An Entropy Based Group Setup Strategy for PCB Assembly

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Abstract. Group setup strategy exploits the PCB similarity in forming the families of boards to minimize makespan that is composed of two attributes, the setup time and the placement time. The component similarity of boards in families reduces the setup time between families meanwhile, the geometric similarity reduces the placement time of boards within families. Current group setup strategy considers the component similarity and the geometric similarity by giving equal weights or by considering each similarity sequentially. In this paper, we propose an improved group setup strategy which combines component similarity and geometric similarity simultaneously. The entropy method is used to determine the weight of each similarity by capturing the importance of each similarity in different production environments. Test results show that the entropy based group setup strategy outperforms existing group setup strategies.

Keywords: Printed circuit board assembly, group setup, entropy method, similarity coefficient.

1 Introduction

This paper considers a group setup problem in a single SMT machine producing multiple types of boards. The head starts from a given home position, moves to feeder carriage on the machine to pick up the component. After picking up the component, the head moves to the placement location on the PCB for this component. Then the component is placed on the board and the head travel back to the feeder carriage to pick up the next component. The pick-and-place process continues until all components required for the board have been completed.

Let K be the total number of family and N_f be the number of boards in family f. Then the total number of boards, $N = \sum_{f=1}^{K} N_f$. We assume that the head velocity, v(mm/sec) and the feeder installation/removal time, σ are constant for all types of boards. Also, let m_f be the number of feeder changes required from family $f-1$ to f and d_i be the length of tour followed by the head to assemble board i. b_i is the batch size of board i. Leon and Peters (1996) proposed the following conceptual formulation of the group setup problem:

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Minimize: Makespan=$\sum_{f=1}^{K}(\sigma m_f + \sum_{i=1}^{N_f} \frac{b_i}{v} d_i)$
Subject to: Feeder capacity constraints
Component-feeder constraints
Component placement constraints

The objective is to minimize the makespan for producing multiple types of boards. The first term of the makespan is the setup time to remove the previous setups and install components on feeders for current family. The second term is the time to place all components on all boards in a batch for current family. If all boards are grouped as a single family, the setup will occur only once minimizing setup time. However, the single family solution will increase the total placement time since the common setup is not prepared for individual boards. On the other hand, if all boards form a unique family of its own, the placement time reduction will be surpassed by setup time. Hence, boards must be grouped such that within the family, boards share as many common component types as possible (i.e., component similarity) in order to reduce setup time between families. Also the placement locations of boards within the family must be similar to each others (i.e., geometric similarity) in order to reduce placement time. Therefore the development of good similarity coefficient is important issue in a group setup strategy.

The decision variables are the number of family K, the types of boards in family f, N_f and the placement sequence of locations in board i and the component-feeder assignment for family f to determine d_i.

The first constraints represent the feeder capacity constraints. Total number of different component types in any family can not exceed the feeder capacity since only one component type can reside in one feeder slot. The second constraints, component-feeder constraints means that each component needed for boards in a family must be assigned to a feeder. The third constraints, component placement constraints are equivalent to traveling salesman problem (TSP) constraints. That is, the placement head must visit all the placement locations on a board. The distance between two placement locations is the time for the head to move from the first placement location to the feeder slot containing component for the second placement then to the second placement location.

Existing group setup strategies (1)considers component similarity only (Leon and Peter 1998) or (2) forms families of boards based on geometric similarity and select the groups of boards based on component similarity in sequential manner (Leon and Jeong 2005) or (3) considers an overall board's similarity coefficient which combines component similarity and geometric measure by assigning equal weights(Quintana and Leon 1999). Leon and Jeong (2005) reported that the performance of group setup strategy of case (2) performs better than other cases.

The motivation of this paper was the belief that the determining appropriate weights of case (3) and combining both similarities simultaneously could achieve a further reduction of makespan . Combining different criteria into a synthesized criterion falls into a well known research area, Multiple Criteria Decision Making (MCDM). In this paper, we use the entropy method for calibrating the weights assigned to the component similarity and the geometric similarity. The entropy concept suggests that if the component similarity or the geometric similarity of boards is the same, the similarity can be eliminated from further considerations in forming the families of boards. Alternately, the weight assigned to a similarity is small if all boards have the similar value of corresponding similarity coefficient.

2 Backgrounds

There are a number of different PCB setup strategies to reduce makespan in the literature (i.e., unique setup, minimum setup, group setup, partial setup). In this section, we focus on partial setup and group setup because the partial setup performs better than other setup strategies (Leon and Peters, 1996) and the implementation of group setup is relatively easier than partial setup in real world. The procedure for partial setup strategy (Leon and Peters, 1996) is summarized in the following steps.

Partial setup procedure
Step 1: Determine an arbitrary board sequence
Step 2: Repeat for a given number of times
- Step 3: For each board.
  - Step 4: Find a feasible component-feeder assignment
  - Step 5: Repeat for a given number of times
    - Step 6: Find a placement sequence given a component-feeder assignment determined at Step 4
    - Step 7: Find a component-feeder assignment given a placement sequence determined at Step 6
- Step 8: Determine the matrix of sequence-dependent changeover times. Sequence-dependent setup time is the time it takes to remove and install necessary feeders when changing from a board to another board.
- Step 9: Determine the board sequences that minimizes the total changeover time given the sequence dependent changeover time.

As shown in Step 8, portions of the previous setup may remains intact when changing over between boards in partial setup. Therefore only a portion of components are removed and installed between boards which might be a complicated operation. However, in group setup, once all the family has been assembled, all of the components are completely removed from feeder slots. The traditional group setup procedure is summarized in the following steps (Leon and Peters, 1996).

Group setup procedure.
Phase 1: Clustering (Form K families of boards with similar boards. Family sizes can not exceed the maximum number of feeder slots.)

Step 1: Put each board-type in a single-member family
Step 2: Compute similarity coefficient, s_{ij} for all pairs of family i and j
Step 3: Compute clustering objective values
Step 4: Set $T = max(s_{ij})$
Step 5: Merge the pair of board i^* and j^*, if $s_{i^*j^*} = T$. Repeat until no more pairs can be merged at similarity level T.
Step 6: Compute clustering objective and save the clustering solution if an improvement was achieved.
Step 7: Repeat Step 2 through 6 while merging is possible.

Phase 2: Component-feeder assignment and placement sequence.
Step 8: Form a composite-board $H(f)$, f=1,..., K, this board consists of the superposition of all the placement locations with their corresponding components of the boards in family f.
Step 9: Determine a feasible component-feeder assignment $C(H_f)$
Step 10: For all $i \in N_f$, find a placement sequence $P(i)$, given $C(H_f)$
Step 11: For all $i \in N_f$, find a component-feeder assignment $C(H_f)$ given $P(i)$
Step 12: Repeat Step 10 and Step 11 for a predetermined number of iterations.

In Phase 1, the hierarchical clustering algorithm merges similar boards into a family. The clustering procedure continues until all boards form a single family. To form good families of boards, it is essential to develop a similarity coefficient which considers both the component similarity and the geometric similarity of any two boards. Another issue in hierarchical clustering is the development of clustering objective in order to evaluate the quality of board clustering (e.g., minimization of the similarity coefficient between families, maximization of the similarity coefficient within families).

In phase 2, we consider each family as a single composite-board,H_f and determine the component-feeder assignment and placement sequence. For a given component-feeder assignment, $C(H_f)$, the placement sequencing problem can be solved as TSP problems. In this paper, we use the nearest-neighbor heuristic to solve the TSP. For a given placement sequences, $P(i)$, the component-feeder assignment problem is a LAP. In this implementation, the LAP is solved using the shortest augmenting path algorithm proposed by Jonker and Vogenant (1987). The LAP/TSP heuristic terminates when it reaches the predetermined number of iteration.

Currently, there exists two group setup strategies (i.e., Placement Location Matrix (PLM) based group setup strategy(Quinntana and Leon,1998) and Minimum Metamorphic Distance (MMD) based group setup strategy (Leon and Jeong, 2005)) which consider both component similarity and geometric similarity in the literature. Each strategy uses the same frame work of two phase procedure except the definition of the similarity coefficient in Step 2 and the clustering objective in Step 5. PLM based group setup strategy uses the following board's similarity coefficient.

s_{ij} : similarity of board i and j.

$x^{i \cap j}$: Number of Common Component (NCC) types between board i and j.

$x^{i \cup j}$: total number of different component types required by board i and j.

D_{ij} : dissimilarity of board i and j.

F_{ij} : frequency ratio of the number of placement locations between board i and j.

$\sqrt{X^2+Y^2}$:point magnitude of coordinate (X, Y).

p_{ki}: point magnitude of kth sorted placement location in ascending order for board i.

n_i: number of placement location of board i.

NP_j:number of placement locations of board j.

$n^* = \min(n_i, n_j)$.

Xrange, Yrange: Cartesian distance of the largest board.

$$s_{ij} = 0.5 s_{ij}^{NCC} + 0.5(1 - D_{ij})F_{ij} \tag{1}$$

where $s_{ij}^{NCC} = \frac{x^{i \cap j}}{x^{i \cup j}}$, $D_{ij} = \frac{\sqrt{\sum_k^{n^*}(p_{ki}-p_{kj})^2}}{n^* \sqrt{Xrange^2+Yrange^2}}$, $F_{ij} = \frac{min(NP_i, NP_j)}{max(NP_i, NP_j)}$,

The nominator of D_{ij} measures the dissimilarity of the magnitude of boards and the denominator is the normalizing factor. Therefore (1- D_{ij}) represents the similarity measure of board i and j. F_{ij} measures the frequency ratio of the number of placement locations between two boards. Therefore, two boards with the same number of placement locations are strongly associated.

There are some limitations on PLM methods. First, point magnitude of two different points could be the same. For example, point magnitude of (a,b) is the same as the one of (b,a). This could be wrongly interpreted such that there is no dissimilarity between two points. Secondly, giving equal weights for similarities may not appropriate in cases where the placement time becomes more important than the setup time or vise versa in reducing makespan.

A sequential treatment of component similarity and geometric similarity has been proposed by Leon and Jeong (2005) namely, Minimum Metamorphic Distance (MMD) based group setup strategy. Suppose that board i and j have the same number of placement locations of component type c. Then the Euclidean distance matrix from locations in board i to board j can be constructed. The problem is to find the best assignment of from-to locations which minimize the total sum of Euclidean distance (MMD_{ij}^c). The solution can be easily found using LAP method. When boards with different number of locations are used, all the locations on the board with more locations are assigned to the locations on the board with less number of locations. In MMD based setup, a new geometric similarity has been proposed as follows:

MMD_{ij}^c: minimum metamorphic distance of board i and board j for component type c.

p : placement locations of board i.

q :placement locations of board j.

d_{pq}^c: Euclidean distance between location p and q with component type c.

$$s_{ij}^{MMD} = 1 - \frac{\sum_{\forall c} MMD_{ij}^{c}}{\sum_{\forall c}\sum_{\forall p} max_{\forall q}(d_{pq}^{c})} \quad (2)$$

As shown in equation (2), when MMD increases, the geometric similarity decreases. The authors suggested a group setup strategy considering the component similarity (i.e.,s_{ij}^{NCC} in equation (1)) and the MMD based geometric similarity (i.e.,s_{ij}^{MMD} in equation (2)) sequentially. In hierarchical clustering, the proposed procedure merges two boards with the largest MMD similarity. Then the clustering objective is the maximization of average s_{ij}^{MMD} within families per unit feeder change between families. Therefore, the clustering objective is maximized when all boards in families are geometrically similar (i.e., placement time is minimized) and the number of feeder change is minimized (i.e., setup time is minimized). The limitation of the MMD based group setup is that the component similarity and the geometric similarity are not considered simultaneously. Forming the families of boards considering only geometric similarity may reduce the possibility of generating solutions which is favorable in reducing setup time. However the authors reported that MMD based group setup outperformed the PLM based group setup. In section 3, we propose a new group setup strategy which combines s_{ij}^{NCC} and s_{ij}^{MMD} using the entropy method.

3 Entropy Based Group Setup Strategy

In the past two decades, there has been of enormous growth in the area of multi-attributes optimization. One of the most important issue in this research area is the development of appropriate weights for different attributes. As each attribute has different scale, synthesizing attributes by giving appropriate weights to each attribute is essential to solve the optimization problem. The entropy method suggests that the weight assigned to a criterion must be small if all alternatives have similar value for the criterion. On the other hand, when the difference between a criterion's values is great, the criterion must be considered as important by giving large weight. Let

$NCC_{ij} = x^{i \cup j}$: number of common component type between board i and board j.

$MMD_{ij} = \sum_{\forall c} MMD_{ij}^{c}$: minimum metamorphic distance between board i and board j $\forall i, \forall j, i \neq j$.

Then the entropy measures of the criteria for NCC and MMD are as follows:

$$e(NCC) = -\sum_{i=1}^{N}\sum_{j=1}^{N} \frac{NCC_{ij}}{S_{NCC}} ln \frac{NCC_{ij}}{S_{NCC}} \quad (3)$$

$$e(MMD) = -\sum_{i=1}^{N}\sum_{j=1}^{N} \frac{MMD_{ij}}{S_{MMD}} ln \frac{MMD_{ij}}{S_{MMD}} \quad (4)$$

where $S_{NCC} = \sum_{i=1}^{N}\sum_{j=1}^{N} NCC_{ij}$, $S_{MMD} = \sum_{i=1}^{N}\sum_{j=1}^{N} MMD_{ij}$ When all NCC_{ij} are equal, then $\frac{NCC_{ij}}{S_{NCC}} = \frac{2}{N(N-1)}$ and the maximum of $e(NCC)$ is achieved which is $e_{max}(NCC) = ln\frac{N(N-1)}{2}$. This implies that if the value of a criterion is evenly distributed, then the entropy of the criterion is maximized and the entropy is minimized when the criterion value is biased. By setting a normalization factor,$K = \frac{1}{e_{max}(NCC)} = \frac{1}{ln(\frac{N(N-1)}{2})}$, $0 \leq e(NCC) \leq 1$ can be achieved. Therefore the normalized entropy measures of equation (3) and (4) are

$$e(NCC) = -K\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{NCC_{ij}}{S_{NCC}}ln\frac{NCC_{ij}}{S_{NCC}} \tag{5}$$

$$e(MMD) = -K\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{MMD_{ij}}{S_{MMD}}ln\frac{MMD_{ij}}{S_{MMD}} \tag{6}$$

We impose a large weight for a criterion when the corresponding entropy measure is small since the information transmitted by the criterion is great (i.e., there exists great difference between the values of the criterion). The weights are calculated as follows:

$$W_{NCC} = \frac{1 - e(NCC)}{2 - (e(NCC) + e(MMD))} \tag{7}$$

$$W_{MMD} = \frac{1 - e(MMD)}{2 - (e(NCC) + e(MMD))} \tag{8}$$

Using the entropy method, we propose a board's similarity coefficient of board i and j as follows;

$$s_{ij} = W_{NCC}s_{ij}^{NCC} + W_{MMD}s_{ij}^{MMD} \tag{9}$$

where s_{ij}^{NCC} is the component similarity as shown in equation (1) and s_{ij}^{MMD} is the MMD based geometric similarity as shown in equation (2). It is important to note that the entropy method can easily be extended to the development of board's similarity coefficient with more than two criteria.

The entropy based group setup strategy uses the generic group setup procedure in section 2 with the board's similarity coefficient in equation (9). The clustering objective is as the same as the one of MMD based setup (i.e., maximization of average similarity within families per unit number of feeder change between families).

4 Experiments

In this paper, we consider a generic machine that has 70 feeder slots with 20mm between the slots. The board dimensions are maximum 320mm 245mm and the coordinates for each board were randomly generated from uniform distributions as follows: X=635+U(0,245), Y=254+U(0,320). The home position coordinate is

(0,0) and the first feeder slot location is (457,0). The number of component types required per board were generated from U(6,20) from 70 different component types. We considered the time to install or remove feeder, in cases of 30(sec) and 60(sec). The head velocity, v was tested for 100(mm/sec) and 300(mm/sec). The batch size of boards, b were generated from U[50,100]. Also the total number of boards, N were generated from U[5,15]. The placement locations and the corresponding component types were generated from a seed board. A seed board is created with location $(L_{sx}(i), L_{sy}(i))$ where $L_{sx}(i)$ is the x-coordinate of ith placement location for seed board and $L_{sy}(i)$ is the y-coordinate. $C_s(i)$ is the component types of ith placement location for the seed board. We fixed the number of placement location to 50 for the seed board. Based on the component similarity (C) and geometric similarity (G), another board (i.e., a child board) is created using the following formula;

$$L_{cx}(i) = L_{sx}(i) + (1 - G) \times 0.5 \times 245 \times U(-1, 1) \tag{10}$$

$$L_{cy}(i) = L_{sy}(i) + (1 - G) \times 0.5 \times 320 \times U(-1, 1) \tag{11}$$

$$C_c(i) = \begin{cases} C_s(i) \text{ with probability } C \\ \mathrm{U}(1,NC_c), \text{ otherwise} \end{cases} \tag{12}$$

Where $L_{cx}(i)$ is the x-coordinate of ith placement location for child board and $L_{cy}(i)$ is the y-coordinate. $C_c(i)$ is the component types of ith placement location for the child board. NC_c is the number of component type of the child board c. Based on these experimental factors and parameters, we generated 16 problem types as shown in Table 4. Each problem set consists of 20 random problems.

Table 1. Problem types

Problem type	Head velocity (mm/sec)	Feeder change time (sec)	Component similarity (C)	Geometric similarity (G)	Problem type	Head velocity (mm/sec)	Feeder change time (sec)	Component similarity (C)	Geometric similarity (G)
1	100	30	0.2	0.75	9	100	30	0.2	0.2
2	100	30	0.75	0.75	10	100	30	0.75	0.2
3	100	60	0.2	0.75	11	100	60	0.2	0.2
4	100	60	0.75	0.75	12	100	60	0.75	0.2
5	300	30	0.2	0.75	13	300	30	0.2	0.2
6	300	30	0.75	0.75	14	300	30	0.75	0.2
7	300	60	0.2	0.75	15	300	60	0.2	0.2
8	300	60	0.75	0.75	16	300	60	0.75	0.2

To measure the performance of the different setup strategies, the deviation from partial setup is computed as follows:

Percent deviation from partial setup=$\frac{M^{setupstrategy} - M^{PS}}{M^{PS}} \times 100\%$
Percent M^{PS} represents the makespan of partial setup (PS) strategy. $M^{\text{setup strategy}}$ corresponds to the makespan of PLM based group setup (PLM), MMD based group setup (MMD) and the Entropy based group setup (ENT).

Table 2 summarizes the average setup time, average placement time and average makespan of different setup strategies. Consider problem type 1 where head velocity is 100mm/sec, feeder change time is 30sec, component similarity is 20% and geometric similarity is 75%. Note that in this specific problem, the placement time is more important than setup time since the head velocity is slow, the feeder change time is short. Result shows that PLM performs better in terms of setup time than PS, MMD and ENT. This is because PS, MMD and ENT achieve an improvement in the reduction of the placement time instead of setup time. In addtion ENT assigns the larger weight for the geometric similarity of boards than MMD under consideration. As a result, ENT dominates PLM and MMD by reducing about 8% and 4% of makespan relatively as shown in Table 2. In summary, test results show that ENT outperforms PLM and MMD in terms of makespan. The maximum percent deviation from PS of ENT is 2.72% while MMD and PLM are 5.6% and 9.35% respectively. This result implies that ENT balances the tradeoff between the setup time and the placement time and finds the solution that minimizes the makespan for all types of problems.

Table 2. Summary of experimental results

Problem type	(PLM-PS)/PS*100*			(MMD-PS)/PS*100*			(ENT-PS)/PS*100		
	Setup time Average	Placement time Average	Makespan Average	Setup time Average	Placement time Average	Makespan Average	Setup time Average	Placement time Average	Makespan Average
1	−25.15	9.51	8.69	3.93	3.45	3.46	9.61	1.04	1.25
2	−21.58	1.21	0.86	−23.51	1.38	1.00	−10.64	0.90	0.72
3	−16.64	8.37	7.37	11.91	2.97	3.32	24.00	−0.30	0.66
4	−3.97	0.95	0.83	−10.99	1.52	1.21	−5.79	0.93	0.76
5	−15.67	8.61	7.25	12.25	4.89	5.30	34.44	−0.66	1.30
6	6.26	1.26	1.43	−3.86	0.97	0.81	15.17	0.53	1.01
7	14.70	0.19	1.02	8.94	0.61	1.09	18.67	0.24	1.29
8	21.71	−0.03	1.19	15.94	0.38	1.25	25.75	−0.11	1.35
9	−22.17	8.96	8.24	2.69	4.46	4.42	16.37	−0.04	0.34
10	−23.50	1.14	0.73	−26.87	1.66	1.19	−11.45	1.23	1.02
11	−24.37	10.79	9.35	4.97	4.93	4.94	13.45	2.26	2.72
12	−2.62	0.78	0.70	−8.26	1.25	1.01	10.06	0.72	0.96
13	−12.87	7.93	6.74	7.01	5.52	5.60	22.69	0.71	1.97
14	−5.38	1.36	1.12	0.67	0.86	0.85	12.31	0.22	0.65
15	12.55	0.04	0.75	12.99	0.10	0.83	39.29	−0.40	1.86
16	36.38	0.11	0.99	−21.54	1.44	0.89	−4.39	0.92	0.79
Overall									
Average	−5.15	3.82	3.58	−0.86	2.27	2.32	13.10	0.51	1.17
Min	−25.15	−0.03	0.70	−26.87	0.10	0.81	−11.45	−0.66	0.34
Max	36.38	10.79	9.35	15.94	5.52	5.60	39.29	2.26	2.72

*:Results from Leon and Jeong (2005)

5 Conclusions

This paper has presented an improved group setup strategy based on entropy method considering both component similarity and geometric similarity. It has demonstrated how the entropy method determines weights for different criteria to adapt to a variety of production conditions. The improved group setup strategy dominated PLM or MMD based group strategy for all types of problems. Overall, improved group setup strategy deviated from partial setup, maximum 2.72% and average 1.17%. Future research includes the extension of the multiple SMT machines and the consideration of multiple criteria in grouping PCBs (e.g., due dates).

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