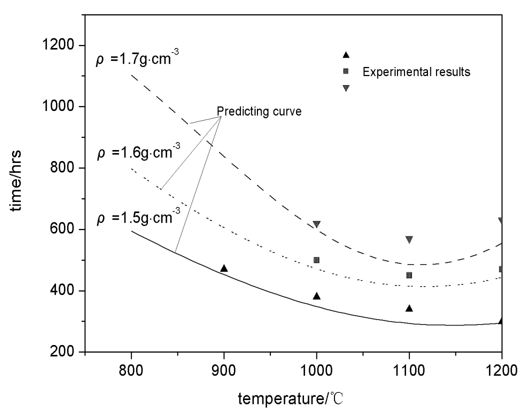

Fig. 4 NFS model predicted processing time vs. experimental results
(P=4.5kPa, V_f=55%, h=20mm, r=0.6, v=0.3$m^3 \cdot h^{-1}$)

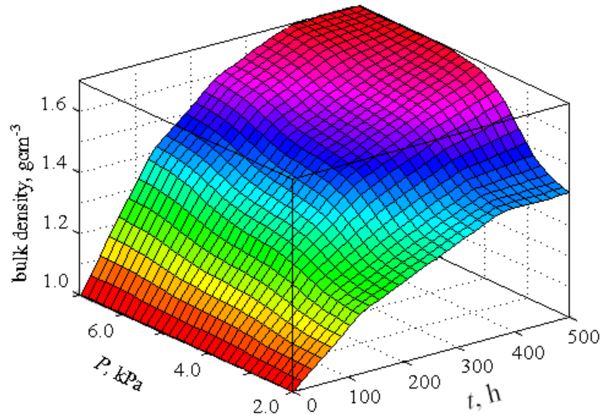

Fig. 5 Influence of pressure on the bulk density
(θ=1000°C, V_f=55%, h=20mm, r=0.6, v=0.3m^3·h^{-1})

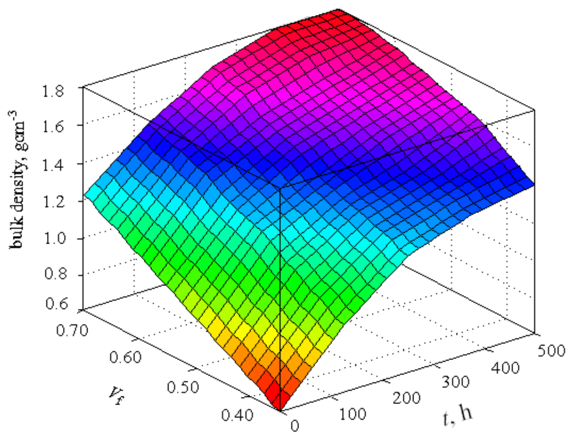

Fig. 6 Influence of fiber volume fraction on the bulk density
(θ=1000°C, P=4.5kPa, h=20mm, r=0.6, v=0.3m^3·h^{-1})

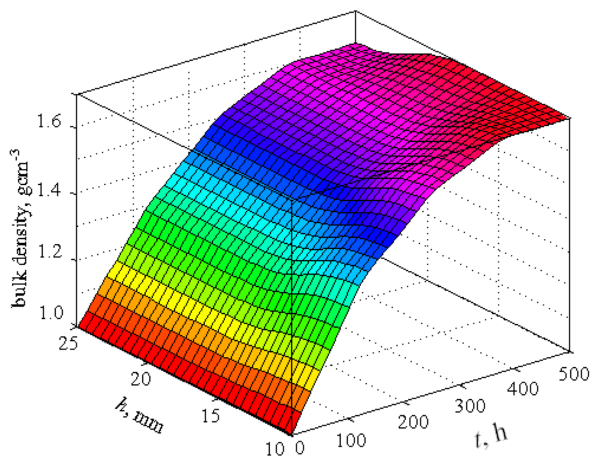

Fig. 7 Influence of preform thickness on the bulk density
(θ=1000°C, P=4.5kPa, V_f=55%, r=0.6, v=0.3m^3·h^{-1})

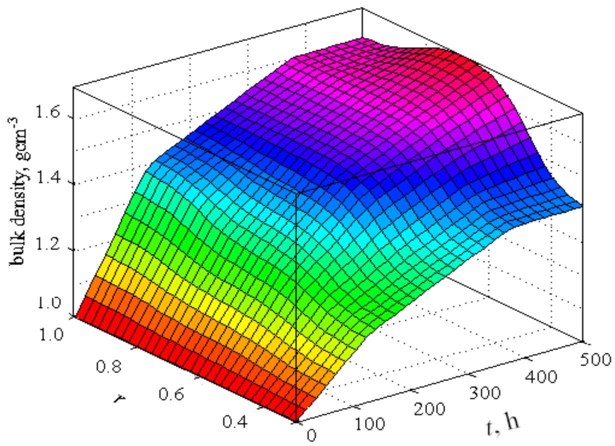

Fig. 8 Influence of gas flow ratio (propylene/nitrogen)
(θ=1000°C, P=4.5kPa, V_f=55%, h=20mm, v=0.3m^3·h^{-1})

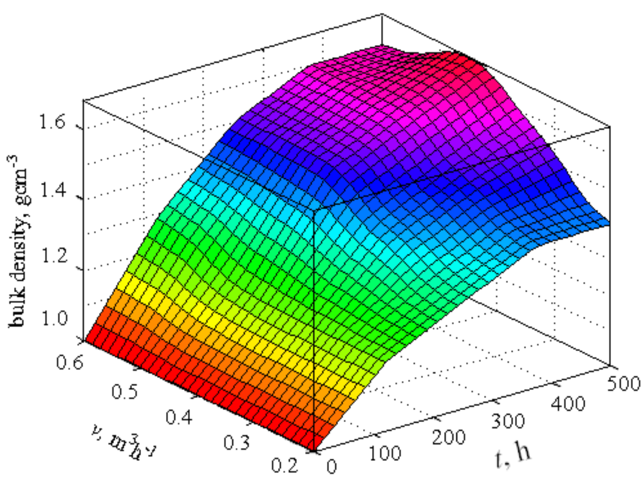

Fig. 9 Influence of gas flow rate on the bulk density
(θ=1000°C, P=4.5kPa, V_f=55%, h=20mm, r=0.6)

The CVI processes of the C/C composites are influenced by factors as the diffusion of gaseous hydrocarbon, the pyrolysis reactions, and the exhaust of residual gases. It is well known that deposition temperature is vital in the competitive relation between the diffusion and the pyrolysis, as well as the matrix structure of pyrolytic carbon, i.e. deposition temperature determines the fabrications and properties of C/C composites to a certain extent. Therefore, special attention should be paid to the deposition temperature in design of CVI processes. From the Fig. 3, at low temperatures (θ < 850°C), the CVI was a reaction-controlled process because of the high activation energy (E_A), indicating the almost equal pyrocarbon deposition rate throughout the whole preform. As a result, the preform usually has a satisfied uniformity. At high temperatures (1000°C ≤ θ < 1200°C), preforms can reach a high density (ρ = 1.6g·cm^{-3}) in a short time

(t = 400hrs). However, if the deposition temperature beyond a certain point ($\theta \geq 1200°C$), the CVI will be a serious diffusion-controlled process. The matrix deposits rapidly at the outer surfaces of the composite, causing a large amount of trapped porosity inside the composite. It is impossible for the resultant C/C composites with high porosity and density gradients to have good mechanical properties.

Fig. 4 showed the bulk density as a function of deposition time and temperature. From the comparison between the results of NFS modeling and experiments, it can be observed that good agreement existed between the model predicting curve and the experimental results. With the temperature increasing, the rate of densification increases by a few of times and the densification time shortens obviously. However, at high temperatures ($\theta \geq 1000°C$), there is little difference in densification efficiency provided the preform bulk density has reached 1.6 $g \cdot cm^{-3}$. Only the results estimated by predicting curve were given, while the densification experiments were not conducted due to the low densification efficiency at temperatures below 900°C.

The effect of the pressure, ranging from 2.0kPa to 7.0kPa, on the deposition rate was shown in Fig. 5. From figure 5 it was known that the preforms bulk densities increased very quickly at high pressures, indicating a higher deposition rate under high pressure than under low pressures. However, lower pressure is advantageous to achieve a uniform deposition of pyrolytic carbon through the substrate thickness. In particular, in order to avoid the occurrence of carbon black and to increase the diffusion coefficient (Fick diffusion is proportional to $\theta^{3/2} \cdot P^{-1}$), the experiments are usually conducted under low pressures and temperatures. Moreover, with the deposition of pyrocarbon, the gas flow pattern in preform changed from viscous flow, molecular flow to slip flow. In the case of Knudsen diffusion, or slip flow, the mean free path is many times larger than pore diameters and the diffusion coefficient of gas is independent of pressure and proportional to $\theta^{1/2}$. Therefore, the pressures were usually kept low (4.5kPa) in our investigation.

The effects of preform fiber volume fraction V_f and thickness h on bulk density were shown in Fig. 6 and Fig. 7. It was shown in figure 6 that a preform with high V_f (> 55%) took short time (t < 400hrs) to achieve a higher density (1.65$g \cdot cm^{-3}$) in certain conditions. On the other hand, a preform with low V_f took long time to achieve a high final density, leading to the greatly increased manufacturing costs. In general, a preform with small thickness h cost short time to achieve a high density because the gas mixture can easily diffuse into the inner part of composites. Therefore, when a component is to be designed, the preform V_f and h should be determined firstly according to the demand of properties, such as bulk density, toughness, tensile strength, and flexural strength.

The flow rate v and ratio r of gas mixture have great influences on the deposition rate, as shown in Fig.8 and Fig. 9. And the influences of v and r on the bulk density shared a common characteristic, namely in the given range there was an optimum region in which the deposition rate remained high for a long time, meaning a shorter process time. Therefore, it was not advisable to increase the concentration of gas precursor propylene limitlessly, while the v and r of gas mixture should be adjusted according to the preforms and deposition time. In general, a fundamental balance between total processing time and uniformity of infiltration should be made in practical design of the isothermal CVI processes.

6. Conclusions

A numerical model for CVI technique was established on the analysis of characteristic of the mass transport in the isothermal process. A neuro-fuzzy system model, which can overcome the disadvantage of FEM numerical simulation, was proposed on the simulation results of numerical model, i.e. the testing virtual samples were selected from the numerical simulation results. The influences of reaction temperature, pressure, volume content of carbon fiber, thickness, flow rate of gas precursor, and their ratio on the preform bulk densities were mined by NFSs model.

Acknowledgements

This research was supported by the National Natural Science Foundation of China under Grant No. 50072019 and the Natural Science Foundation of China for Distinguished Young Scholars under Grant No. 50225210.

References

[1] Zadeh L A. Soft computing and fuzzy logic. IEEE Software 1994; 11(6): 48–56.
[2] Li K, Li H, Jiang K, Hou X. Numerical simulation of isothermal chemical vapor infiltration process in fabrication of carbon-carbon composites by finite element method, Science in China (Series E) 2000; 43(1): 77–85.
[3] Srinivas M, Patnaik LM. Genetic algorithms—a survey. Computer, 1994; 27(6):17–26.
[4] Chuang CC, Su SF, Chen SS. Robust TSK fuzzy modeling for function approximation with outliers. IEEE Transactions on Fuzzy Systems 2001; 9(6): 810–821.