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ORIGINAL ARTICLE

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Development of an artificial neural network to predict lead frame dimensions in an etching process

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Abstract The electronic industry is rapidly developing, creating high demand for IC production. Etched semiconductor lead frames are the basic material used in IC packaging. IC packaging requires high-precision lead frames. The dimensions of the pilot hole are generally required to be highly precise in lead frame manufacturing. The photo-etching process must control the dimension of the pilot hole and record the manufacturing data of the etching machine and inspection data. This study presents the development of an artificial neural network (ANN) model that can be applied to construct the predicting model. The predictive model can estimate the dimensions of the pilot hole and thus determine the process parameters needed to improve lead frame quality in the etching process.

Keywords Artificial neural network · Lead frame · Photo-etching

1 Introduction

The electronic industry is developing rapidly, stimulating high demand for IC production. IC packing is the final step in IC manufacturing. Lead frames are important metal products in IC packing and can send signals outside for wire bonding with accuracies of a few micometers micrometers [1–4]. An etching process is used to manufacture the high-precision lead frame. The etching of a lead frame utilizes advanced manufacturing and measurement equipment to produce high-precision and high-quality products. The automatic etching process is controlled by some of the etching machine parameters. These parameters must be adjusted to produce a high-precision lead frame. The etching machine generally records the manufacturing parameters of the etching process, and then uses Statistical Process Control (SPC) to inspect the lead frame quality.

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The pilot hole of the lead frame is the main quality characteristic. The etching process has to control the mean of the dimension of pilot hole using SPC. The advanced (or automatic) process control (APC) includes a concept that adjusts process parameters to achieve a target value. Numerous time series approaches have been presented to predict the sample target value. APC analyzes and identifies time series models using the shape and structure of the simple autocorrelation and partial autocorrelation functions [5-8]. One model is identified for system prediction. The prediction system will improve the quality in the manufacturing process. Artificial neural networks have been applied to study time series problems for the APC system. These ANN models include the backpropagation (BP) learning strategy and the recurrent neural network (RNN) [5]. The time series models are generated based on inspection of the sample data for the APC system.

In this study, APC is applied to improve lead frame quality in the etching process. A backpropagation neural network is used to generate the prediction model based on etching process data. This ANN model uses the manufacturing parameters of the etching process and forwards period inspection data $(x_{t-1}, x_{t-2}, \ldots, x_{t-n})$ as the numbers of the input nodes. The etching process data and inspection data were used to construct the ANN time series model. After training the network, the model predicted the dimension of the pile hole of the lead frame in the APC system. Moreover, the ANN predicting model could be applied to determine the appropriate etching condition to achieve a specific pilot hole dimension to improve the lead frame quality.

This paper is organized as follows: Sect. 2 describes the manufacturing process of etching the lead frame. Section 3 then outlines the artificial neural network. Next, Sect. 4 develops the application of the ANN model to predict the dimension of the pilot hole of the lead frame in the etching process. Finally, Sect. 5 discusses the performance of the prediction and draws conclusions.

2 Manufacturing process to produce an IC etched lead frame

The ideal IC etched lead frame has high precision and is defect free. Major processes in the manufacturing include the photomask and photo-etching processes. The photomask is designed using a CAD software system. The designs are then compensated and plotted onto photosensitive glass substrates using a precise laser photo plotter, after which the dimensionality is inspected and measured to ensure correct photomask development. To ensure a high-quality product, the work environment is controlled in a cleanroom environment (less than class 1000).

The process of photo-etching begins with the degreasing and cleaning of the raw material. After coating the material with photo-resist, the pattern on the photomasks is printed on both sides of the material using an exposing machine. The shape of the finished products is drawn on the material during the development process. The exposed portion of the material surface undergoes a chemical milling process using the etching machine. After stripping off the resist, the finished products are shipped following the inspections of dimension and appearance. To guarantee product precision and to prevent defects, the etching machine must strictly control the manufacturing parameters involved in the process, including temperature, humidity, and dust, as well as control the density, viscosity, and temperature of chemical liquids to preserve quality.

2.1 Photo-etching process

The photo-etching process includes a four-step manufacturing process. The process is described as follows:

Photoresist coating. The coating process begins with the degreasing and cleaning of the raw material, which helps to achieve good adhesion between the material and the photoresist.

Exposure. After coating the material with photoresist, the patterns of the photomasks are printed on both sides of the material with an exposing machine. Photoresist is a macromolecule material in a resin solution. Photoresist can be either positive or negative. The exposure process for this work uses negative photoresist. Figure 1 illustrates the exposing process. The exposure technology is governed by three main parameters: (1) the resolution represents the minimum dimensional error that the mask transfers to the photoresist, (2) the registration represents accuracy between the mask and pattern, (3) the throughput represents the sheets of exposing per hour.

Development. The development processes stabilizes the photoresist and reveals the patterns. The photoresist is baked, drying the material.

Etching. Following development of the material, the plasticized part does not rust due to the protection offered by the photoresist. Many caustic media can be used in the etching process. For instance, the compounds of $FeCl_3$ hydrofluoric acid and water can deal with steel and copper alloys. An alkaline medium can also be used for some specific metals. The outside surroundings become dented when metal is corroded by a medium solution. Figure 2 shows the etching reaction on the material and the etching process.

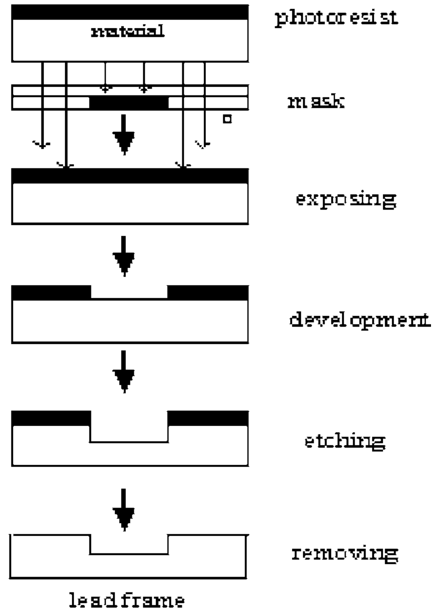

Fig. 1. Exposing and etching processes

2.2 Inspection of the etching lead frame

The etching lead frame must be manufactured to numerous dimensional specifications. Figure 3 shows the etching lead frame and dimension of the pilot hole. The pilot hole's quality is generally controlled by SPC. In the etching process, control charts (X-Chart, R-Chart) are used to monitor the process. Figure 4 shows 72 consecutive samples in the inspection process. The dimension of the pilot hole must be a controlled target value or close to a sample mean line. The etching machine strictly controls some manufacturing parameters to ensure the exact dimension. The value of the etching parameters is adjusted based on past manufacturing experience. This study uses the manufac-

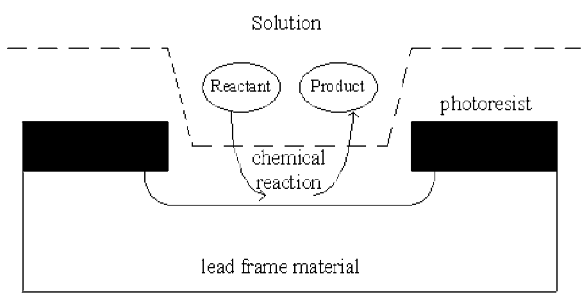

Fig. 2. Etching reaction on the material and the etching process

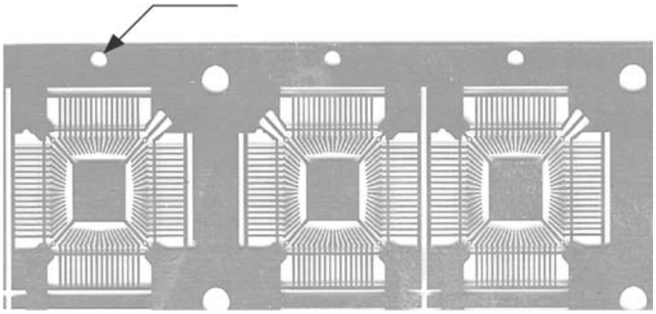

Fig. 3. The pilot hole of a lead frame

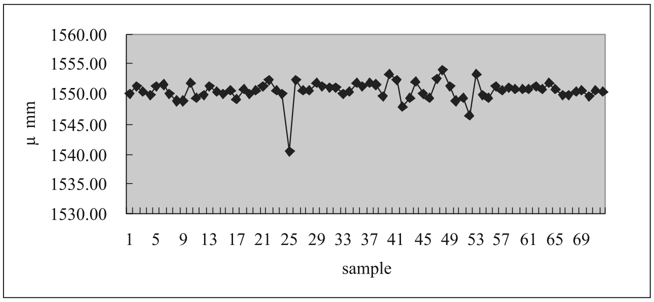

Fig. 4. Samples of a pilot hole

turing data and inspection data to construct an ANN model that will predict the dimension of the pilot hole in the etching process. The ANN model is applied to construct the APC system to improve the etching quality.

3 The artificial neural network (ANN)

A neural network is an algorithm that transforms inputs into desired outputs using highly interconnected networks of relatively simple processing elements (input nodes and output nodes). Neural networks are modeled on the neural activity in human brain. The three layers of the network architecture include the input layer, hidden layer, and output layer. A training algorithm is used to find the network weights for performing the network model. The artificial neural network is typically applied to the following problem areas:

1. Classification, function approximation, and prediction.
2. Clustering problems and optimization.

An ANN can accomplish many of these tasks more effectively than other approaches used to solve these problems. Many approaches apply ANN successfully to solve real engineering problems [9–12].

3.1 Backprogapagation network

Backpropagation networks consist of multiple layers of arranged neural nodes – neural nodes connected to each other through parameters called the weight (w_{ij}). Figure 5 depicts the three layers

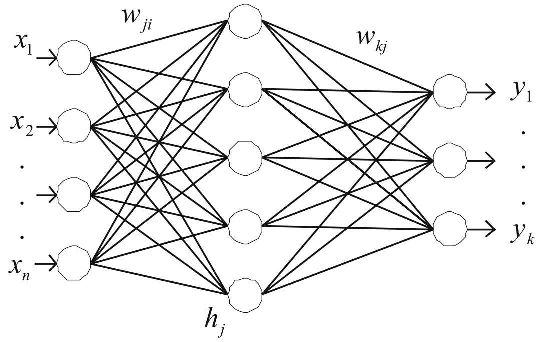

Fig. 5. The backpropagation networks

of backpropagation networks: the input layer, one hidden layer and the output layer. In this case, the relationship between predicted value ($y_1, y_2 \ldots, y_k$), hidden nodes ($h_1 \ldots h_m$), and input node ($x_1, x_2, \ldots, x_n$) can be expressed as:

$$h_m = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{1}$$

$$y_k = f\left(\sum_{j=1}^{m} w_{kj} h_j\right) \tag{2}$$

$f()$ is the activation function. An activation function for a backpropagation net should have several important characteristics. They should be continuous, differentiable and monotonically nondecreasing. Three types of sigmoid functions are usually used, as follows:

$$f(x) = \frac{1}{1+e^{-x}} \quad \text{range } (0, 1) \tag{3}$$

$$f(x) = \frac{2}{1+e^{-x}} - 1 \quad \text{range } (-1, 1) \tag{4}$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad \text{range } (-1, 1) \tag{5}$$

The sum of the square residuals is minimized during the training process.

$$\sum_{s=1}^{t} (y_s - \hat{y}_s)^2, \; t = \text{ number of training patterns } (1, 2, \ldots, t). \tag{6}$$

The correction of the weight (Δweights, Δw_{ij}) is proportional to error obtained and uses the gradient descendent procedure; also, the delta learning rule is used.

$$w^{\text{new}} = w^{\text{old}} + \Delta w \tag{7}$$

$$\Delta w_{kj} = \eta \delta_{kj} y_k + \mu \Delta w_{kj}^{\text{previous}}, \quad \text{for the output layer.} \tag{8}$$

$$\delta_{kj} = (y_k - \hat{y})\hat{y}_k(1-\hat{y}_k), \quad \text{if } f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

$$\Delta w_{ji} = \eta \delta_{ji} h_j + \mu \Delta w_{ji}^{\text{previous}}, \quad \text{for the hidden layer.} \tag{10}$$

$$\delta_{ji} = h_j(1-h_j)\sum \delta_{kj} w_{kj}, \quad \text{if } f(x) = \frac{1}{1+e^{-x}} \tag{11}$$

η is the learning rate, which determines the speed of the weight change. μ is the momentum, which allows an escape from a local minimum, usually between (0.01–0.9). δ is a correction factor that depends on the layer including the output layer and hidden layer. The delta learning rule is used to change the weight in the each training iteration. All training patterns train the network and the weights are adjusted according to Eq. 6. The prediction is carried out using Eq. 2. The input – a vector, $(x_1, x_2, \ldots, x_n)$ – will predict the value $\hat{y}(y_1, y_2, \ldots, y_n)$ for the output node.

3.2 Application of an ANN to solve time series problems for APC

The advanced process control (APC) approaches are applied to detect autocorrelation and to forecast the system behavior accordingly. The main steps are as follows [3]:

1. Identification of the model behind the data.
2. Estimation of the parameters for the identified model.
3. Validation of the model.
4. If the model is correctly validated, use it for a prediction. Otherwise, identify a new model.

Neural networks are used to compute models for time-series forecasting. The network model has one input layer, one hidden layer, and one output layer. In a time-series forecasting problem, the past observations $(y_t, y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ will be used as input nodes. The hidden layer is composed of nodes that are connected to both the input layer nodes and output layer node. The output layer has an output node. The node is the predicted value of the $t+1$th period. Figure 6 is the feedforward neural network model for a time series. Neural networks have been widely used for forecasting problems [10]. The ANN models are nonparametric methods that do not require any assumptions about the forecasting model form. The neural network is a nonlinear model that finds the approximate function between the input variables and output variables. The complex real-world data takes a nonlinear model to forecast. The ANN models can approximate any complex function with arbitrary accuracy given a large enough network. The models have a good forecasting ability for an APC system.

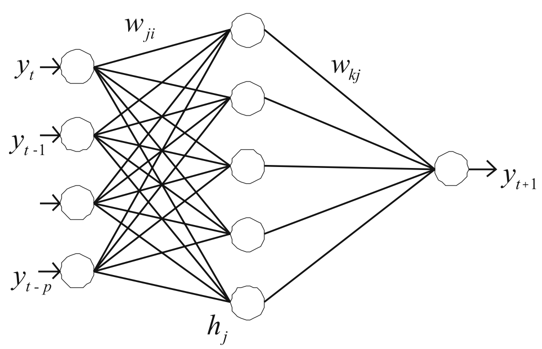

Fig. 6. Backpropagation networks for a time-series problem

4 An artificial neural network to predict the pilot hole of the lead frame in the etching process

APC can be adjusted to compensate for drift in process output, after which a series of regular adjustments to manipulate the variable can keep the process output close to the desired target. The etching process must control the mean of the dimensions of the pilot hole. The $\bar{X}$ chart described the process disturbance. The etching process must monitor the manufacturing parameters and inspect the sample mean of the pilot hole. In this study, we used the etching process data from a lead frame manufacturing company in Taiwan. The etching process must record the manufacturing data and inspection data every 15 minutes. The 72 etching process records are used to construct the ANN model for the APC system, and then the next 26 records are used to examine the ANN prediction model. The ANN model predicts the dimension of the pilot hole to control the dimensions in the target value or at the centerline of $\bar{X}$. The predicting model effectively maintains process stability and supports the adjustment parameters of the subsequent etching process.

4.1 The ANN architecture of the prediction model

The input parameters that significantly influence the dimension of the pilot hole in the etching process must be identified. The input data is mapped onto the output to achieve the desired accuracy. The input nodes in this study include both the etching process data and inspection data. The input parameters are as follows:

Manufacturing data of the etching process:

1. Be: Blaume value of etching solution in time period t.
2. pH: pH value of the etching solution in time period t.
3. ORP: ORP value of etching solution in time period t.
4. ET: temperature of the etching solution (°C) in time period t.
5. Speed: material speed (mm/min) in time period t.
6. Roll number: etching roll number in time period t.

Inspection data:

7. $y(t)$: sample mean in time period t.
8. $y(t-1)$: sample mean in time period $t-1$.
9. $y(t-2)$: sample mean in time period $t-2$.
10. $y(t-3)$: sample mean in time period $t-3$.
11. $y(t+1)$: sample mean in time period $t+1$.

Figure 7 shows the architecture of the ANN, which comprises 10 input nodes, 14 hidden nodes and one output node. The etching process usually references four inspection data from one hour prior. The inputs used are the last four results in the time series for continuing the process. The output node is the sample mean of the pilot hole in time period $t+1$. The ANN model is used to predict and control the etching process quality for the APC system.

4.2 Training process and prediction result

The ANN learning is performed using the training data to determine the weights of the network. The input patterns and target

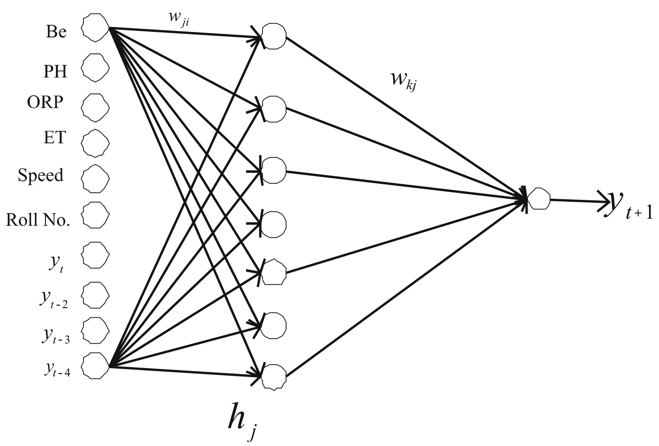

Fig. 7. Architecture of the present ANN

outputs are scaled within the range of 0.1 to 0.9. The learning rate is adjusted during the leaning process to accelerate the convergence. The value of the learning rate is 0.01–0.4. The momentum is 0.8 and number of training iterations is 400 000. In the training process, the root mean square (RMS) errors of the prediction is calculated based on the target output and predicted values according to the equation:

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}} \tag{12}$$

Figure 8 shows the prediction results following the training process. The results obtained RMS = 0.048. This study used the ANN model to predict 26 samples. Figure 9 shows the prediction results for the test process. The maximum prediction error is 7 μmm. Moreover, the tolerance of the pilot hole is 25 μmm. The ANN model can precisely predict the dimensions for controlling the APC system. The prediction model improves the lead frame quality in the etching process.

5 Conclusions

This investigation used an ANN to construct a prediction model based on the manufacturing parameters and inspection data in the etching process. APC and process adjustment were applied to detect autocorrelations and forecast system behavior. The ANN successfully predicted the dimension of the pilot hole of the etching lead frame. The prediction can enhance the quality of the etching process in the next etching stage ($t+1$). This study offers the following conclusions:

1. In the etching process, the manufacturing parameters and inspection data are input into the ANN model to control the dimension of the pilot hole in target. The network model supports the adjustment parameters to improve the etching process quality.
2. A good correlation was found between the test output of the ANN and the dimensions of the pilot hole. The prediction error does not exceed the tolerance of the pilot hole (25 μm).
3. The manufacturing data must be monitored during a high-precision etching process. The ANN model integrates the

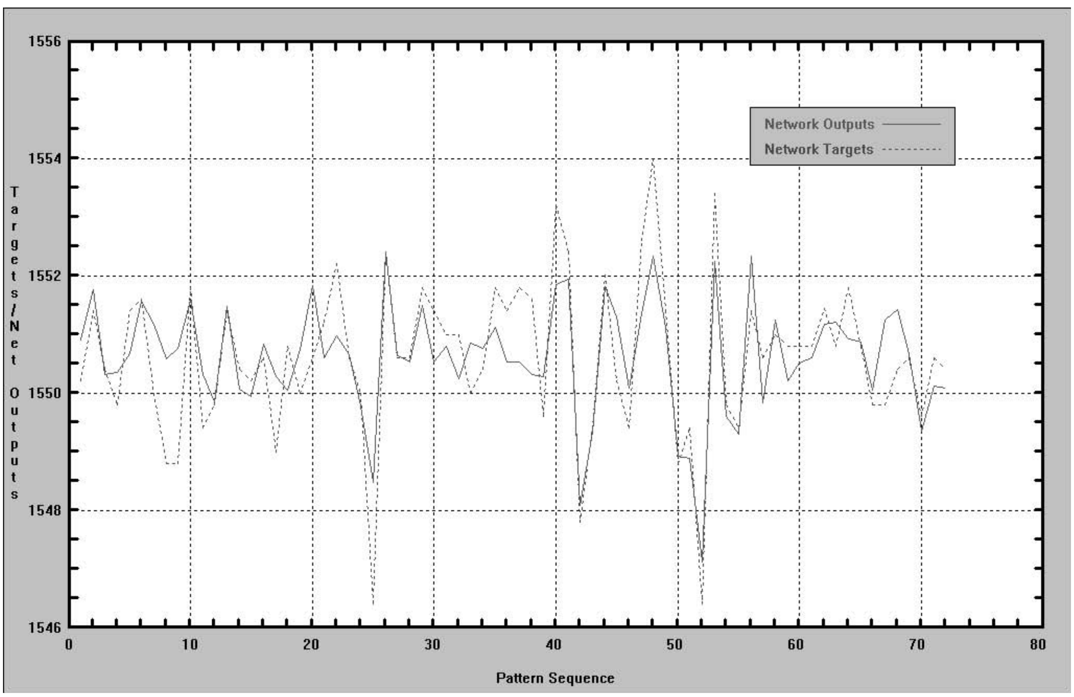

Fig. 8. Predicted values using the ANN model in a training process

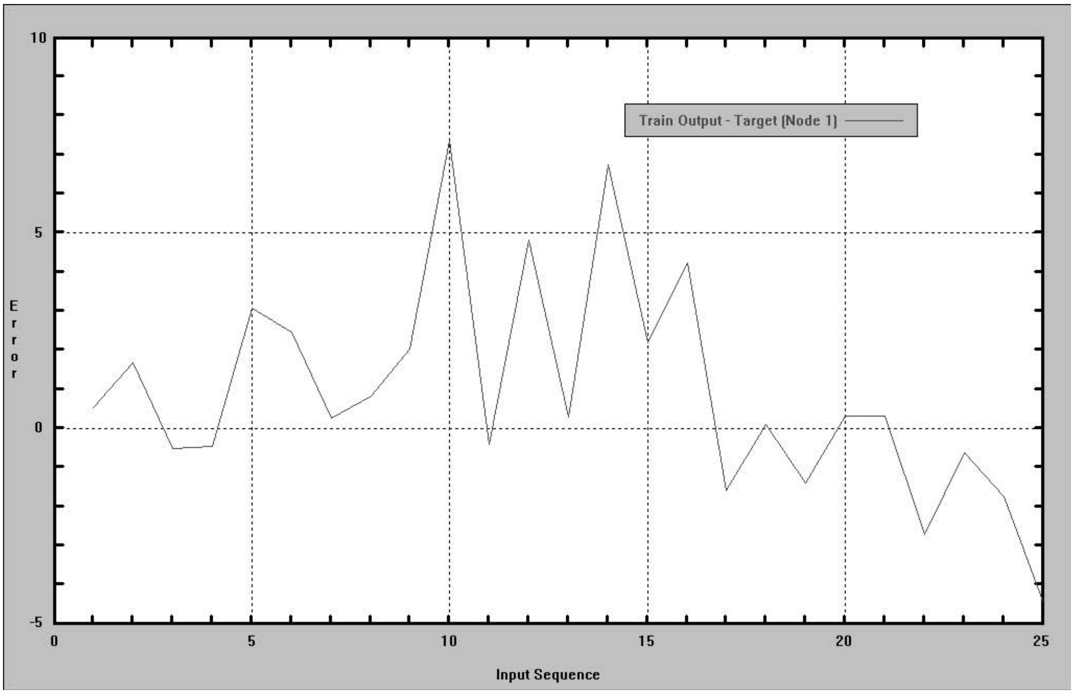

Fig. 9. The prediction error of test patterns using the trained ANN model

time series data and etching process parameters to construct the time series model. The prediction model predicts the quality of the etching process when the process parameters are changed.

4. The BP neural network requires 400 000 iterations to learn. The network spends a substantial amount of time in the training process. The learning time must be reduced.

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