Combining SOM and GA-CBR for Flow Time Prediction in Semiconductor Manufacturing Factory

Pei-Chann Chang[12], Yen-Wen Wang[3], Chen-Hao Liu[2]

[1] Department of Information Management, Yuan-Ze University,
[2] Department of Industrial Engineering and Management, Yuan-Ze University,
135 Yuan-Dong Rd., Taoyuan 32026, Taiwan, R.O.C.
[3] Department of Industrial Engineering and Management, Ching-Yun University, 229 Chien-Hsin Rd., Taoyuan 320, Taiwan, R.O.C.
iepchang@saturn.yzu.edu.tw

Abstract. Flow time of semiconductor manufacturing factory is highly related to the shop floor status; however, the processes are highly complicated and involve more than hundred of production steps. Therefore, a simulation model with the production process of a real wafer fab located in Hsin-Chu Science-based Park of Taiwan is built. In this research, a hybrid approach by combining Self-Organizing Map (SOM) and Case-Based Reasoning (CBR) for flow time prediction in semiconductor manufacturing factory is proposed. And Genetic Algorithm (GA) is applied to fine-tune the weights of features in the CBR model. The flow time and related shop floor status are collected and fed into the SOM for classification. Then, corresponding GA-CBR is selected and applied for flow time prediction. Finally, using the simulated data, the effectiveness of the proposed method (SGA-CBR) is shown by comparing with other approaches.

Keywords: Flow time prediction, Case-Based Reasoning, Genetic Algorithms, Self-Organizing Map

1 Introduction

Flow time prediction is an important feature of a semiconductor manufacturing problem, which is the basis used to estimate the due date of a new order under current shop floor status. Traditionally, assigning due date for each order is accomplished by the production planning and control staffs based on their knowledge of the manufacturing processes and shop floor status. The production planning and scheduling staffs usually estimate the flow time of each order based on products manufactured before and schedule its release to the shop floor for production. Even if the product specification is exactly the same, the status of the shop floor such as jobs in the system, shop loading and jobs in the bottleneck machine may not be identical to the previous production. As a result, due date estimated by the production planning and scheduling staffs might subject to errors.

As the advance in artificial intelligence (AI), tools in soft computing have been widely applied in manufacturing planning and scheduling problems. Ref. [2] reported that back-propagation neural networks (BPN) could be more effective than some traditional direct procedures for due date assignment since neural network can obtain a probable result even if the input data are incomplete or noisy. Using a k-nearest-neighbors (KNN) based case-based reasoning (CBR) approach with dynamic feature weights and non-linear similarity functions; ref. [6] found that further performance improvement could be made. This paper constructs a case-based prediction system with the aid of a Self-Organizing Map (SOM), Genetic Algorithm (GA) and CBR, and we call it SGA-CBR in the rest of the article. The SOM is first used to classify the data, and after the classification GA is used to construct the CBR prediction method by searching the best weights combination.

The rest of the paper is organized as follows: Section 2 reviews some related literatures. Section 3 briefly describes the case that will be discussed in this research. Section 4 presents the framework of the methodology applied in the flow time prediction method. Section 5 presents some experimental results of various models including other compared methods. Section 6 discusses the simulated results from these different models and then the conclusion is made.

2 Literature Review

CBR is a general problem solving method with a simple and appealing definition [10] that emphasizes finding appropriate past experience to the solution of new problems. It solves problems using or adapting solutions from previous experiences. CBR is a problem-solving approach that takes advantage of the knowledge gained from previous attempts to solve a particular problem. Ref. [7] applied the CBR technique to the software estimation problem and found that CBR performs somewhat superior to regression modeling based on the same data. The successful applications of the CBR system in the prediction problem can refer to ref. [8], [12], [17], and [18].

For a CBR system, the retrieval of appropriate cases relies on a similarity metric which takes into account the distance between pairs of cases in their state space of variables, also commonly called “features”. Similarity measurements between pairs of features play a central role in CBR [11]. Many CBR systems represent cases using features and employ a similarity function to measure the similarities between new and prior cases [15]. A CBR system may perform ineffectively in retrieving cases when the features are irrelevant for cases matching. Therefore, to minimize the bias associated with the features, it is crucial to identify the most salient features leading to effective case retrieval. Generally, the performance of the similarity metric and the weighting of features are keys to this reasoning process [10].

In general, feature weights are used to denote the relevance of features. They allow similarity functions to emphasize features according to their relevance. Several research works attempted to determine feature weight settings with the aid of GA. Ref. [16] proposed methods for feature subset selection using genetic algorithms. Ref. [1] developed a GA-based, weighted K-NN approach to construct CBR. They suggested that the types of similarity functions, feature weights, and the indexing method could affect the retrieval performance of CBR. To the best of our knowledge, none of the above studies considered the non-linear feature value distance between an old case and a new case. Therefore, this paper aims to investigate the effect of GA-based feature weighting together with a number of non-linear similarity functions.

3 Problem Description

The basic configuration of the wafer fabrication factory is same as a real-world one located in the Science-Based Park in Hsin-Chu, Taiwan, R.O.C. There are 66 single-server or multiple-server workstations in the shop floor. The major wafer manufacturing processes are divided into two sections, i.e., the front-end process and the back-end process. A flowchart of the basic front-end processes is described in Figure 1. The production steps are just a step-by-step process. Real floor shop manufacturing processes are more complicated with many detailed processing procedures.

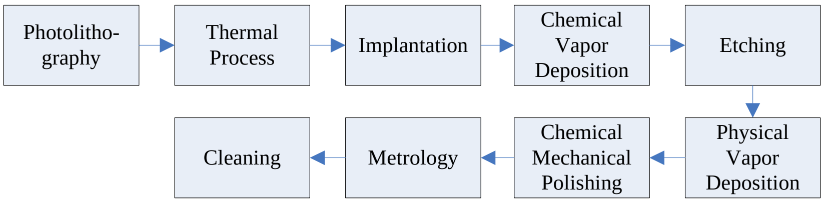

Fig. 1. Basic Front-End Processes

After the front-end processes, wafers are fed into the back-end processes. A simple flowchart of the back-end processes is also shown in Figure 2.

Fig. 2. Basic Back-End Processes

The time series plot of 300 flow time data is depicted in Figure 3. The pattern of the flow time is not stable in this plot. The traditional approach by human decision is very inaccurate and very prone to fail when the shop status is totally different even for the same product. This is the motive for this research to develop an approach to cut down the forecasting error based on such non-stationary situation.

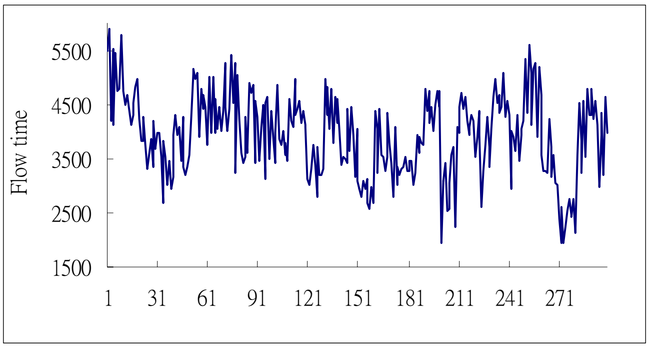

Fig. 3. Time Series Plot of Flow Time

4 A Hybrid System Combining SOM and GA-CBR

This research first uses SOM to cluster past cases to the different groups, and the training cases in each sub-group are used to train the best weights between features by GA. In the testing process, the most similar sub-group to the new case then could be retrieved by CBR from past case. New case is compared to each case within the selected group in order to find the most similar case to get the forecasting flow time of the new case. Hopefully, the hybrid model could improve the effect of flow time forecasting. The framework of SGA-CBR can be described as figure 4. Totally 300 records of data are randomly divided into 240 records of training data and 60 records of testing data. Following briefly describes the operation process for the SGA-CBR:

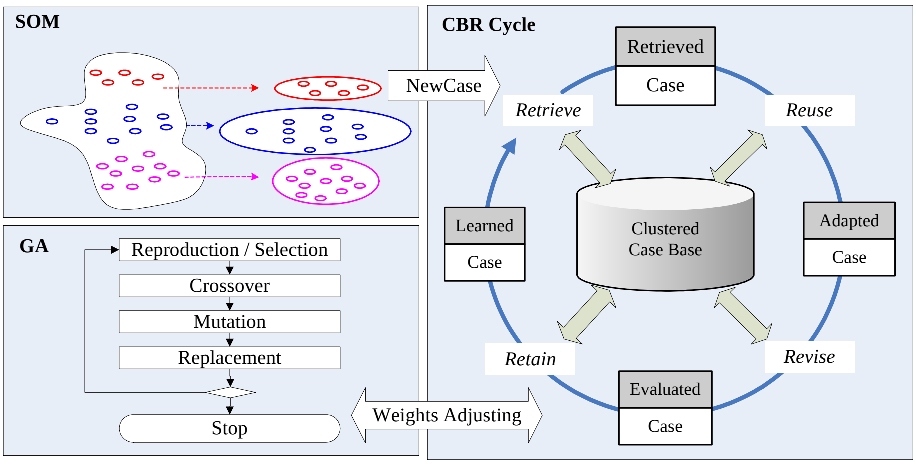

Fig. 4. The Framework of the research

Step 1. Classify the training data by SOM

From the data collected, each new case is composed of six features: order quantities (X_1), existing order qualities when the order arrived (X_2), average shop workload when the order arrived (X_3), average queuing length when the order arrived (X_4), workstation queue when the order arrived (X_5), and utilization rate of work station when the order arrived (X_6). Uses these six features to be the input variables of SOM, and SOM will produce output-processing elements similar to neighboring elements, which means that the cases in the same group would have similar connection weight.

Training Process

Step 2. Initial weights generation

Randomly generate the initial weights W_j^i of the $j-th$ feature in sub-group i.

Step 3. Case retrieving

This step would find out the most matching case from case base using similarity rule in order to predict the flow time for the new case. The similarity rule as follows:

$$S_{mn} = Dis\left(C_m^i, C_n^i\right), \quad \forall n \neq m \tag{1}$$

S_{mn} is the similarity degree between case m (C_m^i) and n (C_n^i) in group i. And $Dis(\ )$ is the distance between two cases, $Dis(\ )$ is compute as:

$$Dis\left(C_m^i, C_n^i\right) = \sqrt{\sum_f W_j^i \left(F_f^m - F_f^n\right)^2} \tag{2}$$

where F_f^m means the value of the $f-th$ feature of case m. Thus, $Dis(C_m^i, C_n^i)$ computes the summarized weighted distance between case m and n.

Step 4. Case reusing

After the steps above, KNN is added to gain more matching cases to forecast the flow time of case. For example, when $k = 5$ in the sub-group, the forecast flow time of new case is determined by the 5 best matching cases. And the parameter k of each sub-group is generated by trail-and-error separately.

Step 5. Error computing

Root of mean square error (RMSE) is adopted to be the performance measure in this research.

$$RMSE = \sqrt{\frac{\sum_{l=1}^{N}\left(forecasted\ value - real\ value\right)^2}{N}} \tag{3}$$

where, N is the total number of case in the sub-group.

Step 6. Weights revising by GA

Uses GA approach to find the optimal weight for each feature in the sub-group. Some parameters setting of GA are list in following:

Table 1. Parameters settings in GA

Parameters	Setting
Selection	Binary tournament
Crossover	Single point crossover
Crossover rate	0.85
Mutation	Swap mutation
Mutation rate	0.1
Reproduction	Elitism strategy
Population size	30
Stopping criteria	1000

Step 7. Cases and weights retaining

The best weight combination of each sub-group is retained for the further testing process.

Testing Process

Step 8. New testing case retrieving

The same as process above, similarity rule is used to compute the similarity of cases.

Step 9. New testing case reusing

Find the most *k* similar cases of new case.

Step 10. Forecasted flow time generating

Forecast the flow time of new case from *k* similar cases.

5. Experimental Results

5.1. Data clustered by SOM

The main purpose of data clustering is to reduce the effect of data noise. As mentioned previously, SOM is applied to cluster the data in this study. The cluster results diagram can be found in figure 5, which shows the results of two and three clusters for 240 data. The number of clusters might influence the forecasting result; therefore, the number of clusters will be discussed in the next sub-section.

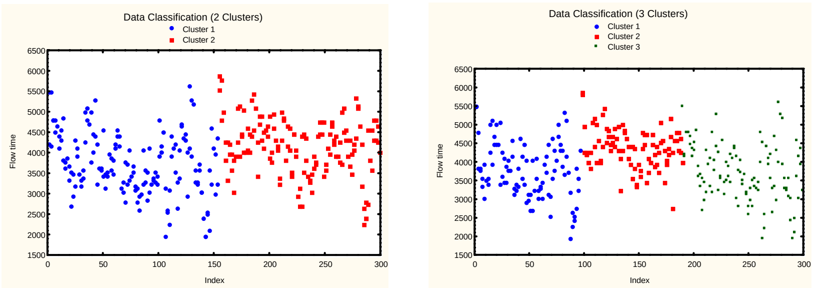

Fig. 5. The two and three clustered results by using SOM

5.2. SGA-CBR with Different Clusters

Forecast results under different number of cluster are shown in figure 6. By observing the figure 6, when the cluster number is increasing, the forecasting and real data will be more matched. Furthermore, according to the Mean Absolute Percentage Error (MAPE) and RMSE, figure 7 shows the performance of different number of clusters.

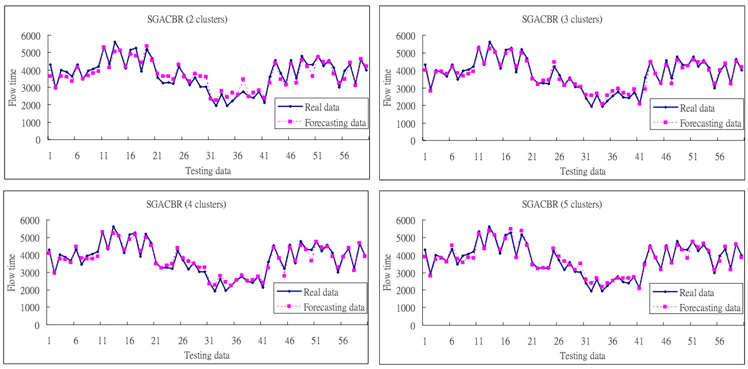

Fig. 6. SGACBR with different number of cluster

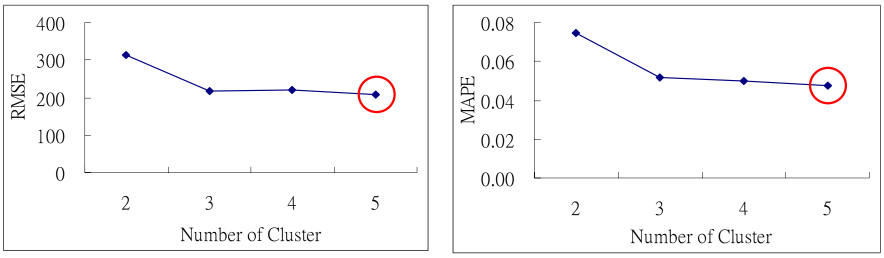

Fig. 7. The convergence chart of MAPE and RMSE from different number of cluster

Table 2. Parameters settings in GA

Number of Cluster	2	3	4	5
MAPE	7.44 %	5.18 %	5.01 %	4.73 %
RMSE	312.5231	218.3532	218.6860	208.2776

We chose 5 clusters as the number of sub-groups in the research. As shown in Table 2, we can find that when the number of clusters is large than 3, the accuracy of forecasting will converge, and it has no obviously improvement when using large number of clusters. Therefore, further cluster number will stop to test.

5.3. Comparison with other Methodology

Other forecasting methodologies are compared with SGA-CBR in this research, such as general CBR, Back-propagation neural network (BPN), GA and fuzzy rule based method (GA&WM), GA and CBR hybrid method (GA-CBR), and Fuzzy rule based SOM method (SOM&WM). The detail of these methods can refer to the previous research [3], [4], and [6].

By observing table 3, SGA-CBR proposed in this research performs superior to other methods that performed well in the previous research. The reason why SGA-CBR of this research outperforms others is because GA can fine-tune the weights. CBR is one of the famous forecasting methods while resolving this kind of forecasting problem with multiple features considering. By adopting the Euclidean distance to retrieve the similar cases, CBR is an effective and efficient method. Otherwise, in the real world, each feature may play a different important role. It means we should take different importance of each feature into consideration; thus, we use GA to search the best weights combination of features in our CBR process.

Table 3. Parameters settings in GA

Methodology	RMSE	Improving rate
CBR	538	-
BPN	480	10.78%
GA&WM	479	10.97%
GA-CBR	391	27.32%
SOM&WM	320	40.52%
SGA-CBR	208	61.34%

In the comparative study, the overall average RMSE of SGA-CBR is 208, the overall average RMSE of other methods can be found in table 3. Hence the results of our limited comparative studies show that the proposed SGA-CBR method produces the lowest RMSE value.

6 Conclusion

The experimental results in section 5 demonstrate the effectiveness of the SGA-CBR that is superior to other effective approaches. In summary, this research has the following important contribution in the flow time prediction area and these contributions might be interested to other academic researchers and industrial engineers and managers:

No matter what kind of data, some noise may influence the forecasting result a lot. In the recent research, data preprocessing seems to be more and more important. After the numerical testing of this study, data pre-clustering is a better way to increase the forecasting accuracy. As shown in table 3, the methods with SOM clustering (SOM&WM, and SGA-CBR) perform better than other method without data classifier.

This research compared some well forecasting methods; RMSE was the performance measure index. SGA-CBR proposed in this research was the best one with the minimum RMSE.

This research discussed how to integrate the SOM and GA-CBR approaches to construct a hybrid system of flow time prediction. It can help industrial managers to make a better project scheduling or some other forecasting matters.

References

1. Brill, F.Z., Brown, D.E., Martin, W.N.: Fast Genetic Selection of Features for Neural Network Classifiers. IEEE Transactions on Neural Networks, Vol. 32. (1992) 324-328
2. Chang, P.C., Hsieh, J.C.: A Neural Networks Approach for Due Date Assignment in A Wafer Fabrication Factory. Int. J. Ind. Eng., Vol. 10. (2003) 55-61
3. Chang, P.C., Hsieh, J.C., Liao T.W.: Evolving Fuzzy Rules for Due-Date Assignment Problem in Semiconductor Manufacturing Factory. Journal of Intelligent Manufacturing, Vol. 16. 5 (2005) 549-557

4. Chang, P.C., Liao, T.W.: Combing SOM and Fuzzy Rule Base for Flow Time Prediction in Semiconductor Manufacturing Factory. Applied Soft Computing, Vol. 6. (2006) 198-206
5. Chiu C.C.: A Case-based Customer Classification Approach for Direct Marketing. Expert Systems with Applications, Vol. 22. (2002) 163-168
6. Chiu, C.C., Chang, P.C., Chiu, N.H.: A Case-based Expert Support System for Due Date Assignment in A Wafer Fabrication Factory. J. Intell. Manuf., Vol. 14. (2003) 287-296
7. Finnie, G.R., Witting, G.E.: Estimating Software Development Effort with Case-Based Reasoning. Lecture Notes in Computer Science, Vol. 1266. Springer-Verlag, Berlin Heidelberg New York (1995) 13-22
8. Jo, H., Han, I., Lee, H.: Bankruptcy Prediction Using Case-Based Reasoning, Neural Networks and Discriminant Analysis. Expert Systems and Applications, Vol. 13. (1997) 97-108.
9. Kim, K., Han, I.: Maintaining Case-based Reasoning Systems Using A Genetic Algorithms Approach. Expert Systems with Applications, Vol. 21. (2001) 139-145
10. Kim, S.H., Shin, S.W.: Identifying the Impact of Decision Variables for Nonlinear Classification Tasks. Expert Systems with Applications, Vol. 18. (2000) 201-214
11. Kolodner, J.L.: An Introduction to Case-Based Reasoning. Artificial Intelligence Review, Vol. 6. (1992) 3-34
12. Liao, T.W., Zhang, Z.M., Mount, C.R.: A Case-Based Reasoning System for Identifying Failure Mechanisms. Engineering Applications of Artificial Intelligence, Vol. 13. (2000) 199-213
13. Louis, S.J., Xu, Z.: Genetic Algorithms for Open Shop Scheduling and Re-Scheduling. In Proceedings of the ISCA 11th International Conference on Computers and Their Applications. (1996) 99-102
14. Ramsey, C., Grefensttete, J.: Case-based Initialization of Genetic Algorithms. Proceeding of the Fifth International Conference on Genetic Algorithms, San Mateo, California (1993)
15. Shin, K., Han, I.: Case-Based Reasoning Supported by Genetic Algorithms for Corporate Bond Rating. Expert Systems with Applications, Vol. 16. (1999) 85-95
16. Siedlecki, W., Sklansky, J.: A Note on Genetic Algorithms for Large-Scale Feature Selection. Pattern Recognition Letters, Vol. 10. (1989) 335-347
17. Watson, I., Gardingen, D.: A Distributed Cased-Based Reasoning Application for Engineering Sales Support. In Proc. 16th Int. Joint Conf. on Artificial Intelligence, Vol. 1. (1999) 600-605
18. Watson, I., Watson, H.: CAIRN: A Case-Based Document Retrieval System. In Proc. of the 3rd United Kingdom Case-Based Reasoning Wrokshop, University of Manchester, Filer, N & Watson, I (Eds). (1997)