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Using Artificial Intelligence in IC Substrate Production Predicting

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Technology industries are becoming increasingly competitive, and in such environments, the veracity of companies' decision-making directly affects the future development of enterprises. Therefore, the way in which an enterprise formulates and constructs a set of appropriate decision-making systems, to accurately predict future market trends, is a particularly important issue. In the study presented here, an artificial intelligence-based prediction system was used to estimate manufacturing capacities and client demands, which can provide manufacturing managers with a point of reference for inventory arrangements, so that stockholdings can be adjusted appropriately to avoid excessive inventory levels. In recent years, neural networks have been widely and effectively applied to many prediction problems. A key reason for their popularity is that backward neural networks can be used to construct non-linear models. Here, we propose a prediction model combining grey correlation and a neural network, which can be used to establish a high-accuracy prediction system for integrated circuit (IC) production. Firstly, grey correlation analysis was used to screen for the most relevant factors. These were then inputted into the neural network prediction model for training and prediction. We found that the training prediction error and the empirical error value were about 14%, indicating good prediction ability and the suitability of the proposed prediction model for use in the case of IC substrate production. Our findings can serve as a point of reference for the design of other predictive systems and support accurate, convenient and fast decision-making that will enhance companies' competitiveness.

Keywords: artificial intelligence, IC substrate production, prediction, grey method, neural network

1. INTRODUCTION

In recent years, in response to changes in market demand, improvements in packaging processes and continuous growth in IC technology, flexible electronic packaging products have developed rapidly and have been widely used in the semiconductor packaging industry (among which is the chip on film (COF) innovation). The products of placement technology and flexible substrate-carrying technology are mainly used in the IC packaging process for panel displays. The finished products include flat-panel displays, notebook computers, mobile phones and other related electronic products. Since COF is the largest application in display driver IC packaging, the maturity of the technology is directly related to development and growth of the flat-panel display industry. According to the current market, COF driver IC packaging is mainly used for higher-end displays and has particular advantages, especially in driver IC packages that require thinner circuits, which can avoid

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loss of panel scraps due to driver IC bonding errors.

In recent years, the display industry (see Fig. 1) has been booming globally, and there is a global market for new COF soft boards. The next few years will be a period of high COF growth. COF is the carrier material for driver ICs and a key element of components, but demand for COF can be problematic in the flat-panel industry chain. Therefore, the COF industry is likely to become a strategic key component industry [1]. Global panel manufacturers continue to adjust their inventories, affecting global panel production. Industry demand for terminal products also affects the prosperity of the electronics industry. Compared with traditional manufacturing, the current production pattern of the electronics industry is more complex, with diverse and small product portfolios, unstable orders, quick turnarounds and other issues, coupled with factors such as the global economic downturn, rising unemployment and sluggish prosperity. All of these factors have an impact on supply and demand. The semiconductor packaging industry is a kind of order-to-order manufacturing service industry, with production based on customer orders. The demand for production capacity also varies with market demand and fluctuating inventory levels. However, changes can make it impossible to accurately provide capacity strategies as an investment benchmark. Therefore, the semiconductor packaging industry not only pays attention to information integration between upstream and downstream manufacturers, but also pays particular attention to issues of capacity strategy and application. In order to reduce inventory pressure, companies need to accurately predict the volume of orders from customers so that they can remain competitive and profitable, and stay ahead of their competitors. It is therefore crucial to have an efficient production-prediction mechanism [2].

In this study, the research object was COF products in the display driver IC packaging industry, and changes in future market output were explored. Compared with other manufacturing industries, this industry is particularly focused on continuous innovation. Finding ways to produce lighter, thinner and more durable products is a goal that needs to be pursued continuously. Therefore, establishment of an effective and accurate capacity-prediction system may improve performance and reduce cost backlogs caused by overproduction and avoid loss of orders due to shortages. After researching and collecting data, it was determined that smart prediction systems are more accurate than traditional prediction models. In particular, neural network research theories are widely used in the field of prediction. Therefore, this research adopted this type of prediction mode. The main research objectives were as follows:

(1) To focus on COF products and establish a production prediction model;
(2) To combine grey relational analysis and neural network predicting methods to predict output and improve prediction accuracy;
(3) To develop a model that can provide companies with a more objective and accurate prediction method in practice, thereby reducing company costs.

Generally speaking, IC carrier boards are divided into four categories: (1) material properties; (2) packaging form; (3) connection technology between the chip and carrier; and (4) the number of packaged chips. Other categories can also be created, based on these four initial categories. In this study, data on monthly requirements for IC carrier boards were used, and the network training data related to the period from January 2018 to December 2019 [3, 4].

The first section of this paper presents the research background, motivation for and contributions of the study. Section 2 focuses on relevant work, grey theory and recurrent neural network (RNN) methods. Section 3 includes the research design and method. Section 4 comprises the experimental results analysis and comparison, and Section 5 presents the conclusions and suggestions for future work.

2. LITERATURE REVIEW

2.1 IC Carrier Board Manufacturing Process and Application

(1) IC carrier board: At present, IC substrate technology can be divided into two categories, one of which is rigid IC substrates, such as ball array (BGA), flip chip (FC), wire bonding (WB) and chip-level packaging (CSP). The other type is soft IC carriers, such as TCPs (tape carrier packages) and reel chip carrier packages, COG (chip on glass) flip glass, and COF flip chip packages (chip on film). The soft IC carrier board can be divided into CSP/BGA, TAB, COG and COF. As the screen resolution increases, the number of driver IC pins also increases, making the IC pin pitch increasingly small. According to IEK statistics, the main foot pitch of an IC driver will be reduced from the previous range of 40um–50um to 35-40μm. Due to the limitations of materials and manufacturing processes, a TCP carrier board will not be able to compete with a COF carrier board due to the significant decrease in yield rate when the driver IC pitch is reduced to 35-40μm [5, 6].

COF carrier boards are large, highly stable and heat-resistant so are more suitable for high-density packaging; they are also characterized by high bendability and thin packaging, and they can hold passive components in place and help drive ICs. Therefore, COF carrier boards will gradually replace TCPs, become the mainstream of driver IC packaging and gradually be applied to markets such as liquid-crystal display (LCD) TVs and plasma display panel (PDP) TVs. Many domestic manufacturers have stopped using TCPs and switched to the next generation of COF product lines. To reduce component costs, downstream LCD panel manufacturers are bound to support COF substrate manufacturers more actively. Once manufacturers can achieve effective breakthroughs in product yield control, they will greatly expand their production capacity and further divide the driver IC substrate market. There are few installations, and the production cost is significantly higher than that for hard substrates. In recent years, with the rapid development of IC substrate technology, flexible CSP/BGA substrates have gradually been replaced [7, 8].

(2) Classification of IC carrier boards: In the current industrial structure, IC substrates can be classified according to materials, electroplating types, product circuit specifications and application areas, as follows: material, *e.g.*, a three-layer material or flexible copper-clad laminate (FCCL). IC substrates made from this type of material are called COF products. Because this material is thinner, the precision is higher than that of a TCP, and the process cost is lower. IC substrates can be classified according to the route, *e.g.*, the end customer's application requirements and product design specifications. Two types of designs can be distinguished, *i.e.*, gate and source. IC substrates can also be classified according to the electroplating category.

(3) IC carrier board manufacturing process: The production process for flexible IC substrates will be adjusted according to the needs of end users, product categories and material form specifications, and there will be different production sequences or process adjustments.

2.2 Prediction Definition

(1) Method of prediction: The overall production plan is based on predictions, and without accurate predictions of production demand, production plans cannot proceed smoothly. Prediction methods are divided into three categories: (1) qualitative methods; (2) time series analysis and projection; and (3) causal models; in addition to these three categories, there are six categories of statistical prediction methods, artificial intelligence and grey system theory. Traditional prediction methods are relatively effective, but with technological advances, information technology has become more and more sophisticated, and more computationally complex models have been developed. Previous prediction models could not meet the demand adequately, and artificial intelligence-based prediction methods and models have emerged as a result. Artificial intelligence refers to computer systems or computer programs with human-like behaviour and knowledge, including reasoning and problem-solving, knowledge storage and learning, and the ability to recognize and interpret human language [9, 10].

(2) Smart prediction methods: In artificial intelligence-based systems, computers can be used to simulate human learning processes and knowledge organization, including expert systems, fuzzy theory, artificial neural networks and genetic algorithms. With the grey theory method, the information is incomplete, and numerical estimates can be calculated. The mode of operation is relatively simple; the modeller does not need to have a deep statistical foundation, and the amount of data required is very small, so it is suitable for use when there are insufficient data or data are difficult to obtain. With statistical prediction, surveys and statistics are conducted for different objects according to projects and goals, and the predicted development trend for a project is determined. This method is used to analyse current development of the thin film transistor (TFT) panel industry and future development trends. It can also be used to explore the relevance of the TFT panel industry's capacity utilization rate and the business performance of the TFT panel industry under the pressure of global market competition, so that specific suggestions can be made for planning future production capacity and capacity utilization strategies to be adopted [11].

2.3 Grey Association Analysis

Grey system theory focuses on the uncertainty of a system model and the incompleteness of system data, relational analysis, model construction and use of prediction and decision-making methods to analyse and discuss system conditions. Grey theory can be used for multi-inputs and where there is a lack of certainty or insufficient discrete data. Efficient analysis has a wide range of applications. Application of grey system theory to management and engineering can be roughly divided into grey generation, grey relational analysis, grey models, grey prediction, grey decision-making and grey control. These six types are as follows:

(1) Grey generation: Grey generation is used in the processing of supplementary information data. It can be used as a means of reducing randomness in messy data, and it can reveal hidden rules and characteristics, which can then be used to improve and modify the regularity. This method operates at the data transformation level, and the purpose is to discover laws among the data.

(2) Grey relational analysis: Grey relational analysis focuses on comparison of the evolution of a system development pattern and quantitative description. According to the mathematical foundation of space theory, there are four theorems (proximity, symmetry, integrity and standardization), used to confirm the analysis and comparison. The degree of correlation between the sequence and the reference sequence is calculated, along with the correlation coefficient. Grey correlation is a quantitative method used to measure and evaluate the degree and size of the correlation between various factors, and to identify the key factors and characteristics that affect things or the target value, so that the system in question can become faster and more effective. Grey relational analysis has the following advantages: the calculation method is simple; the sample sizes are small; and the data do not have to conform to a typical distribution. Therefore, it is suitable for dealing with prediction models with unclear and incomplete data [12].

(3) Grey model (GM): The model or differential equation of grey theory is established by using the data in the generation process to generate a set of grey differential equations and grey differential equation models, which is called grey modelling.

(4) Grey prediction: Using existing data, the GM prediction model (1, 1) can be used to find out the future state of each element in a certain series. According to its purpose, it is divided into the following four types: (1) data prediction: a series of predictions is made based on the size of the data, such as numerical predictions; (2) anomaly prediction: prediction of whether an abnormal phenomenon will occur within a certain period of time is often used for weather or disaster prediction; (3) graphical predictions: these predictions are made by constructing graphics for development of existing data; and (4) system predictions: for these, GM(1, 1) and GM(1, N) models are combined to predict multiple variables in a system and to predict the relationship between different variables [13].

(5) Grey decision-making: When a certain event occurs, it has different effects due to different countermeasures, and the decision made by combining countermeasures with the GM(1, 1) model is called a grey decision.

(6) Grey control: Grey control determines the regularity of development behaviour through system data in order to predict future behaviour. When a predictive value is obtained, this is sent back to the system for application of system control law, which belongs to the feedforward control method. This is similar to artificial intelligence and has the function of self-adjustment. The sales volume and share of the automobile market and the sales volume and share of the mainland automobile market are statistical data, and the GM(1, 1) model in the grey theory can be used as a research method to predict the sales volume of the mainland automobile market, and compare this with the time series method, expert prediction method and other methods. Empirical results have shown that the average accuracy of

the GM(1, 1) model for predicting the mainland automobile market is more than 90%, indicating that the grey theory system is also applicable to the automobile industry.

2.4 Neural Networks

Hidden layer learning algorithms have facilitated a resurgence of neural networks and new breakthroughs. The current definition of an artificial neural network is a computing system that includes software and hardware, and consists of numerous non-linear computing units (neurons) and connections between these computing units. Calculations are generally performed in a parallel and decentralized manner, so that a large amount of data can be processed at any one time. This design can be used to solve various applications requiring calculation of large amounts of data, such as vehicle engine diagnosis and electronic circuit diagnosis, *etc.* As neural networks can deal with non-linear operations and learning, they have excellent performance in certain fields. They are widely used for diagnostic and classification problems and have an extensive range of applications. Neural networks have the following characteristics: parallel processing, fault tolerance features, associative memory, optimization, storage capacity and inductive ability [14].

There are many types of network modes in the class of neural networks. The most representative learning mode among neural networks is the backward neural network, and this is also the most common mode. Backward neural networks are supervised learning networks, so they are especially suitable for diagnosis and prediction applications. Experimental results have shown that the hybrid artificial intelligence method is significantly better than the two traditionally used prediction methods (grey prediction and regression analysis), when evaluating prediction errors and accuracy. MIMO process prediction and a control mode can be established with a backward neural network. The two neural networks are used to establish the process output prediction mode and the process adjustment mode. At the same time, the backward neural network is used to establish the process input and output relationship model, which is used to verify the prediction ability of the neural network and the benefits of the controller [15, 16]. Objects can be evaluated and the prediction and control model of the process used to compensate for the error caused by interference. Research results have shown that backward-propagation neural network prediction and a controller can effectively control the interference output and reduce changes caused by process interference. Future research can consider control cost factors in order to optimize process control [17, 18]. By combining the empirical mode decomposition method and a neural network, data can be decomposed into several intrinsic mode functions via the empirical mode decomposition method and the decomposed signal used for prediction, combined with a neural network (NN), for analysis of stock-price time series data. A new method has been proposed for analysing signals, to evaluate the results of predictions, which can be used as a basis or indicator for future stock-price estimation [19, 20]. Research has shown that this method produces better stock-price predictions than a single BPN prediction model in terms of MAPE, MSE, MAD, DS and CD evaluation indicators, used in combined EMD and BPN prediction models. EMD removes noise from the original data, and after analysing the phase characteristics, it can effectively improve the accuracy of BPN model predictions [21, 22].

3. RESEARCH METHODS

3.1 Industry Demand

The IC substrate industry is related to the IC manufacturing industry. Therefore, in this study, five manufacturing and related industries were selected, and the following indicators were used:

(1) Electronics manufacturing sales volume index: This index is a measure of the relative change in product sales volume in a certain period and the base period.

(2) Electronics manufacturing production index: This index is a measure of relative changes in the production volume of the overall manufacturing sector at a certain time and during the base period.

(3) Computer communication and audio-visual electronic product index: This was used as computer communication and audio-visual electronic products account for a high proportion of IC products. This index measures relative changes in production of computer communications and audio-visual electronic products at a certain time and during the base period.

(4) The production index of electronic components: Electronic components are used in all kinds of electronic products, and IC downstream products also rely on various electronic components. Therefore, the relationship between the electronic component industry and IC products was also considered in this research, and the relevant indicators of the electronic components industry in the electronic component production index were used.

(5) The output of packaged ICs: The substrate is the chip that provides load-bearing and heat-dissipating functions during the assembly process. In response to assembly requirements for high pin counts, high performance and heat dissipation, a carrier board carrying IC chips and signal connections is currently the most cost-effective. Increasingly complex circuits with peripheral pins and area array pins can mean greatly increased numbers of pins and a reduction in the volume of the overall package. Therefore, the output of packaged products also needs to be considered.

(6) Downstream demand: In recent years, consumer electronics products have become highly developed, which has driven the demand for optoelectronics and semiconductors. According to one survey, more than 70% of downstream products of IC substrates in the region are used in computers and peripheral equipment, and about 20% are used in communication products. IC products are key components of electronic products. From the data, it is known that half of the output of IC products comes from information hardware, with the main products being notebook computers, desktop computers, motherboards, servers, picture tube monitors, LCD monitors and mobile phones. The total value of digital cameras and other products accounts for nearly 90% of the total output value of the information hardware industry. With popularization of mobile communication systems and development of mobile products, the digital age has driven the consumer market for audio-visual entertainment products and increased demand for related equipment.

3.2 Grey Relational Method

The main function of grey correlation analysis is to measure the degree of correlation between different sequences. Grey correlation analysis entails quantitative analysis of the dynamic development process of a system. It is based on the degree of similarity or difference between factors in the development situation. When measuring the degree of correlation between factors, the closer the development trend, the greater the correlation between factors. Grey correlation analysis is a practical analysis method, which can be used in cases where the amount of data is insufficient or cannot meet the specific allocation, to analyse the relationship between factors. It is more practical than the regression model or econometric models commonly used in traditional statistics. The grey relational method has the following features: (1) it does not require a large amount of data; (2) it does not need to assume that the data in the series of comparisons conform to a specific distribution; (3) the established model is a non-functional sequence model; (4) the calculation methods are simple. Grey relational analysis was used in this study to screen for the most suitable prediction factors. The main steps are as follows:

Step 1: Determine the analysis sequence: Suppose the original sequence is

$$X_i(k) = [X_i(1), X_i(2), \ldots, X_i(n)]. \tag{1}$$

Among these, $i = 1, 2, ..., m \in N$, representing a total of m sets of numbers (influence factors); and $k = 1, 2, ..., n \in N$, representing that each series contains n factors (items of data). Therefore, Eq. (1) can be written as follows:

$$\begin{aligned} X_1(k) &= [X_1(1), X_1(2), \ldots, X_1(n)] \\ X_2(k) &= [X_2(1), X_2(2), \ldots, X_2(n)] \\ &\ldots \\ X_m(k) &= [X_m(1), X_m(2), \ldots, X_m(n)] \end{aligned} \tag{2}$$

The group number sequence is defined as the reference number sequence as $X_0(k) = [X_0(1), X_0(2), \ldots, X_0(n)]$; the purpose is the m group number sequence associated objects, so m sets of sequences are called comparison sequences.

Step 2: Data pre-processing: Since the units used for each factor in the data are not the same, in order to avoid data extremes, the data must be normalized first; that is, all the data must be converted into the same interval. Generally speaking, normalization converts all data into values between (0, 1).

Step 3: Calculate the grey correlation coefficient: After pre-processing of m sets of numbers, the m sets of numbers ($X_i(k)$) can be converted into an m-dimensional array A. The array each column in A subtracts the reference number sequence and takes the absolute value, and the array A can be converted into an array Δ. Each element in the array Δ is denoted as $\Delta 0_i$, where the largest element is Δ max, and the smallest element is Δ min. The grey correlation resolution coefficient is defined as ρ; the main function is comparison of the background value and the object to be tested, and the value range is [0, 1].

Step 4: Grey relation: The grey correlation degree can express the correlation coefficient value between the comparison series and the reference series, but if there are n factors, there will be n grey correlation coefficient results, which will cause information to be scattered and will not be conducive to evaluation and comparison. Therefore, the grey correlation degree for each time sequence must be concentrated to a point, and this point is called the grey correlation degree. The grey correlation degree can be calculated according to the difference in weight, and there are two calculation methods, namely the equal weight correlation degree and the weighted correlation degree. Generally speaking, however, the grey correlation degree is mainly based on equal rights relevance.

3.3 Neural Network Method

An artificial neural network is a parallel calculation system, which includes hardware and software. It is composed of multiple artificial nerve cells (also called artificial neurons), large numbers of which form a network, imitating the ability of biological neural networks. In the current intelligent control field, artificial neural networks have become the mainstream of modern intelligent control. These computing systems are composed of many nodes (neurons) and are generally divided into three layers: the input layer, hidden layer and output layer. The input layer has no neurons and only input values. In the output layer, if there are only output values without neurons, then three neurons are included. Neurons between the input and output layers belong to the hidden layer, and the hidden layer is optional.

(1) The architecture of a neural network: The entire network can be divided into three elements, namely neurons (processing units), layers and networks.
(2) A backward neural network: Backward neural networks are widely used. The network architecture of a backward neural network is the multilayer perceptron (MLP), and a commonly used learning algorithm is the error backward algorithm (error back propagation, EBP), referred to as the BP (back propagation) algorithm. This combination (MLP+EBP) is called a back-propagation neural network (BPN).

The basic principle of the backward neural network is to use the concept of the steepest descent to minimize the error function. Generally, the learning process will proceed one training example at a time, until all learning and training examples are completed, that is, a learning round. A network can learn training examples repeatedly until the network learning achieves convergence.

The standard architecture of the backward neural network can be divided into two parts, as follows:

(1) Data forwarding: This means that the output value of the input layer is passed to the neurons of the hidden layer after the integrated function operation, and the neurons of the hidden layer are converted into output values via the conversion function through the value obtained in the integrated function. This output value passes the integration function to the output layer, and the output layer uses the value obtained in the integration function to convert it into an output value through the conversion function.
(2) Backward propagation of errors: So-called error back propagation compares the value obtained from the output layer with the actual value, and then adjusts the weight from the

output layer to the hidden layer and the hidden layer to the input layer according to this error value. The calculation steps of the backward neural network are as follows:

Step 1: Set network parameter values and conversion functions
Because the range of input variables is very different, some input variables with a smaller range may lose their effect, which makes the weight error of the network become larger during training. Therefore, it is necessary to normalize each input variable to change the value of the variable. The minimum and maximum values are mapped to the expected minimum and maximum values. This is called the interval response method.

Step 2: Initialize weights and partial weights
Before learning, it is necessary to initialize the weight of each neuron connected within the network and set the initialized weight value to a very small random value. Too large a weight can easily lead to unit saturation and make the network error higher. Therefore, a small initial weight value can make the network easier to converge.

Step 3: Calculate the hidden layer output
For each hidden layer neuron, the sum of the products is calculated from the corresponding weight.

Step 4: Calculate the output of the output layer
For each neuron *k* in the output layer, the sum is calculated from the product and the corresponding weight, and converted through a conversion function.

Step 5: Calculate the weight correction value between the hidden layer and the output layer
The difference between each output value and the actual value is calculated, and also the weight correction value between the hidden layer and the output layer, and the weight correction value of the hidden layer partial weight.

Step 6: Calculate the weight correction value between the input layer and the hidden layer
For each hidden layer neuron, the total error in value from the output layer is calculated, and the error value of each neuron. The weight correction value between the input layer and the hidden layer and the weight correction value of the bias weight of the input layer can be calculated, along with the learning rate of the network.

Step 7: Adjust and update the weights and partial weights of each layer.

Step 8: Test whether the network stop condition has been reached.
If the network stop condition is not met, the system proceeds to Step 2. If the network stop condition is met, the network learning is ended. The termination conditions reached by the network can be divided into four methods:
(1) Learning times: Specifying the network to complete the pre-set number of learning times can be used as one of the conditions for the network to end learning. In this study, this method was used as the network stop condition.

(2) Gradient method: The learning achieved by the inverted transfer network enables it to change to the direction of the maximum slope. When the gradient is unchanged or the gradient change is small, the weight will not change at this time, and the learning will stop.
(3) Mean square error: When the root mean square error value of the network is less than a certain convergence value, having reached a certain degree of convergence, the network stops learning.
(4) Cross-validation: The samples are divided into training and test data. One set is used as a training dataset, and the other set is used for testing. If the error level of training and testing is less than a certain set value at any one time, the learning can stop. If the training is good but the test is not good, this indicates over-learning; if the training is not good but the test is good, this indicates under-learning.

4. EXPERIMENT ANALYSIS

4.1 Evaluation Index

In order to evaluate the prediction accuracy and prediction error performance of each model, the following evaluation indicators were used, namely the mean absolute percentage error (MAPE), the mean absolute deviation (MAD) and mean square error (MSE):

(1) Mean absolute percentage error (MAPE)

$$MAPE = \tfrac{1}{n}\sum_{i-1}^{n}\frac{|F_t - A_t|}{A_t} \tag{3}$$

F_t: prediction value for period t
A_t: actual value for period
t_n: number of periods

(2) Mean absolute deviation (MAD)

$$MAD = \tfrac{1}{n}\sum_{i-1}^{n}|F_t - A_t| \tag{4}$$

F_t: prediction value for period t
A_t: actual value for period
t_n: number of periods

(3) Mean square error (MSE)

$$MSE = \sum_{i-1}^{n}(y_i - y_i^p)^2 \tag{5}$$

In the evaluation method above, the smaller the value the better; smaller values will have a higher level of agreement between the estimated results of the prediction model and the historical data. In this study, in order to achieve an objective and fair evaluation standard, MAPE was chosen as the accuracy measure for the evaluation and prediction results.

Table 1. The grey relation for ICs.

Three levels	Impact factor	IC	
		Grey relational degree	Grey relational degree > 0.7
Overall economy	Unemployment rate () %	0.66	
	Unemployment rate (global) %	0.76	△
	National economic growth rate %	0.58	
	Import value	0.68	
	Export value	0.73	△
	Average gross domestic product	0.75	△
	Consumer price index	0.73	△
	Domestic boom indicator	0.59	
Industrial manufacturing	Electronics manufacturing sales volume index	0.74	△
	Electronics manufacturing production index	0.73	△
	Computer communications and audio-visual electronic products	0.67	
	Electronic components production index	0.75	△
	Package IC output	0.73	△
Downstream demand	TV monitor sales	0.66	
	Laptop sales	0.73	△
	Mobile phone sales	0.64	
	Tablet PC sales	0.67	

4.2 Application of Grey Relational Analysis

The 18 factors related to COF packaging products were divided into three levels for discussion purposes. However, the difference in degree of impact on packaging production between the factors considered affects the prediction results of the inverted neural network. To reduce the level of error in the prediction results, grey correlation analysis was performed on various factors in the historical data, and factors with a high degree of correlation with the prediction standard were selected as the basis for selection of input factors for the backward neural network. To improve the accuracy of the predictions, we firstly determined the grey correlation degree between 18 factors and the COF packaging production volume of the prediction target, set the selection factor to a correlation degree of more than 0.7 and selected a total of nine factors, as shown in Table 1. The nine factors are as follows: unemployment rate (global), export value, average domestic production, consumer price index, electronics manufacturing sales volume index, electronics manufacturing production index, electronic component production index, package IC production and NB computer sales.

Three levels of factors were selected on the basis of the grey correlation analysis of the above COF products. Among these, four factors had a relevance greater than 0.7 at the overall economic level and industrial manufacturing level, while there was only one at the downstream demand level. It can be seen from Table 1 that the production volume of COF products has a greater correlation with changes in overall economic and industrial manufacturing levels. The downstream demand level will be affected by the timing of sales inventory processing, so it initially seems that the correlation is low.

4.3 Prediction of Backward Neural Network

The BNN model has different parameters (*e.g.*, number of hidden layer units, learning rate and inertia factor), set to distinguish different modes and separate the data, which are then inputted into the BNN to start learning and training. The steepest descent method was adopted for weight correction. Once the training was complete, the training datasets were used to test the prediction performance of the network, as shown in Table 2.

(1) Parameter setting

Table 2. Neural training parameter setting.

Input layer	X_1: Unemployment rate (global) X_2: Export amount X_3: Average domestic production X_4: Consumer price index X_5: Electronics manufacturing sales volume index X_6: Electronics manufacturing production index X_7: Electronic components production index X_8: IC production X_9: Notebook computer sales (a total of nine input units)
Output layer	Y_1: IC production (a total of one output unit)
Hidden layer	There is one hidden layer, and the number of neurons in the hidden layer is 5, 10 and 15, respectively.
Initial learning rate	0.1, 0.5, 0.9
Inertia factors	0.1, 0.5, 0.9
Iteration cycles	10,000 times and 30,000 times

(2) Analysis of dataset for results of BPN training

Data for the period from January to December 2019 were used for the training dataset, and data for the period from January to December 2018 were used as the test dataset; 10,000 and 30,000 iteration cycles were performed for parameters of the same conditions. After comparing the training results for various parameter settings, the error results for the test example and the training example showed that the error value with 30,000 iterations was lower than the error value with 10,000 iterations.

Fig. 1 is a comparison between the actual value of the training example and the predicted value of the BPN. It can be seen that the predicted results of the BPN are very close to the actual value, and the difference is not particularly large. Fig. 2 is a comparison of the value predicted by the backward neural network and the actual value, for the test example.

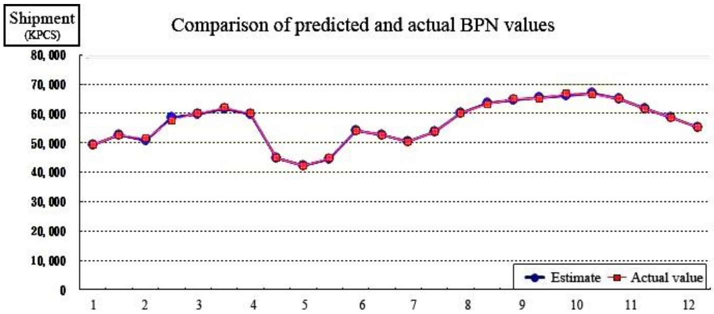

Fig. 1. Comparison of value predicted by the backward neural network and the actual value, for the training example.

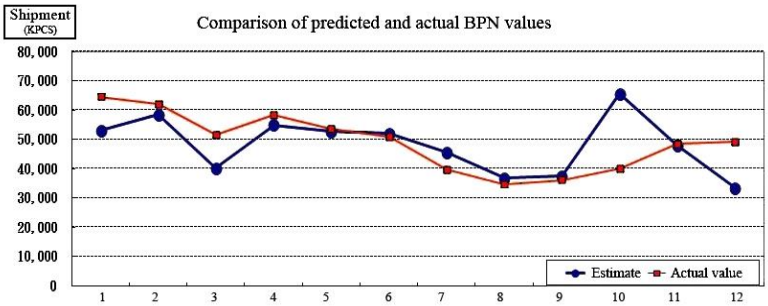

Fig. 2. Comparison of value predicted by the backward neural network and the actual value, for the test example.

The next step was to compare the MSE (mean squared error). It was evident that the results of training with 30,000 iterations were more convergent than the results with 10,000 iterations, as shown in Table 3 below. The training error results showed that training with 30,000 iterations, for hidden layer 5, with a learning rate of 0.9 and inertia factor of 0.5, was the best result. The MSE finally converged to 0.00001. The training error was the lowest (0.37%), and the test error was the second lowest (13.33%), so this group of parameters was selected for subsequent analysis and research.

Table 3. Training results for BPN output.

IC						
Training condition	10,000 (0.7) times			30,000 (0.7) times		
	MSE	Training example error	Test example error	MSE	Training example error	Test example error
ANN5_0101	0.00061	3.6%	18.9%	0.00035	1.8%	12.4%
ANN5_0105	0.00052	3.3%	17.6%	0.00011	0.4%	17.0%
ANN5_0109	0.00005	1.0%	13.4%	0.00001	0.4%	17.9%
ANN10_0101	0.00055	3.5%	18.2%	0.00034	2.9%	17.2%
ANN10_0105	0.00047	3.3%	17.6%	0.00012	1.9%	17.7%
ANN10_0109	0.00005	9.9%	15.1%	0.00001	0.4%	19.4%
ANN15_0101	0.00054	3.6%	18.32%	0.00020	2.38%	22.1%
ANN15_0105	0.00040	3.0%	19.40%	0.00007	1.46%	19.7%
ANN15_0109	0.00003	0.81%	25.01%	0.00001	0.43%	23.27%

Based on the training example and prediction values for the selected parameters (number of hidden layer neurons = 5, learning rate = 0.9, inertia factor = 0.5), the MAPE was calculated to be 1.1%, and the MAPE was used as a reference for the evaluation criteria. A value of less than 10% indicates that the predictive ability was excellent. It can be seen from Table 3 that the inverted neural network-based predictive model, with this group of parameters, is suitable for use to predict the production volume of IC products. The MAPE was calculated to be 12.4%, and the MAPE was used as a reference for the evaluation criteria.

4.4 Comparison of Predicted and Actual Values for COF Production

The training weights of the best parameters selected by the above training results (number of hidden layer neurons = 20, learning rate = 0.5, momentum = 0.9) were then used as the verification condition and were applied. Actual production data for the period from January to April were used as a verification example. The calculated prediction result had a MAPE value of 23.9%, as shown in Table 4. Although the value was higher than the result for the training example, it was between 20% and 50% according to the MAPE evaluation standard, indicating that the prediction ability is still within a reasonable range.

Table 4. Comparison of MAPE for COF production.

Month	MAPE	MAD
13 Jan	41.8%	23,770,200
13 Feb	22.5%	12,733,900
13 Mar	17.4%	5,699,300
13 Apr	14.0%	2,018,700
Add up	96.0%	44,222,200
Average prediction error	23.9%	11,055,500
Standard deviation	12.4%	9,571,400
Maximum	41.8%	23,770,200
Minimum	14.0%	2,018,700

The issue concerning the December 2019 annual chassis point settlement of orders in advance affected the order volume in January 2020. Therefore, the January data were shaved and recalculated. The calculation result was 17.9%. Reference to the MAPE standard (whose value was between 10% and 20%) indicated that the predictive ability was excellent. It was evident that (excluding the large difference in January) the error value for February to April was about 18%. The prediction value was quite close to the actual output value (see Fig. 3), indicating that the prediction results from application of the backward neural network can be used as a reference basis for production of COF products in the future.

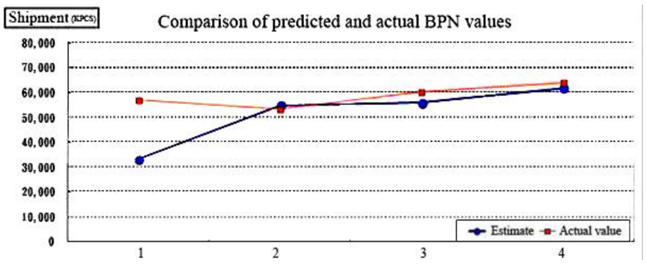

Fig. 3. Comparison of predicted and actual values of COF production verification results.

5. CONCLUSIONS

In this paper, we have presented a model for prediction of IC output, based on BNN architecture. This accurate and simple prediction model can be used by enterprises seeking a scientific and modern management model for output prediction, so that production managers can plan and execute material preparation operations in advance, reduce costs, and increase profits and competitiveness. In the research process, different parameters and iteration times were set for the prediction model, and the output was predicted and analysed. The average absolute error was then used to select and evaluate which was the most effective prediction model. The results showed that the training prediction error was less than 11%; the average error for three months was also less than 13% for the backward neural network model, which is suitable for prediction of IC products. The results and contributions of our study are as follows:

1. The data collected were based on IC industry factors, which were divided into three levels. Firstly, grey correlation analysis was used to screen for the factors with highest correlations, and the factors with the lowest correlations were deleted to improve the accuracy of the model's predictions.
2. When establishing the backward neural network prediction model, different parameters were set to verify and perform two different iteration experiments and to obtain the best MSE value. The results showed that when the number of iterations reached 30,000, the MSE value was more convergent, and the prediction result was more accurate than after 10,000 iterations. In future work, we can prepare appropriate materials in advance to reduce companies' raw material inventories. This would mean that customers could be given accurate and fast delivery times, and companies could offer more competitive delivery times than their industry competitors. A limitation is the uncertainty of forecasting situations. Forecasts are based on unknown situations that may arise in the future and are subject to the uncertainty associated with the impermanence of related factors. Although related factors can sometimes be predicted, the degree of their mutual impact is difficult to measure.

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