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Multi-objective Design Optimization of MCM Placement

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Abstract :- Placement of multiple dies on an MCM substrate is a difficult combinatorial task in which multiple criteria need to be considered simultaneously to obtain a true multi-objective optimization. Our design methodologies consider multi-objective component placement based on thermal reliability, routing length and chip area criteria for multi-chip module. The purpose of the multi-objective optimization placement is to enhance the system performance, reliability and reduce the substrate area by obtaining an optimal cost during multi-chip module placement design phase. For reliability considerations, the design methodology focuses on the placement of the power dissipating chips to achieve uniform thermal distribution. For route-ability consideration, the total wire length minimization is estimated by Steiner tree approximation method. For substrate area consideration, the area is estimated by minimum area contains all chips. The cost function is formulated by the weight sum calculation. For design flexibility, different weights can be assigned depending on designer's considerations. Various methods including iteration, simulated annealing and generic approximation are applied to solve the placement solutions. An auto generated optimal placement layout based on the analytical solution is presented.

Key-Words: -Multi-chip module, placement, multi-objective, simulate annealing algorithm, generic algorithm, fuzzy thermal placement algorithm

1. Introduction

Optimal electronic component placement studies have traditionally focused on single objective optimization [1,2]. It has mainly used a single objective of minimizing the overall wire length or minimizing the overall heat generation or minimizing the overall time delay in its functioning. Osteman et al. [3] developed a force directed placement methodology to solve coupled reliability and routability placement procedure for arranging electronic components on a convectively cooled two-dimensional workspace. Queipo et al. [4] introduced a genetic algorithm for the search of optimal or near optimal placement solutions on printed wiring boards. Deb et al [5] use evolutionary algorithms to solve a two-objective optimization problem including minimizing the overall wire length and minimizing the failure rate of the board. A fuzzy analytical model for the optimal component placement on the multichip module (MCM) substrate is presented in [6, 7]

There are many factors to consider in selecting the correct MCM package design. In a conventional layout flow, placement studies have focused on single objective optimization. For instance, placement and routing are optimized for timing, with little or no consideration for power, routability or signal integrity. Some of the important goals for the MCM placement designs are: even heat distribution, minimization of the total substrate area, the total routing length, and the number of routing layers. Therefore, the design must consider the combined cost of the heat dissipation, area, routing length … etc., not just each cost in isolation.

In this paper, we focus on the multi-objective placement optimization studies. These objectives are routing length, substrate area, and thermal distribution. The main design issue addressed is on the multi-objective optimization placement for reliability, route-ability and substrate area. The weighted sum approach is used to formulate the placement cost function. The optimum solutions of the cost function are obtained based on simulated annealing, and generic approximation algorithms. The rest of this paper is organized as follows. Section 2 provides problem formulation. Section 3 explains different solution techniques. Section 4 presents experimental results. Section 5 concludes our paper.

2. Problem Formulation

The placement problem can be stated as follows: Given a set of modules (cells) M = $\{m_1, m_2, \cdots m_n\}$, a set of signals S = $\{s_1, s_2, \cdots s_k\}$, and a set of power $P = \{p_1, p_2, \cdots p_n\}$. Each module $m_i \in M$ is associated with a set of signals S_{c_i} , where $S_{c_i} \subset S$. Also each signal $s_1 \in S$ is associated with a set of modules M_{s_i} , where $M_{s_i} = \{m_j \mid s_i \in S_{c_j}\}$. M_{s_i} is called a signal net. The power set indicates the associate power value for the corresponding module in module set. Placement consists of assigning each module $m_i \in M$ to a unique location such that a given cost function is optimized and constraints are satisfied.

The objective of an multi-chip module (MCM) placement is to minimize a weighted sum of some optimization criteria subject to constraints on others. E.g., if k criteria are considered, the objective is to minimize the single-valued cost function

$$C = \sum_{i=1}^{j} w_i f_i \quad s.t. \quad \forall \quad i = j+1, \ldots, k : f_i \le F_i \qquad (1)$$

for some j, $1 \le j \le k$. Here f_i is the cost of the solution with respect to the i'th criterion. w_i and F_i 's are user-defined weights and bounds, respectively.

Three objectives representing the general performance of a placement system are considered in this study. There are minimizing substrate area, minimizing routing length, and minimizing thermal gradient. The cost due to these objectives f_i can be defined as follows:

a. Substrate Area= area that contains all the dies
b. Routing length=Entire Steiner tree lengths connect all the die
c. Power cost=Thermal distribution on the entire substrate

The weight sum approach is applied in order to combine these three objectives. The optimized solution is to obtain a minimum sum of weights of the form given as:

$$\min \sum_{i=1}^{k} w_i f_i \qquad (2)$$

where w_i are the weighting coefficients representing the relative importance of the objectives f_i . It is usually assumed that

$$\sum_{i=1}^{k} w_i = 1 \qquad (3)$$

The fuzzy thermal placement algorithm [8] is used to estimate the power cost. The average repulsive force among the dies can be expressed as the following formula:

$$P = \frac{\sum F_{ij}}{N(N-1)} \qquad (4)$$

Where F_{ij} is the repulsive force based on fuzzy Z function [7, 8], N is the total number of dies.

3. Solution Methodology

The basic consideration to approach the multi-objective approximation optimize solution is to make the final cost as low as possible. Due to different purposes and requirements, various weight settings can be assigned to the three objectives to calculate the total combined cost of thermal, power and area. Various methods including iteration, simulated annealing, convergence perturbation and genetic algorithm are applied to solve the placement solutions.

Simulated annealing method [9] could escape from the local minimum solution to approach the global minimum solution. During iteration process, the new reading will be always accepted as long as the new energy value E becomes smaller. If the value increased, then it could be accepted in a certain probability. The accepted probability P can be determined from the following equation.

$$P = \exp \frac{-(E_{next} - E_{current})}{Temperature} \qquad (5)$$

The temperature is set to high value at the beginning such that it could escape from the local minimum solution. It then continues to cool down the temperature to approach the best solution. The pseudo code of the simulated annealing algorithm is listed in Table 1.

Table 1 Simulated annealing algorithm for MCM Placement

```
Algorithm Simulated_annealing(S0, T0, T1, α, M);
(*S0 is the initial solution*)
(*T0 is the initial temperature *)
(*T1 is the final temperature *)
(* α is the cooling rate *)
(*M represents the time until the next parameter update *)
Begin
 T=T0;
 S=S0;
 repeat
        Iteration=M;
         repeat
          NewS=RandomPosition(S);
          ρH=Cost(NewS)-Cost(S);
          if ((ρH<0) or (random<e-ρH/T) then S=NewS;
          Iteration=Iteration+1;
         until (Iteration=0)
         T= α x T;
 until (T<T1)
End.
```

For iteration technique, the solution methodology start to randomly exchange the die position and set a loop to approach the optimize solution. With random choice of the new position, it is difficult to converge to the global minimum solution. If we could randomly change the die position at the beginning and then limit the new position to the area around previous position, then it could be easier to get the better global solution. To achieve this goal, we apply small perturbation approximation method to limit the area of random position.

The advantage of the simulated annealing method is that it can escape from the local minimum. But it would not be easy to get the global minimum solution if we randomly set the new position. To rapidly get the global minimum solution, we set the converging position instead of random position. To combine the advantages of simulated annealing method and small perturbation method, we develop the simulated annealing with small perturbation method. It could not only escape the local minimum solution in the beginning, but also can fast to get closer to the solution. The pseudo code of the simulated annealing with small perturbation program is listed in Table 2.

Table 2 Simulated annealing with small perturbation algorithm for MCM Placement

```
Simulated_Annealing_with_Small_Perturbation(S0, T0, T1, α, M);
(*S0 is the initial solution*)
(*T0 is the initial temperature *)
(*T1 is the final temperature *)
(* α is the cooling rate *)
(*M represents the time until the next parameter update *)
Begin
 T=T0;
 S=S0;
 repeat
        Iteration=M;
         repeat
          NewS=LimitePosition(M, T);
          ρH=Cost(NewS)-Cost(S);
          if ((ρH<0) or (random<e-ρH/T) then S=NewS;
          Iteration=Iteration+1;
         until (Iteration=0)
         T= α x T;
 until (T<T1)
End.
```

The simulation results for random choice of the switch position and small perturbation of the chosen position is shown on Figure 1, respectively. The blue diamonds are random choice of the switch position and the red rectangles are small perturbation of the chosen position.

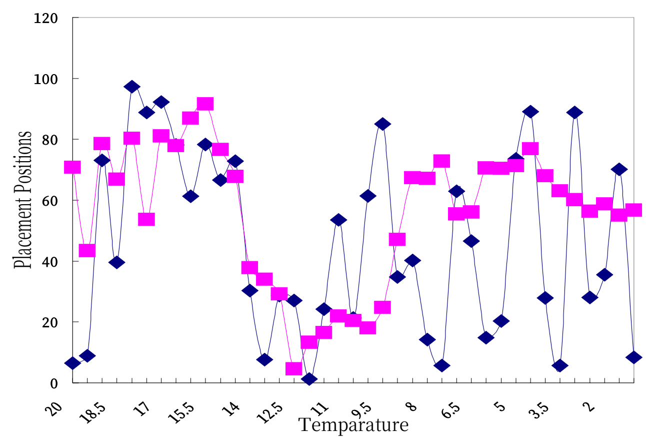

Figure 1 Comparison with random choice and small perturbation method

Generic Algorithm is used to exchange the sequence of the die positions including crossover, mutation and reproduction [10]. Crossover is an operation where two parent sequences exchange parts of their corresponding chromosomes. We set two kinds of initial positions to be parent chromosomes as shown on Figs 2, 3. The

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parent chromosome position 1 describes the best power dissipation. And the parent chromosome position 2 describes the smallest area requirement.

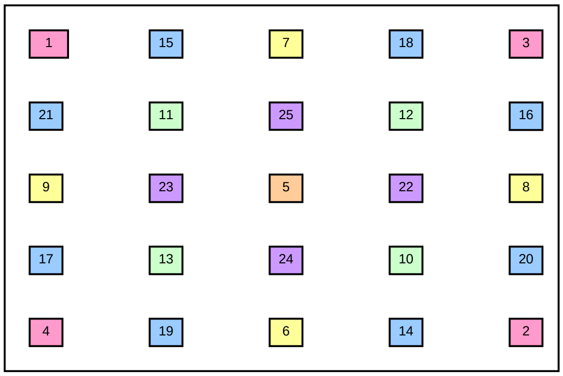

Figure 2 Generic parent chromosome position 1

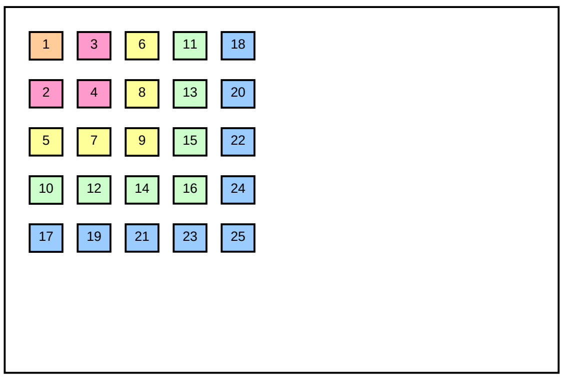

Figure 3 Generic parent chromosome position 2

For example, two parent sequences (123456) and (654321) are selected according to pre-defined crossover probabilities. A crossover point is randomly selected, and then a new sequence (654123) is created. Mutation is an operation that randomly changes the sequence. We also use the reproduction to reverse the sequence of parent one. The pseudo code of the generic algorithm program is listed in Table 3.

4. Experiment Results

In this section, the simulation results of the multi-objective component placement are presented. Various weighting factors are used to observe the multi-objective component placement. Depending on the values of the selected weighting factor, the placement procedure allows the designer to place components for optimal reliability, area, or routability. In addition, the placement procedure can be used to observe the trade-offs relationship among reliability, area, and routability.

. Table 3 Generic Algorithm for MCM Placement

```
Algorithm Generic(S0,M0, N0);
(*S0 is the initial solution*)
(*N represents the time for chromosome exchange*)
(*M represents the time for rearrange die position*)

Initialize die position;
Begin
For N= 1 to N0
   S=S0;
For M=1 to M0
NewS[1] = Crossover sequence;
NewS[2] = Crossover sequence;
NewS[3] = Crossover sequence;
NewS[4] = Crossover sequence;
NewS[5] = Crossover sequence;
NewS[6] = Crossover sequence;
NewS[7] = Reproduction sequence;
NewS[8] = Mutation sequence;
For L=1 to 8
if (NewS[L] < S) then S=NewS[L];
      next L
next M
    Rearrange die position;
next N;
End.
```

We set the input condition as shown on Table 4. In this case study, there are 20 dies with different length, width and power, and three different nets to interconnect these chips. Figs 4, 5 shows the results obtained by simulated annealing and simulated annealing with small perturbation methods for the weighting factors of Power : Routing : Area=1:1:2, respectively. In the figures, the blue diamonds are the power costs curve, the purple rectangles are the routing costs curve, the green triangles are the area costs curve and the red Xs denote the total costs curve. The horizontal axis represents the simulation time, and the vertical axis represents the normalized total cost value. The traditional loop iteration method applied in this case study cannot always reach the global minimum solutions. However, with simulate annealing method, it can obtain the approximation global minimum solution. The solution with loop iteration with small perturbation method will be more close to the minimum solution.

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Table 4 Input condition for program simulation

Length	Width	Power	Net1	Net2	Net3
10	10	1	V		
10	20	1	V		
10	30	1	V		
10	40	1	V		
10	50	1	V		
10	60	1	V		
10	70	1	V		
10	80	1	V		V
10	90	1	V		V
10	100	1		V	V
50	50	5		V	V
20	10	1		V	
30	10	1		V	
40	10	1		V	
50	10	1		V	
60	10	1		V	
70	10	1		V	
80	10	1		V	
90	10	1		V	
100	10	1		V	

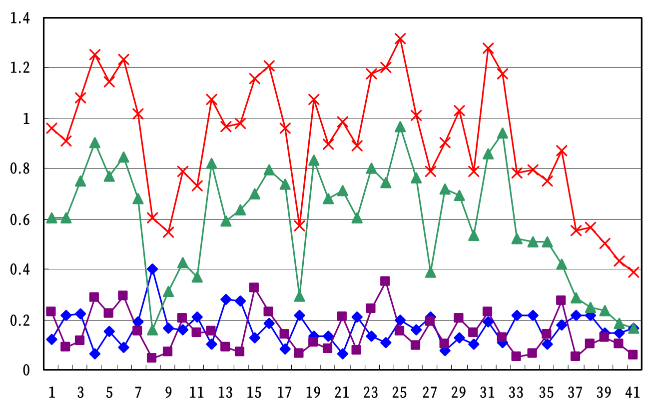

Figure 4 Results of simulated annealing method

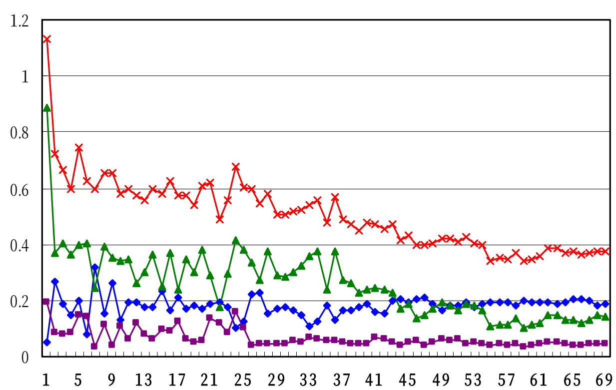

Figure 5 Results of simulated annealing with small purturbation

Figs 6, 7, 8, 9 show the results of auto generated optimal placements layout based on the analytical solutions for weighting factors to 1:0:0, 0:1:0, 0:0:1 and 1:1:1.

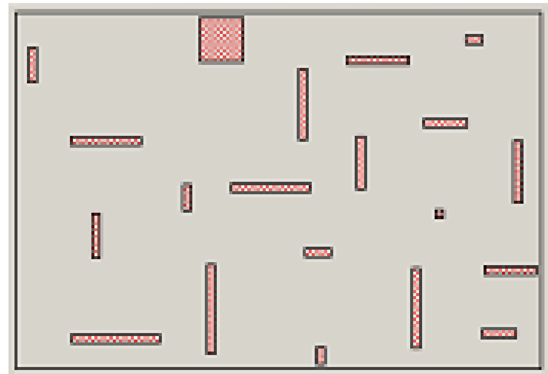

Figure 6 Auto generated optimal placement layout with power:routing:area=1:0:0

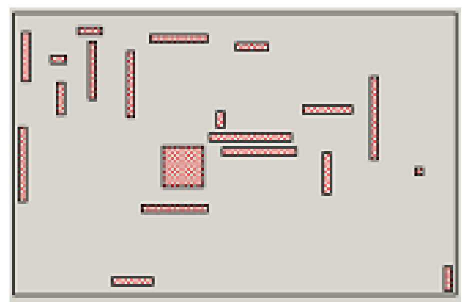

Figure 7 Auto generated optimal placement with power:routing:area=0:1:0

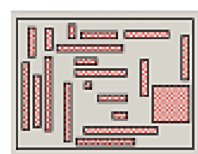

Figure 8 Auto generated optimal placement layout with power:routing:area=0:0:1

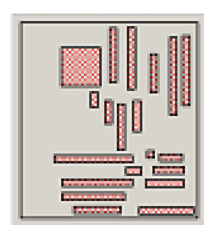

Figure 9 Auto generated optimal placement layout with power:routing:area=1:1:1

The final costs for these four different weighting factors are summarized on Table 5.

Table 5 Summary of four different weight settings

Power	Wire	Area	PowerCost	WireCost	AreaCost	TotalCost
0	0	100	0.33	0.53	0.03	0.89
0	100	0	0.40	0.07	0.35	0.82
33	33	33	0.26	0.18	0.10	0.54
100	0	0	0.04	0.99	0.99	2.02

The simulation results obtained from generic algorithm for power, wire, area, and total cost under various weighting assignment are shown in Figure 10. As shown in the power cost figure, when the power weighting factor is higher, then the final power cost becomes lower. The area and wire cost figures have the similar effect. Note that power and area weight settings have the opposite effects on cost evaluation.

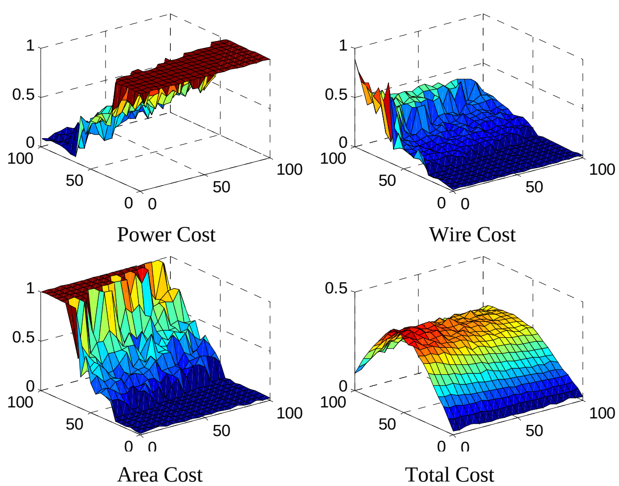

Figure 10 Generic method with different weight settings

5. Conclusions

In this paper, we formulated the multi-object cost function for MCM evaluation. The objective function of the optimization problem consists of cost estimates for power dissipation, routing length, and substrate area. Depending on the selected weighting factor, different placement configurations based on simulated annealing approach and generic algorithm can be obtained. An auto generated optimal placement layout based on the analytical solutions can help designers to make trade-offs among multi-objective selections for MCM design considerations.

Acknowledgments

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