AN ORDER CLUSTERING SYSTEM USING ART2 NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION METHODN

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Abstract: Surface mount technology (SMT) production system set up is quite time consuming for industrial personal computers (PC) because of high level of customization. Therefore, this study intends to propose a novel two-stage clustering algorithm for grouping the orders together before scheduling in order to reduce the SMT setup time. The first stage first uses the adaptive resonance theory 2 (ART2) neural network for finding the number of clusters and then feed the results to the second stage, which uses particle swarm K-means optimization (PSKO) algorithm. An internationally well-known industrial PC manufacturer provided the related evaluation information. The results show that the proposed clustering method outperforms other three clustering algorithms. Through order clustering, scheduling products belonging to the same cluster together can reduce the production time and the machine idle time.

1 INTRODUCTION

Unlike regular personal computer (PC) manufacturing, high mix low volume, or high customization, is one of the characteristics of the industrial PC industry. It is also the biggest challenge facing the industrial PC industry. In this industry, printed circuit board (PCB) assembly is a fundamental manufacturing process, in which surface mount technology (SMT) plays a very important role. By applying an SMT production system, not only can there be more components on the limited space of a PCB, but also the production efficiency and product stability can be enhanced. However, the high mix low volume production style is still a difficulty for the SMT production system. In this production system, production line-change is a very serious bottleneck since before line-change, production labor must prepare for the materials and also bind these materials, which is very time consuming. If production labor can not complete these tasks before the next order starts, it would both cause idle time for these expensive machines and decrease the production capability utilization. Currently, this problem is frequently encountered in the SMT production system, and the only way it can be handled is to prepare for more materials and increase the binding labor. Thus, how to reduce the setup time for SMT line-change operation is a very important issue.

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Therefore, this study applies a clustering technique to cluster bills of materials (BOMs) for all orders or products. After clustering, production engineers can to schedule similar orders together for production. This can simplify the material-preparation time in order to reach reducing SMT line-change time. For the clustering technique, this study proposes a novel two-stage clusering algorithm. The first stage employs an adaptive resonance theory 2 (ART2) neural network to find the number of clusters and feed it to the second stage. The second stage applies particle swarm K-means optimization (PSKO) algorithm to reach the final solution.

In the model evaluation, data provided by Advantech Company which is an internationally well-known industrial PC manufacturer, shows that the proposed two-stage clustering algorithm is better than three other algorithms in accuracy. This can dramatically reduce the SMP production system setup time and increase the utilization of production capability.

2 BACKGROUND

This section briefly presents the general literature survey for the clustering analysis and particle swarm optimization algorithm.

2.1 Clustering Analysis

There have been many algorithms being applied in clustering analysis. With artificial intelligence (AI) and soft computing, many clustering algorithms based on these techniques and theories have been proposed. Thus, the following discussions will focus on AI related clustering algorithms (Xu and Wunsch, 2005).

An artificial neural network (ANN) is a system that has been derived through models from neurophysiology. ANN-based clustering has been dominated by self-organizing feature maps (SOM) and adaptive resonance theory (ART) (Kohonen, 1990, Carpenter and Grossberg, 1987, and Carpenter and Grossberg, 1987).

Fuzzy clustering is different from hard clustering since its restriction is relaxed and the object can belong to all of the clusters with a certain degree of membership. The methods of fuzzy clustering include fuzzy C-means (Hoppner et al., 1999) and fuzzy c-shells (Bezdek and Hathaway, 1992).

Clustering can also be regarded as a category of optimization problems that use evolutionary algorithms, like genetic algorithms (GA) or ant colony optimization algorithms. But the main drawback of these clustering algorithms is the process of parameter selection. Many techniques supporting this method such as genetic K-means algorithm (Krishna and Murty, 1999), Tabu search clustering (Al-Sultan, 1995), simulated annealing clustering (Brown and Huntley, 1992 and Smyth, 1998) and ant colony clustering algorithm (Kuo et al., 2005b).

Due to limitations of some clustering algorithms, which need to know the number of clusters before implementing clustering, a two-stage framework is proposed here to overcome this problem. The basic idea of the two-stage clustering algorithm is to first find the number of clusters using an automatically clustering algorithm, such as an ART2 neural network, and then feed this number to the other clustering algorithm to find the final solution.

Kuo et al. (2002) proposed a two-stage method which integrates both the SOM and K-means, with results indicating that the proposed method is much better than using only SOM or K-means. Then, Kuo and his colleagues modified the GKA by Krishna and Murty (1999) and used SOM's solution as the initial solution for the modified GKA (Kuo et al., 2004). The results showed that this method was better than the previously published method, SOM + K-means. Kuo and his colleagues also presented a method integrating of ART2 and a genetic algorithm (Kuo et al., 2005a), and one that used a different coding method (Kuo et al., 2006).

2.2 Particle Swarm Optimization

The PSO algorithm shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, the PSO algorithm has no evolutionary operators, such as crossover and mutation. In the PSO algorithm, the potential solutions, called particles, move through the problem space by following the current optimum particles. The main developments in the PSO algorithm can be generally divided into three phases as follows.

Xiao et al. (2003) proposed a hybrid clustering approach based on an SOM neural network. The proposed algorithm uses a PSO algorithm to evolve the weight for the SOM neural network. The weights are trained by the SOM neural network in the first stage, and in the second stage they are optimized by the PSO algorithm. The experimental results show that the hybrid method tries to tune the original SOM such that it can achieve a better tradeoff between the average quantization error and the topographic error.

Merwe and Engelbrecht (2003) proposed two new approaches using a PSO algorithm to cluster data. The first method, called the PSO clustering algorithm, shows how the PSO algorithm can be used to find the centroids of a user-specified number of clusters. The second method, called the Hybrid PSO algorithm, first uses K-means clustering to seed the initial swarm and then uses PSO algorithm to refine the clusters formed by K-means. These new PSO algorithms were evaluated on six data sets, and compared with the performance of K-means clustering. Results show that both PSO clustering techniques have much potential. Chen and Ye also proposed a clustering analysis algorithm based on the PSO algorithm (Chen and Ye, 2004). But the concept of that algorithm is similar to others in the literature (Merwe and Engelbrecht, 2003), and its main difference is only in the fitness function. Finally, the experimental results obtained using four artificial data sets show the algorithm proposed here has better performance than K-means and fuzzy C-means.

3 METHODOLOGY

This section presents the proposed order clustering system which includes data collection and transformation, principle component analysis, and clustering analysis. The following subsections briefly discuss these three components.

3.1 Data Collection and Transformation

In order to classify the product group for the up coming orders belonging to it, all the previous orders must first be collected and make clustering analysis made for them. Basically, for most companies, these data can be retrieved from the enterprise resources planning system. Then, the bill of materials (BOM) for each order is used as the feature for each order, or product.

3.2 Principle Component Analysis

Due to the vast number of materials used for each order, it is very time consuming to use these data for clustering analysis, and it is more feasible to condense these data in advance. A statistical method, principle component analysis, is employed for this purpose so that each order will have a limited number of features. This can result in shorter computational time and without influencing the computational results.

3.3 Clustering Analysis

After implementing principle component analysis, the data obtained is applied for clustering analysis using a two-stage clustering with ART2 neural network and a proposed particle swarm K-means optimization algorithm as well.

3.3.1 ART2 Neural Network

ART2 architectures are designed for processing analog as well as binary input patterns. The ART2 neural network consists of F1 and F2 layers. There are seven nodes in the F1 layer (W, X, U, V, P, Q). The input signal is processed by the F1 layer and then is passed from the bottom to top value (b_{ij}). The result of the bottom-to-top value is an input signal of F2 layer. The nodes of F2 layer compete with each other to produce a winning unit and the winning unit returns the signal to the F1 layer. The match value is then calculated with top to bottom value (t_{ji}) in the F1 layer and compared with the vigilance value. If the match value is greater than the vigilance value, then the weight of b_{ij} and t_{ji} is updated. Otherwise, the reset signal is sent to the F2 layer and the winning unit is inhibited. After inhibition, the other winning unit will be found in the F2 layer. If all of the F2 layer nodes are inhibited, the F2 layer will produce a new node and generate the initial corresponding weights to the new node. The detailed learning procedure can be found in [Grossbert 1976].

3.3.2 PSKO Algorithm

Particle swarm optimization, like GA, is a population-based stochastic search process. The algorithm maintains a population of particles, where each particle represents a potential solution to an optimization problem. By referring to Krishna and Murty’s concept (1999) of integrating GA with K-means, this article proposes to integrate K-means with PSO algorithm (Merwe and Engelbrecht, 2003). It is called the particle swarm K-means optimization (PSKO) algorithm and the computational procedures are as follows.

Step 1: Set up parameters including population size (number of particles), maximum velocity, V_{max}, inertia weight, W, and two learning factors, c_1 and c_2.

Step 2: Initialize each particle randomly with initial position X_{id} and velocity V_{id}. In PSO clustering, we need in advance to know the number of clusters, k. In this study ART2 neural network will provide this information to the PSKO algorithm. Since each particle is a vector containing k cluster centroids, each cluster' s position, X_{id}, can be represented as:

$$X_{id} = (z_{i1}, \cdots, z_{ij}, \cdots, z_{ik}) \tag{1}$$

where z_{ij} denotes the jth cluster's centroid for the ith particle.

Step 3: Calculate fitness value for each particle.

$$fitness\ value = \sum_{j=1}^{k} \left[\sum_{\forall x \in n_{ij}} \| x - z_{ij} \| \right] \tag{2}$$

where x denotes the data vector, n_{ij} denotes the number of data for jth cluster of the ith particle, and $\| x - z_{ij} \|$ denotes the Euclidean distance of data vector to all cluster centroids.

Step 4: Update the local best, P_{id}, and global best, P_{gd}.

Step 5: According to the best position of P_{id} and P_{gd}, update the velocity and position for each particle using Equations (3) and (4). It should be noted that V can not be larger than V_{max}.

$$V_{id}^{new} = W \cdot V_{id}^{old} + c_1 \cdot rand_1 \cdot (P_{id} - X_{id}) + c_2 \cdot rand_2 \cdot (P_{gd} - X_{id}) \tag{3}$$

$$X_{id}^{new} = X_{id}^{old} + V_{id}^{new} \tag{4}$$

where c_1 and c_2 are learning factors, respectively, while $rand_1$ and $rand_2$ denote random numbers between (0, 1).

Step 6: Calculate the Euclidean distance of every piece of data x to all cluster centorids for each particle.

Step 7: For each particle, assign each piece of data, x, to the cluster with the closest cluster centroid.

Step 8: Recalculate the cluster centroid vectors for every particle, using

$$z_{ij} = \frac{1}{n_{ij}} \sum_{\forall x \in n_{ij}} x \tag{5}$$

Step 9: Stop if the specified number of iterations is satisfied; otherwise, go back to Step 3.

4 MODEL EVALUATION RESULTS

This section will apply the proposed clustering method for order clustering in order to reduce the SMT production system setup time. Advantech Company provided the related data for assessment. The setup of production line change for different orders has become a critical bottleneck in SMT production system because that implementing material-preparation and material-binding tasks by hand for production line change is very time consuming. If this can not be ready before next order starts production, it will cause machines idle time and result in low production capability utilization. Therefore, we apply a two-stage clustering method (Kuo et al. 2002) to group similar products or orders together and find the same materials (shared materials) that will be used for all the products in the same group. This enables the production engineers to put the same needed materials in the same material positions for SMT retrieval equipment, so production engineers can arrange for similar products to be produced together. Thus, the material preparation operation can be simplified in order to reduce the SMT setup time.

4.1 Data Collection

A material report was provided by Advantech Company. Using ACCESS SQL query, there is a total of 2826 different products, or orders, and a total of 2517 materials used. In order to cluster these products, it is necessary to filter the noise of product and material data and then transform them into a 2826×2517 two-dimension matrix.

4.2 Principle Component Analysis

That there are 2517 features for product feature matrix and it is very time consuming for clustering analysis if there are many features. In order to reduce the computational time and also maintain the solution quality, this study uses Matlab 6.5.1 to make the principle component analysis for the product feature matrix in order to extract the dimensions for the principle component factors. The selection of factor is according to the Eigne value which should be larger than 1. After analysis, there are a total of 200 principle component factors. The cumulative explanation variance is 81.98%.

4.3 Clustering Analysis

After reducing the original feature matrix with size of 2826×2517 to 2826×200 through principle component analysis, it is necessary to know the number of clusters in advance. Based on our previous research (Kuo et al., 2005), this study applies a two-stage clustering method, ART2+PSKO which is a kind of method for processing gray value in the first stage, ART2 automatically finds the number of clusters, while the second stage uses the PSKO algorithm to find the final solution.

4.3.1 Determination of Cluster Number

The ART2 algorithm was coded by using Matlab 6.5.1. Since in ART2 algorithm the number of clusters is determined by the vigilance value, once it is well determined ART2 can automatically cluster the data. Thereafter, the second stage employs K-means, PSO clustering, hybrid PSO, and PSKO algorithms to find the final solutions. Since the vigilance value will dramatically affect the clustering outcome, this study uses Wilk's Lambda value as the indicator for determining the number of clusters. Wilk's Lambda is frequently applied by MANOVA as the indicator for determining the number of clusters. If Wilk's Lambda value suddenly increases in two different numbers of clusters, then the number of clusters before variance can be treated as the best number of clusters. Theoretically, Wilk's Lambda value is defined as:

$$Wilk's\ \text{Lambda} = \frac{SS_{within}}{SS_{total}} \quad (6)$$

where SS_{WITHIN} and SS_{total} are the within-cluster and total variances, respectively.

Table 1 lists the corresponding Wilk's Lambda values for different vigilance values. The result shows that 35 is the best number of clusters.

Table 1: Wilk's Lambda value of ART2.

Vigilance Value	Cluster Number	Wilk's Lambda value
0.9372	43	0.67823
0.9347	41	0.685
0.932	39	0.69358
0.9295	37	0.69955
0.972	**35**	**0.70688**
0.926	33	0.72989

4.3.2 Comparison of Different Clustering Algorithms

Based on the ART2 algorithm's result, four different clustering algorithms are used to further find the final solution for comparison. Table 2 depicts the Sum of Euclidean Distances (SEDs) of four algorithms, which indicates that the ART2+PSKO algorithm has the smallest SED value, 83373.859.

Table 2: SED values for each clustering algorithm.

Clustering Algorithms	ART2 + K-means	ART2 + PSO clustering	ART2 + Hybrid PSO	ART2 + PSKO
SED	90276	94407	90153	**83373**

4.4 Shared Materials

According to the clustering results of ART2+PSKO, the products are grouped into thirty five clusters. Totally, there are eleven clusters whose numbers of shared materials are over one hundred.

4.5 Performance Evaluation

This study simulates the production line-change efficiency through on-field collection of the production plan. We first use the regular scheduling method to schedule the jobs for two days. Then, this study further groups similar products belonging to similar clusters to be scheduled together for production in order to reduce the SMT line-change time. According to these simulation results, we found that using the proposed ART2 + PSKO clustering algorithm really can efficiently reduce material binding time by 10.9% due to considering shared materials. Also, total production time decreased 7.3%, and the most dramatic improvement was the 89.3% reduction of machine idle time.

5 CONCLUSIONS

This study has demonstrated that the use of a clustering technique can reduce both production time and machine idle time since similar products or orders are scheduled for production together. In addition, this study also proposed a novel clustering algorithm that integrates both the K-means algorithm and the PSO algorithm for order clustering. Integration of the PSO clustering algorithm and the K-means algorithm gives the particles both global and local search capabilities. The results show that its performance is better than those of other three clustering algorithms for Advantech Company's order clustering problem.

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