

# Large-Scale Circuit Placement: Gap and Progress

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Tony F. Chan  
Kenton Sze

Mathematics Department, UCLA  
Los Angeles, CA 90095-1555  
{chan,nksze}@math.ucla.edu

Jason Cong  
Joseph Shinnerl  
Min Xie

Computer Science Department, UCLA  
Los Angeles, CA 90095-1596  
{cong,shinnerl,xie}@cs.ucla.edu

The presentation reviews results from some recent optimality studies and recent progress in the UCLA mPL placer.

## 1 Placement Examples with Known Optima (PEKO)

Recently, the PEKO studies have given evidence of how far computed placement solutions are from optimal and how much the deviation from optimality is likely to grow with respect to problem size. The original PEKO examples have all cells of equal size. Each PEKO is constructed to match the net-degree distribution of a given benchmark exactly, but with all nets defined to support a placement in which each net is purely local and has the minimum possible half-perimeter wirelength.

Four state-of-the-art placers from academia including Dragon [12], Capo [3], mPL [4], mPG [6], and one industrial placer, QPlace [2] were compared on PEKO. Overall, their computed wirelengths were 1.59 to 2.40 times the optimal in the worst cases and are 1.43 to 2.12 times the optimal on average. As for scalability, the average solution quality of each tool deteriorates by an additional 9% to 17% when the problem size increases by a factor of 10.

The PEKO studies present strong evidence that the quality gap between globally optimal and computed solutions remains large. Although recent work suggests that the gap is shrinking fast on the smaller benchmarks ( $10^4 \leq N \leq 10^5$ ), with specialized approaches [11, 13] achieving quality ratios as low as 10%, the gap remains large on larger test cases. Internal unpublished studies show that simple perturbations of the PEKO test cases, e.g., aggregating large sets of standard cells into large macro blocks, create cases for which the quality gap may exceed  $8\times$ .

In addition to quantifying suboptimality, these benchmarks provide clues useful in targeting algorithm weaknesses. Recent work by Ono and Madden [11] examines placements computed by existing tools on PEKO and shows that displacements of cells from known optimal locations may all be small, even when corresponding total wirelength is more than 30% longer than optimal. While this result might be seen as indicating a need for improved algorithms for detailed placement, we will show displacements whose global regularity suggests otherwise.

## 2 Progress in UCLA mPL5

The mPL5 framework [5] makes several improvements to the Kraftwerk framework for generic force-directed placement [7] and embeds this improved engine in a multilevel-optimization flow. A bounding-box weighted half-perimeter wirelength objective is approximated by the log-sum-exp model [10, 9], in which  $W(\mathbf{x}, \mathbf{y}) =$

$$\gamma \sum_{\text{nets } e \in E} \left( \log \sum_{\text{nodes } v_k \in e} \exp(x_k/\gamma) + \log \sum_{v_k \in e} \exp(-x_k/\gamma) + \log \sum_{v_k \in e} \exp(y_k/\gamma) + \log \sum_{v_k \in e} \exp(-y_k/\gamma) \right),$$

where  $\mathbf{x}$  and  $\mathbf{y}$  denote vectors of cell  $x$ - and  $y$ -coordinates. The smaller the parameter  $\gamma$ , the more accurate the approximation. For simplicity, restrict attention to area density constraints only. These are explicitly imposed separately in each rectangular bin of a uniform grid laid over the placement region. Let  $d_j$  denote the cell-area density of bin  $B_j$  and let  $K$  denote total cell area divided by the total placement area. The

area-density constraints are initially expressed simply as  $D_j = K$  over all bins  $B_j$ . Viewing the  $D_j$  as a discretization of a continuous density function  $d(x, y)$  defined at points  $(x, y) \in R$ , these constraints are smoothed by approximating  $d$  by the solution  $\psi$  to the Helmholtz equation

$$\begin{cases} \Delta\psi(x, y) - \epsilon\psi(x, y) = d(x, y), & (x, y) \in R \\ \frac{\partial\psi}{\partial\nu} = 0, & (x, y) \in \partial R \end{cases} \quad (1)$$

where  $\epsilon > 0$ ,  $\nu$  is the outer unit normal,  $\partial R$  is the boundary of the placement region  $R$ ,  $d(x, y)$  is the continuous density function at a point  $(x, y) \in R$ , and  $\Delta$  is the Laplacian operator  $\Delta \equiv \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$ . The smoothing operator  $\Delta_\epsilon^{-1}d(x, y)$  defined by solving (1) is well defined, because (1) has a unique solution for any  $\epsilon > 0$ . As the solution of (1) has two more derivatives [8, e.g.] than  $d(x, y)$ ,  $\psi$  is a smoothed version of  $d$ . Discretized versions of (1) can be solved rapidly by fast numerical multilevel methods. Recasting the density constraints as a discretization of  $\psi$  gives the nonlinear programming problem

$$\min W(\mathbf{x}, \mathbf{y}) \quad \text{s.t.} \quad \psi_j = -K/\epsilon, \quad 1 \leq i \leq m, 1 \leq j \leq n,$$

where the  $\psi_j$  are obtained by solving (1) with the discretization defined by the given bin grid. Interpolation from the adjacent coarser level defines a starting point. This nonlinear-programming problem is solved by the Uzawa iterative algorithm [1], which does not require second derivatives or large linear-system solves.

Experiments indicate that mPL5's results are extremely competitive in both total wirelength and speed and scalability.

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