Prediction of the Actuation Property of Cu Ionic Polymer–Metal Composites Based on Backpropagation Neural Networks

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Cite This: ACS Omega 2020, 5, 4067−4074

ABSTRACT: Ionic polymer–metal composite (IPMC) actuators are one of the most prominent electroactive polymers with expected widespread use in the future. The IPMC bends in response to a small applied electric field as a result of the mobility of cations in the polymer network. This paper proposes a Levenberg–Marquardt algorithm backpropagation neural network (LMA–BPNN) prediction model applicable for Cu/Na–based ionic polymer–metal composites to predict the actuation property. The proposed approach takes the dimension ratio (DR) and stimulation voltage as the input layer, displacement and blocking force as the output layer, and trains the LMA–BPNN with the experimental data so as to obtain a mapping relationship between the input and the output and obtain the predicted values of displacement and blocking force. An IPMC actuating system is set up to generate a collection of the IPMC actuating data. Based on the input/output training data, the most suitable structure was found out for the BPNN model to represent the IPMC actuation behavior. After training and verification, a 2-9-3-1 BPNN structure for displacement and a 2-9-4-1 BPNN structure for blocking force indicate that the structure can provide a good reference value for the IPMC. The results showed that the BPNN model based on the LMA could predict the displacement and blocking force of the IPMC. Therefore, this model can become an effective solution for IPMC control applications.

1. INTRODUCTION

Ionic polymer–metal composites (IPMCs) are an important class of electroactive polymers consisting of a thin layer of ionic polymer film and two layers of metal electrodes.1−3 As shown in Figure 1, the membrane contains anions (SO₃⁻) connected to the backbone, cations that can freely travel within the membrane, and water molecules.4,5 At applied voltage, the transportation of hydrated cations and water molecules to the cathode leads to the expansion of the membrane on one side of the cathode, which leads to the bending motion of the IPMC sample (Figure 1). Because of the low driven voltage, flexibility, biocompatibility, and large deformation, IPMCs have been widely used in different fields such as biomechanical and biomedical applications, robotics, flexible sensing, as well as the aerospace and vehicle industry.4−9

The types of ions in polymer membranes, the type and thickness of metal electrodes, the size and hysteresis of polymer membranes, and environmental factors can influence the behavior of IPMCs.10−12 These factors may lead to oscillations and instabilities in IPMC performance, and the combination of these factors makes it difficult to accurately model the behavior of IPMC actuators. Therefore, it is important to establish a precise IPMC model to study its bending characteristics and apply it to the system control of the executive mechanism. Punninget13 found that resistances of both electrode surfaces of the IPMC sheet changed during the bending operation. Vahabi14 proposed a parametric identification method for IPMC actuators as the combination of nonlinear and linear least-squares methods. Caponetto15 developed an improved electromechanical gray box model with...
experimental features. On the other hand, forward methods,\textsuperscript{16} auto-regressive moving average exogenous methods,\textsuperscript{17} the NARX structure fuzzy model and particle swarm optimization methods,\textsuperscript{18} and the adaptive neuro-fuzzy inference system \textsuperscript{19} have been proposed to identify the IPMC actuation behavior. However, none of the models mentioned is sufficient to accurately describe the nonlinear behavior of the IPMC, or the large bending behavior of the IPMC actuator is not taken into account in the identification of their nonlinear behavior. Moreover, the fits of models were not ideal, which limits the applicability of the proposed models.

Backpropagation neural networks (BPNNs) have good abilities of nonlinear mapping, generalization, and fault tolerance and are suitable for dealing with complex systems difficult to describe with accurate mathematical models. To meet the current demands for IPMC modeling methods and to refine the research on the characteristics of IPMCs, we present a BPNN model for nonlinear identification of IPMC actuators in large deformations. Our goal is to develop an accurate and transparent identification method for IPMCs with large displacements using BPNNs. Moreover, the displacement and blocking force model of IPMCs is established by BP neural networks. The displacement and blocking force of IPMCs is predicted, which indicates that the established BPNN model has high precision for the prediction of IPMCs. It is of great significance to better determine the input (stimulation voltage) and size (dimension ratio) parameters of IPMCs.

2. RESULTS AND DISCUSSION

2.1. Characterization of IPMCs. Figure 2 exhibits the scanning electron microscopy (SEM) images and energy-dispersive spectroscopy (EDS) of the electrode layer of IPMCs. As shown in Figure 2, the IPMC surface was fully covered by copper, and it also shows that copper distribution is uniform and compact with smaller copper particles, and the presence of Cu on the surface of the IPMCs was confirmed by EDS measurements. Moreover, the Cu content is 85.47\% from EDS data, and it further reveals that Cu particles have been deposited well on the surface of membranes, which is beneficial to the actuation performance of IPMCs. Meanwhile, we also found that the oxygen content is 10.14\% from the EDS data, which is mainly due to the oxidization of some of the Cu on the surface. The presence of Ag is due to the fact that Ag\textsuperscript{+} is not completely replaced during the electroless plating process and a portion remains on the surface.\textsuperscript{9}

2.2. Actuation property of IPMCs. The relationship between maximum displacement and voltage under different $L/W$ ratios is displayed in Figure 3. The results showed that the working principle of an IPMC actuator. Before applying electrical stimulation (top) and after applying electrical stimulation (bottom).

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Working principle of an IPMC actuator. Before applying electrical stimulation (top) and after applying electrical stimulation (bottom).}
\end{figure}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{SEM image and EDS of the electrode layer.}
\end{figure}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure3.png}
\caption{Maximum displacements of the IPMCs with various sizes under different voltages.}
\end{figure}

\begin{table}
\centering
\begin{tabular}{|c|c|c|}
\hline
Element & $W_e$, \% & $W_m$, \% \\
\hline
O & 10.14 & 31.38 \\
Cu & 85.47 & 66.61 \\
Ag & 4.39 & 2.02 \\
\hline
\end{tabular}
\caption{EDS data of IPMCs.}
\end{table}
the displacement first increased and then decreased as the voltage increased. The four samples continuously increased to maximum displacements at 9 V, and it is 30 mm for the \( L/W = 4 \) sample. At the same time, we find that the size effect has a great influence on the displacement of IPMCs. The larger the size ratio is, the greater the output displacement is and the higher the performance of IPMCs is. The high performance of IPMCs is related to the interface of dispersed Cu particles near the ionic membrane surface, leading to high transport and adsorption at the electrodes when the voltage is greater than 9 V, the displacement decreases gradually, mainly because the water molecules contained in the IPMCs are decomposed, resulting in the lack of hydrated cations in the membrane that can move. Figure 4 shows the maximum blocking forces of the IPMCs with various sizes under different voltages. In general, the force of all samples peaked and then fastly decreased. The \( L/W = 1 \) and \( L/W = 4 \) samples continuously increased to the maximum blocking forces of 15 and 8.8 mN at 8 V, respectively. Moreover, the \( L/W = 2 \) and \( L/W = 3 \) samples had maximum blocking forces of 14.6 and 13 mN at 9 V, respectively. The suitable stimulation voltage for the maximum blocking force output is 8–9 V, and it was observed that the larger the \( L/W \) ratio, the smaller the blocking force output at the same voltage; on the contrary, the smaller the \( L/W \) ratio, the larger the blocking force. This is similar to previous studies of platinum IPMCs.

2.3. Nonlinear Model for the IPMC Actuators Based on BPNNs. The BPNN is a multilayer feedforward network trained according to the error backpropagation algorithm. It is one of several prediction methods, which determines the relationship between network input factors and outputs by historical sample data for learning and training. The learning rule is to use the steepest descent method to minimize the error sum of squares by adjusting the network weights and threshold in backpropagation. The BPNN consists of forward propagation of the input signal and backpropagation of the error signal.

The input signal is propagated through some hidden layers and propagating to the output layer. During the propagation, weights and thresholds of the network are maintained unchanged, and the status of each node affects the next layer. In the forward propagation, error exists between the real output value of the output layer and the excepted value, so the backpropagation of the error signal is needed. The error signal is noted as the difference between the real output of the output layer and the excepted output signal. The error signal is propagated from the output layer, going through hidden layers and to the input layer. During this propagation, the weights of the neural network are regulated. With the continuous regulation of weights and thresholds, the error signal can be kept small enough to make the output signal closer to the excepted output signal.

In this paper, a network prediction model is designed for Cu-IPMC materials to predict the displacements or blocking forces. It is necessary to launch some prediction work on displacements or blocking forces as evidence to improve the actuation performance of IPMCs. The dimension ratio \( (L/W \) ratio, where \( L \) is the length of IPMCs and \( W \) is the width) and stimulation voltage can be used as input variables, and the output is displacement or force. Figure 5 shows the structure of a BPNN. The BPNN operating process includes the following steps:

1. Initialization, each connection weight \((w_{ij})\) and threshold \((\theta_j)\) of the model are assigned a random value within the interval \([-1, 1]\).

2. The number of network input layer nodes \(k\), the number of hidden layer nodes \(p\), the number of output layer nodes \(q\), the neuron excitation function of the hidden layer \(\phi\), the neuron excitation function of the output layer \(\psi\), the input sample \(x\), the target output \(y\), the target precision \(\varepsilon\), and the learning rate are determined.

3. Hidden layer input and output calculation. The hidden layer input \(S\) and output \(B\) are calculated from the input vectors \(w\) and \(\phi, f\) is the Sigmoid function.

\[
S_j = \sum_{i=1}^{k} w_{ij}x_i - \theta_j \quad (i = 1, 2, 3, \ldots, k; j = 1, 2, 3, \ldots, p)
\]

(1)

\[
B_j = f(S_j) = \frac{1}{1 + e^{-S_j}} \quad (j = 1, 2, 3, \ldots, p)
\]

(2)

4. Output layer input and output calculation. The BP neural network predictive \(L\) and \(\gamma\) are calculated according to the hidden layer output \(B\), the connection weight \(v\), and the threshold \(\gamma\).

Figure 4. Maximum blocking forces of the IPMCs with various sizes under different voltages.

Figure 5. Structure of a BPNN system.
\[ L_t = \sum_{j=1}^{q} w_{ij} B_j - \chi_t \quad (j = 1, 2, 3, \ldots, p; t = 1, 2, 3, \ldots, q) \]  
(3)

\[ \chi_t = f(L_t) = \frac{1}{1 + e^{-L_t}} \quad (t = 1, 2, 3, \ldots, q) \]  
(4)

(5) Error calculation. The network prediction error \( E \) is calculated based on the network prediction output \( \chi_t \) and the expected output \( Y_t \).

\[ E = \frac{1}{2} \sum_{i=1}^{n} (Y_t - \chi_t)^2 \]  
(5)

(6) Weight and threshold correction of the output layer.

\[ \nu_{\mu} (N+1) = \nu_{\mu} (N) - \alpha \left( \frac{\partial E}{\partial \nu_{\mu}} \right) \]  
\[ \gamma_{\mu} (N+1) = \gamma_{\mu} (N) - \alpha \left( \frac{\partial E}{\partial \gamma_{\mu}} \right) \]  
where \( N \) is the number of trainings; \( \alpha \) is the variable that controls the speed of the modification.

(7) Weight and threshold correction of the hidden layer.

\[ w_{ij} (N+1) = w_{ij} (N) - \beta \left( \frac{\partial E}{\partial w_{ij}} \right) \]  
\[ \theta_{ij} (N+1) = \theta_{ij} (N) - \beta \left( \frac{\partial E}{\partial \theta_{ij}} \right) \]  
In the equation, \( \beta \) is also the variable that controls the speed of the modification.

(8) If the error \( E < \epsilon \), the training is completed, otherwise go to step (2) until the accuracy requirement is met.

2.4. BPNN Model Training and Verification. Prior to training, the data is normalized by the mapminmax function.

\[ X = \frac{2(x - x_{\min})}{x_{\max} - x_{\min}} - 1 \]  
(10)

where \( x \) is the original vector value, \( x_{\min} \) and \( x_{\max} \) are the minimum and maximum values of \( x \), respectively, and \( X \) is the vector value normalized by the \( x \) vector.

In this paper, the transfer function of the hidden layer of the BP neural network selects the tansig function, the transfer function of the output layer adopts the purelin function, and the training target is set for 0.0001. The trainlm function is used as the training function based on the Levenberg–Marquardt algorithm (LMA). The LMA is interpolated between the Gauss–Newton algorithm (GNA) and the method of gradient descent. The LMA is more robust than the GNA, that is, in many cases, even if it starts far from the final minimum, it can find a solution. Letting the Jacobian of target function be denoted \( J \), then the Levenberg–Marquardt method searches in the direction given by the solution to the equations. Note that the Jacobian matrix \( J \) of connection weight \( (w) \) is defined as follows in the algorithm

\[ J(w(i)) = \begin{bmatrix} \frac{\partial f_1(w(i))}{\partial w_1} & \frac{\partial f_1(w(i))}{\partial w_2} & \cdots & \frac{\partial f_1(w(i))}{\partial w_n} \\ \frac{\partial f_2(w(i))}{\partial w_1} & \frac{\partial f_2(w(i))}{\partial w_2} & \cdots & \frac{\partial f_2(w(i))}{\partial w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m(w(i))}{\partial w_1} & \frac{\partial f_m(w(i))}{\partial w_2} & \cdots & \frac{\partial f_m(w(i))}{\partial w_n} \end{bmatrix} \]  
(11)

The standard statistical parameters were used to calculate the determination coefficient (\( R \) or DC) and the root-mean-square error (RMSE) according to eqs 12 and 13.

\[ R^2 = \frac{\sum_{i=1}^{n} (\tilde{Y}_i - \bar{Y})^2}{\sum_{i=1}^{n} (T_i - \bar{Y})^2} \quad (i = 1, 2, 3, \ldots, n) \]  
(12)

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (T_i - \tilde{Y}_i)^2} \quad (i = 1, 2, 3, \ldots, n) \]  
(13)

where \( T \) and \( n \) are the target (training or experimental) data vector and the total number of training data, \( \tilde{T} \) and \( \tilde{Y} \) are the average of the training values and model output (predicted) values, respectively.

In the BP neural network, the number of nodes in the hidden layer greatly influences the performance of the neural network. Too few nodes will result in a small amount of information obtained by the network, which is not sufficient to refine rules contained in samples. Too many nodes will lead to the extension of the training time, weakening of the generalization ability, and even lead to the phenomenon of "overfitting". Therefore, it is very important to set a reasonable number of nodes in the hidden layer. Calculation of the number of neurons in the hidden layer is as follows

\[ p = \sqrt{k + q + m} \quad (1 \leq m \leq 8) \]  
(14)

The number of neurons in the hidden layer is examined in the range from 3 to 9, based on the model calculations and the requirement of model accuracy. Next, the BPNN is trained with different hidden layers using the LMA mechanism. In the process of training, the data is automatically divided into a training set, a validation set, and a test set. A data set that is chosen in random sets are used for training and the rest of them (validation set and test set) are then employed for blind testing of the BPNN. Moreover, the error between three data sets and the target will change constantly. When all three of them tend to be consistent, a better prediction result can be obtained. It is found from repeated training that nine neurons in the hidden layer could estimate IPMC displacement and blocking force with the highest accuracy. The detailed data are shown in Table 1 and Figure 6. It can be seen that the

| index | layers | \( R^2 \) | RMSE | epochs | accuracy |
|-------|-------|----------|-------|--------|----------|
| displacement | 2-9-1 | 0.88725 | 1.53160 | 16 | 2.25 \times 10^{-3} |
| blocking force | 2-9-1 | 0.93251 | 3.21854 | 8 | 2.58 \times 10^{-5} |
prediction results are highly correlated in general. The RMSE values of displacement and blocking force are 1.53160 and 3.21854, and DC values are 0.88725 and 0.93251, respectively. This indicates that the BPNN has a strong ability to characterize the bending behavior of IPMCs.

However, we also found from Figure 6 that there is a small amount of data that deviates from the target to a certain extent. To further improve the accuracy of the prediction, the optimization of the training structure for the hidden layer is shown in Figure 7. A hidden layer is added to the double hidden layer to train repeatedly as mentioned in the above process. The IPMC modeling results using the optimized NBBM are displayed in Table 2 and Figure 8. As for the displacement, the comparison between before and after optimization showed that the accuracy increased from $2.25 \times 10^{-5}$ to $4.14 \times 10^{-7}$, $R^2$ from 0.88725 to 0.95155, and RMSE from 1.53160 to 1.027114. Similarly, for blocking forces, the accuracy and $R^2$ improved one magnitude and 5.82%, respectively, while RMSE decreased about 56.93%. Therefore, the neural network structures of the layers (2-9-3-1 and 2-9-4-1) are selected, which have high precision and are suitable for IPMCs. After 9 and 13 iterations, the systems quickly converge and the system’s error reaches the training target.

Meanwhile, the modeling diagram for using the optimized BPNN model is then displayed in Figure 9. The actual actuator response is compared with the estimated response by the optimized BPNN model. From this figure, the predicted values of each point are basically consistent with the experimental values. It is clear that the optimized NBBM model can accurately estimate the displacement and blocking force of IPMCs. The comparison results demonstrated convincingly that the optimized BPNN always provides the best results in predicting behavior. The BPNN model provides a theoretical basis for the selection of the stimulating voltage and the design of the dimension ratio.

The BPNN with the mentioned optimum designation is successfully incorporated to numerically model the actuation characteristics of the investigated Cu-IPMC. Moreover, as indicated in the results, the well-trained ANN has better prediction capability over the displacement and blocking force model considering stimulating voltage and dimension ratio. This examination confirms the outstanding function estimation potential of the multilayer BPNN to simulate the actuation property of this Cu-IPMC.
3. CONCLUSIONS

Predicting the actuation property of Cu-IPMCs accurately is quite important and indispensable for improving the reliability of IPMC applications. We propose the LMA−BPNN model to predict the actuation property of the Cu-IPMCs. The model is based on the recurrent multilayer perceptron neural networks and optimized the weight and threshold of the randomly initialized BPNN by the Levenberg–Marquardt algorithm (LMA). Based on the input/output training data, the most suitable BPNN model structure was found out to represent the IPMC actuation behavior. The optimized BPNN model has been investigated to evaluate the modeling accuracy. After calculation, an RMSE of 1.03 and a DC of 0.95 for displacement and an RMSE of 1.26 and a DC of 0.99 for blocking force were obtained, which manifest that the model can provide a good reference value for IPMCs. The optimized BPNN can better describe the bending of the IPMC actuator and accurately predict the displacement and blocking force of the IPMC.

4. EXPERIMENTAL SECTION

4.1. Materials. Naion 117 membranes (A sulfonated tetrafluoroethylene-based fluoropolymer–co-polymer) with a thickness of 0.183 mm were used as the substrate membranes. Platinum is usually used as the electrode material, and we deliberately choose copper-substituted platinum. The unstable corrosive copper is beneficial for the improvement of IPMC performance.

4.2. Preparation of Cu-IPMCs. As shown in previous studies, to increase the interfacial area and enhance adhesion, the surface of Naion was roughened using sandpaper and ultrasonically cleaned in deionized water. The membranes were soaked in 3 g/L silver nitrate for 12 h and then immersed in the plating solution for electroless copper plating. Finally, they were immersed in a lithium chloride solution to let the H+ ions of Naion get replaced with small Li+ ions. After the preparation steps were complete, the IPMCs are ready for further use.

Figure 8. Correlation between experimental and predicted IPMC displacement for the 2-9-3-1 structure (a) and blocking force for the 2-9-4-1 structure (b).

Figure 9. Comparison experimental and predicted IPMC displacement for the 2-9-3-1 structure (a) and blocking force for the 2-9-4-1 structure (b).
was cut into different sizes (40 × 10, 30 × 10, 20 × 10, 10 × 10 mm²; free-moving end).

4.3. Performance Test. The microstructures and morphologies of the IPMCs were characterized using scanning electron microscopy (SEM, JEM 2010). The displacement and blocking force of the Cu-IPMCs were measured by a digital camera (a frame grabber) and a load cell (FA2004, 0.0001 g) in the test setup composed of a signal generator, a power amplifier, a DC power supply, and a DAQ. The experiments were carried out at room temperature, and the average value over three measurements was adopted.

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**NOTES**

The authors declare no competing financial interest.

**ACKNOWLEDGMENTS**

This work was financially supported by the Key Science and Technology Program of Shaanxi Province, China (2016KZTDGY-02-03).

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