

# Fast and Accurate Curvilinear OPC with ML-Guided Curve Correction

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**Abstract**— In curvilinear OPC, each pattern segment is assumed as a cubic Bézier curve, which is defined by two endpoints and two intermediate points. Iterative correction of the curves is very time consuming even with simple heuristic [1]. Two ML models are introduced for fast and accurate curve correction. An MLP is used to locate the new endpoints, while correction error (called VPE) from the previous iteration and a few PFT signals representing local light intensity are provided as inputs. VPE predictor is constructed with both target and mask patterns being modeled with nested GCNs; the output is average VPE. Intermediate points are identified while the VPE predictor is optimized with a goal of minimizing average VPE and violations of curvature constraints and geometric continuity constraints. The proposed OPC is compared to the reference [1]: the number of OPC iterations is reduced from 12 to 3 while final average VPE is reduced from 0.49nm to 0.44nm.

## I. INTRODUCTION

Optical proximity correction (OPC) is iterative as shown in Figure 1. A layout polygon is divided into a number of line segments. In one iteration, each segment is shifted and lithography simulation is applied to predict a wafer contour, which is compared to a target while edge placement error (EPE) is measured. Iteration repeats until average (or maximum) EPE becomes small enough.

Recently, curvilinear OPC has been actively studied for better OPC quality. Each segment is assumed as a curve instead of a line. A cubic Bézier curve is most popular representation; it is defined by two endpoints,  $a$  and  $d$ , and two intermediate points,  $b$  and  $c$ , as shown in Figure 2(a). The curve itself, indicated by a dotted shape, is given by:

$$P(t) = a(1-t)^3 + 3b(1-t)^2t + 3c(1-t)t^2 + dt^3, \quad (1)$$

with  $0 \leq t \leq 1$ .

### A. Curvilinear OPC: Review

The first step of correction is to move leading endpoints  $a_i$ s of all segments; note that trailing endpoint is shared with the leading endpoint of adjacent segment, e.g.  $d_i = a_{i+1}$  in Figure 2(b). The amount of move is usually in proportion to EPE from previous iteration, similar to line segment move in Manhattan OPC. The second step, with new endpoints set, is to identify the position of intermediate points. This step is not trivial, and a simple heuristic has been applied [1]. The angle bisector of the angle formed by  $a_{i-1}$ ,  $a_i$ , and  $a_{i+1}$  is identified;  $b_i$  is positioned on a line  $90^\circ$  from the angle bisector with distance in proportion to  $\overline{a_i d_i}$ ;  $c_i$  is positioned similarly.

## II. CURVILINEAR OPC WITH ML MODELS

EPE is not a measure appropriate to curvilinear OPC; vertex

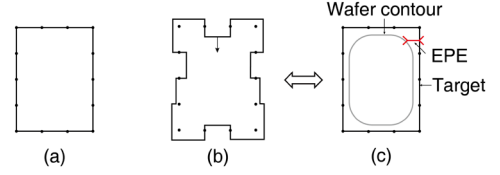


Figure 1. OPC steps: (a) fragmentation; iteration of (b) correction and (c) lithography simulation with EPE calculation.

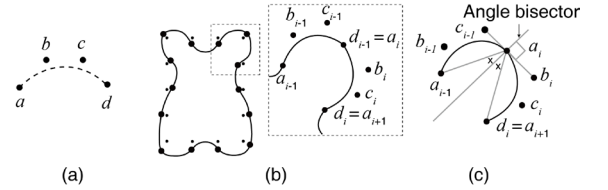


Figure 2. (a) A cubic Bézier curve, (b) segment correction in curvilinear OPC and (c) a heuristic method to find intermediate points.

placement error (VPE) is introduced in this paper instead. Segment correction as reviewed in Section I.A is not ideal. We apply machine learning (ML) models to both steps for more accurate correction, which ultimately helps reduce the OPC iterations. In particular, multi-layer perceptron (MLP) model is applied to the first step. VPE predictor is constructed with graph convolutional networks (GCNs); it allows intermediate points to be identified in a way that average VPE is minimized.

### A. VPE

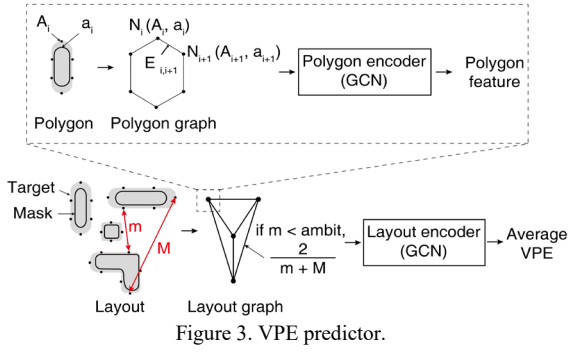
EPE has been used for conventional Manhattan OPC, in which error is measured between target line segment and corrected segment contour as illustrated in Figure 1. It is not a proper measure when both target- and printed-segments are assumed as curves. We introduce VPE as a new measure for curvilinear OPC. VPE is defined by the distance between the leading endpoint of the target and its closest corresponding point on the wafer contour.

### B. UPDATE OF BÉZIER CURVE ENDPOINTS

In standard OPC, correction is based on EPE from previous iteration. A smarter approach is to inspect the neighbor patterns [2] of segment (in Manhattan OPC) or endpoint (in curvilinear OPC). We construct a simple MLP model, with 24 polar Fourier transform (PFT) signals and a VPE from previous iteration as inputs and a new coordinate of leading endpoint of Bézier curve as output. PFTs are popular quantities employed in light intensity calculation, and they represent printing quality of endpoint's neighbors (within ambit distance) well.

### C. ML-GUIDED EXTRACTION OF BÉZIER CURVE INTERMEDIATE POINTS

VPE predictor is constructed with nested GCNs. Intermediate points are identified while VPE predictor is



optimized with a goal of minimizing estimated average VPE and violations of curvature constraints and geometric continuity constraints. VPE predictor is outlined in Figure 3. Each mask polygon is associated with a target polygon. Note that both are a set of curves, and the former is variable (i.e. endpoints are fixed after MLP runs but intermediate points are unknowns) and the latter is constant.

Each polygon is modeled with a polygon graph, where a vertex is associated with leading endpoints (of both target and mask); two vertices are connected if their endpoints are neighbors, with edge weight being assigned by a custom MLP. The graph is processed by GCN to yield a polygon feature.

The whole layout consisting of a number of polygons is now modeled with a layout graph. Each vertex corresponds to a polygon while polygon feature is associated with it. Two vertices are connected if minimum distance ( $m$ ) between corresponding polygons is within ambit distance; edge weight is harmonic mean of  $m$  and maximum distance ( $M$ ). The layout graph is processed by another GCN to yield the average VPE.

In curvilinear masks, maximum curvature is limited [3] and geometric continuity should be satisfied for mask manufacturability. Curvature constraint can be formulated by:

$$\kappa = \left| \frac{dP'(s)}{ds} \right| = \frac{|P'(t) \times P''(t)|}{|P'(t)|^3} < \kappa_{th}, \quad (2)$$

where  $\kappa$  is curvature and  $\kappa_{th}$  is threshold value. For geometric continuity constraint, tangent vector of the  $(i-1)$ th curve and the  $i$ th curve should be parallel at  $a_i$ . From the differentiation of Bézier curve equation, it is formulated as  $\overrightarrow{c_{i-1}a_i}$  and  $\overrightarrow{a_i b_i}$  being parallel (i.e., cross product of these vectors should be zero). The loss function of the VPE predictor is now given by:

$$L = VPE + \lambda_1 \cdot p_{curvature}(b, c) + \lambda_2 \cdot p_{continuity}(b, c), \quad (3)$$

where  $\lambda_1$  and  $\lambda_2$  are coefficients that penalize violations of constraints,  $p_{curvature} = \max(0, \kappa - \kappa_{th})$  and  $p_{continuity} = \sum_i |\overrightarrow{c_{i-1}a_i} \times \overrightarrow{a_i b_i}|$ .

Intermediate points are identified while  $L$  is minimized. Gradient descent method is applied to update  $b$  and  $c$  until  $L$  converges to its minimum value.

$$b_{new} = b_{old} - \eta \cdot \nabla_b L, \quad (4)$$

$$c_{new} = c_{old} - \eta \cdot \nabla_c L, \quad (5)$$

where  $\eta$  is learning rate,  $\nabla_b L$  and  $\nabla_c L$  denote gradients of  $L$  with respect to  $b$  and  $c$ , respectively. Backpropagation is performed over VPE predictor to compute the gradients.

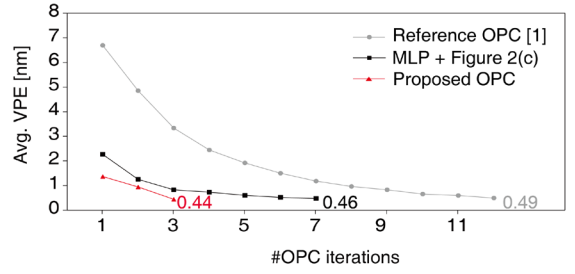


Figure 4. Comparison of three curvilinear OPC methods in average VPE and the number of OPC iterations.

### III. EXPERIMENTS

Experiments are performed while ArF lithography with 193nm wavelength is assumed. The training dataset is from a  $5\mu\text{m} \times 5\mu\text{m}$  M1 layout [4], which consists of approximately 1k segments; three other layouts with the same size are used for testing. The curvilinear OPC described in Section I.A [1] serves as a reference; maximum OPC iteration is set to 15 and target average VPE is set to 0.5nm, so OPC terminates if either is reached.

The proposed OPC (triangles) is compared to the reference (circles) as shown in Figure 4. The number of iterations is substantially reduced from 12 to 3, since curve correction through two ML models is much more accurate than that in the reference. Decrease in actual OPC runtime is less substantial (from 200 min. to 60 min.) due to extra time required for optimizing VPE predictor to find intermediate points. Final average VPE is also reduced, from 0.49nm to 0.44nm.

The proposed OPC consists of two ML models, MLP and VPE predictor. We mix the proposed OPC with the reference to understand the benefit of each model; in particular, MLP is used to find endpoints and the heuristic illustrated through Figure 2(c) are used to determine the intermediate points. This OPC (boxes in Figure 4) lies between the proposed and the reference, as we expect. This suggests that the proposed OPC, in fact, benefits from both ML models.

### IV. SUMMARY

A new curvilinear OPC method has been addressed. It relies on two ML models, MLP and VPE predictor, for accurate curve correction. In particular, MLP inspects the neighbors of endpoints (through PFT signals) so it identifies new endpoints more efficiently while neighbor patterns are taken into account. Intermediate points are located while VPE predictor is optimized with a goal of minimizing average VPE and violations of curvature and geometric continuity constraints. Experiments have shown substantial reduction in the number of OPC iterations (from 12 to 3) while VPE is also reduced.

### REFERENCES

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