SimE/TS fuzzy hybrid for multiobjective VLSI placement

S.M. Sait and M.R. Minhas

A hybrid heuristic for multiobjective VLSI cell placement is presented, which draws from the memory concept of Tabu search (TS) and the goodness feature of Simulated Evolution (SimE). Experimental results using ISCAS-89 benchmark circuits illustrate improvement in quality as compared to our best canonical TS implementation.

Introduction: The focus in this work is on combining the strong characteristics from two popular iterative algorithms, namely Simulated Evolution (SimE) and Tabu search (TS), applied to the VLSI standard cell placement problem. SimE is an evolutinary algorithm that iteratively runs one main loop consisting of three basic steps: evaluation, selection and allocation, which are executed in sequence until stopping criteria are reached. The algorithm starts from an initial assignment and assumes a population comprising a set of movable elements, where the assignment of each is associated with a certain goodness (fitness) relative to its present location. TS is an aggressive search technique based on the systematic exploration of the solution landscape, controlled by memory functions that record recent move history to avoid cycling. In-depth descriptions of the working of SimE and TS can be found in [1]. The VLSI cell placement problem is multiobjective and addresses reducing wirelength, power consumption and timing delay achieved within a defined layout width. Owing to the inherent infeasibility of determining precise cost parameters, the goodness values of individual elements in their current locations as required by SimE and the overall quality of the placement solution are both described in linguistic terms using fuzzy logic.

Multiobjective fuzzy cost function: The objectives considered in our cell placement problem include optimising power consumption, improving timing performance (delay), and reducing overall wirelength, while considering layout width as a constraint. A semi-formal description of the placement problem can be found in [2]. The cost functions associated with the defined objectives are similar to those formulated in [3].

The three possibly confiicting objectives are accumulated using fuzzy logic into a single scalar cost function. The fuzzy rule used to govern the role of these objectives in the final cost function is as follows:

Rule R1: **IF** a solution has *SMALL wirelength* **AND** *LOW power consumption* **AND** *SHORT delay* **THEN** it is a *GOOD* solution.

The above rule is translated to *and-like* OWA fuzzy operator [4] and the membership $\mu(x)$ of a solution x in fuzzy set *GOOD solution* is obtained by:

$$\mu(x) = \begin{cases} \beta \min_{j=p,d,l}\{\mu_j(x)\} + (1-\beta)\frac{1}{3}\sum_{j=p,d,l}\mu_j(x); \\ \qquad \text{if width} - w_{\text{avg}} \le \alpha w_{\text{awg}}, \\ 0; \qquad \text{otherwise} \end{cases} \tag{1}$$

Here $\mu_j(x)$ for $j = p, d, l$ are the membership values in the fuzzy sets *LOW power consumption, SHORT delay,* and *SMALL wirelength*, respectively. β and α are constants in the range [0, 1]. 'Width' is the layout width of the placement, while w_{avg} is the average layout width. The solution that results in the maximum value of $\mu(x)$ is reported as the best solution found by the search heuristic.

Fuzzy goodness evaluation: In the SimE algorithm, following the generation of an initial solution, the goodness of each cell in its current location is determined. A designated location of a cell is considered good if it results in short wirelength for its nets, reduced delay, and reduced power, and can be conveniently expressed by the following fuzzy rule:

Rule R2: **IF** cell i is *near its optimal wire-length* AND *near its optimal power* AND [*near its optimal net delay* OR $T_{\max}(i)$ *is much smaller than* $T_{\max}$] **THEN** it has a high goodness.

where $T_{\max}$ and $T_{\max}(i)$ are the delay of the most critical path and the delay of the longest path traversing cell i in the current iteration, respectively.

With the AND and OR fuzzy operators implemented as OWA operators, rule **R2** evaluates to the expression:

$$g_i = \mu_i(x) = \beta \min_{j=p,w,d}\{\mu_j(x)\} + (1-\beta)\frac{1}{3}\sum_{j=p,w,d}\mu_j(x)$$

Here g_i is the goodness of cell i while β is a constant between 0 and 1 to control the OWA operator, and $\mu_j(x)$ for $j = p$, w, d represents the memberships in the fuzzy sets of good power, good wirelength and good timing performance. Further discussion on the above, and on membership functions of the base values is available in [3].

SimE/TS hybrid algorithm: The structure of the SimE-TS hybrid heuristic is shown in the SimE-TS hybrid algorithm below. An initial solution is randomly generated and the fuzzy goodness values (g_i) of each cell i are evaluated. Using these goodness values, a candidate list (CL) of moves is generated. The lower the value of g_i, the higher is the probability of cell i being included in the CL. The process is:

Algorithm SimE-TS hybrid;
Begin
  (* S_0 is the initial solution. *)
  (* *BestS* is the best solution. *)
  (* *CurS* is the current solution. *)
  (* *CL* is the Candidate List. *)
  (* *BM* is the Best Move. *)
  (* g_i is goodness of cell i. *)
  Generate S_0;
  $Best_S = S_0$;
    While *iteration-count* < *max-iterations*
      EVALUATION: /* Evaluate fuzzy goodness for all cells */
        ForEach $i \in S_0$ compute g_i;
      Generate *CL* subject to g_i's;
      /* CL likely to contain cells with lower goodness */
      Try each move in *CL* and compute cost;
      Find *BM* subject to tabu restrictions and aspiration criteria;
      Update *BestS*; /* by applying *BM* on *BestS* */;
    EndWhile
  Return (*BestS*)
End.

This process then searches the current solution's local neighborhood by trying each move in the CL and computing the resulting fuzzy fitness. The best move (BM) from these is selected subject to Tabu restrictions and aspiration criteria. The fuzzy goodness values for the cells are then re-computed and a new CL is constructed. The above process is repeated for a fixed number of iterations.

Table 1: Comparison of TS with proposed SimE/TS hybrid in terms of solution fitness and run time

Circuit name	Number of cells	TS		SimE/TS	
		Fitness $\mu(x)$	Time	Fitness $\mu(x)$	Time
s298	136	0.777	33	0.807	35
s386	172	0.688	52	0.712	57
s641	433	0.785	934	0.799	971
s832	310	0.644	74	0.685	95
s953	440	0.661	195	0.701	225
s1196	561	0.653	374	0.682	416
s1238	540	0.633	357	0.668	401
s1488	667	0.603	259	0.629	310
s1494	661	0.601	268	0.630	316
s3330	1961	0.699	1186	0.726	1360
s5378	2993	0.669	1850	0.691	2104
s9234	5844	0.631	5571	0.667	6166

Experimental results and discussions: ISCAS-85/89 circuits were used as performance benchmarks for evaluating the proposed SimE/TS hybrid technique. These circuits are of various sizes in terms of number of cells and paths, and thus offer an adequate variety of test cases.

Table 1 compares the aggregate fuzzy fitness of solutions reached within the same number of iterations by the proposed SimE/TS hybrid and a traditional TS implementation. The consistently higher quality solutions lend strong credibility to this hybridisation approach. It should be noted that even a very small increase in the fitness value could be due to a fairly large increase in one of the objectives. This is due to the nature of the OWA operator, which employs the min function in the fuzzy fitness calculation (1) and a fairly large value of β (equal to 0.7). With regards to run times, the SimE/TS hybrid took a little longer in reaching better solutions owing to the overhead introduced by the 'goodness' evaluation routine. This increase in run time is quite fairly compensated for by the solution quality improvement, which undoubtedly is more important than the run time increase.

Acknowledgment: The authors thank King Fahd University of Petroleum & Minerals, Saudi Arabia, for support under project code # COE/CELLPLACE/263.

8 December 2005
Electronics Letters online no: 20064272
doi: 10.1049/el:20064272

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References

1 Sait, S.M., and Youssef, H.: 'Iterative computer algorithms and their application to engineering' (IEEE Computer Society Press, 1999)
2 Sait, S.M., and Youssef, H.: 'VLSI physical design automation: theory and practice' (World Scientific, Singapore, 2001)
3 Khan, J.A., Sait, S.M., and Minhas, M.R.: 'Fuzzy biasless simulated evolution for multiobjective VLSI placement'. Proc. IEEE Congress on Evolutionary Computation, (CEC), 2002, Vol. 2, pp. 1642–1647
4 Yager, R.R.: 'On ordered weighted averaging aggregation operators in multicriteria decision making', *IEEE Trans. Syst. Man Cybern.*, 1988, **18**, (1)