Performance and Correlations of Weighted Circuit Networks

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ABSTRACT The patterns and evolution of man-made complex networks have been topics of interest in recent years. Herein, we define appropriate metrics to quantify the correlations between circuit performance and the complex network characteristics regarding the physical design of circuits. The experimental results show that circuit performance differs due to the optimization tools, both at placement and routing. The strength of the correlations with placement design follows the order of average distance, betweenness, average strength, and the clustering coefficient; the strength of the correlations with layout design follows the order of betweenness, average strength, average distance, and the clustering coefficient. The correlation between performance and betweenness has been further strengthened after routing and presents a remarkable difference in comparison with other characteristic parameters, which indicates its significance to the dynamic correlation with circuit performance.

INDEX TERMS Weighted complex network, circuit design, correlation, performance, complex network characteristics.

I. INTRODUCTION

With the enormous progress of semiconductor manufacturing technology, VLSI (very-large-scale integration circuit) design has achieved rapid development following Moore’s Law. Billions of components are integrated into a single chip to improve the performance, which substantially increases the design complexity simultaneously [1]. The cost, quality and predictability of IC (integration circuit) design have become intertwined challenges to the ability of designers to exploit advances in underlying patterning, device and integration technologies [2]. The physical design is a crucial stage for the resulting circuit performance. Conventional optimization tools may not be efficient enough to solve such problems, and considerable efforts are devoted to the development of new methods and algorithms for improving the performance of EDA tools [3].

As a subject that explains the phenomena and complexity of existing systems, complex networks have experienced booming interest in recent years. The study of complex networks spans a multitude of research fields from natural science to social science [4]–[11]. In recent decades, theories and growth models for explaining phenomena in the optimization of complex networks have been established [12]–[14]. Especially, research on robustness and controllability of the network indicate the close correlation to the properties of complex networks (such as scale-free, small-world, etc.) [15]–[19].

As a special category of network, man-made networks are typically designed for distribution of some commodity or resource. The studied distribution networks include airline networks [20], [21], railways [22], [23], power grids [12], [24], electronic circuits [25], etc.

The electronic circuit can be viewed as a network in which components are considered as vertices and wires between components are considered as edges. The evolution of electronic circuits underwent transitions from analog circuits to digital circuits, then to high integration. Early research showed that both analog and digital circuits exhibit small world behaviors [25]. Later, Teuscher et al. demonstrated that the chip system with small-world characteristics can adapt to scale growth and presents superior performance and robustness with respect to regular structured chips [26], [27]. Oshida et al. investigated the network-on-chip (NoC) performance with different structures through dynamic flow analysis. They found that the NoC architecture constructed with the topology in which hubs mostly connect to lower-degree nodes achieves short latency and low packet loss ratio [28].
Zhan et al. devised a multi-layered design architecture to capture favorable characteristics of biological mechanisms for the application of electronic circuit design. This demonstrates that utilizing biological mechanisms for engineering design is a promising approach for building intelligent systems [29]. To identify the infringement of intellectual property, Tan et al. introduced subgraph intensity as the geometric mean of link weights and coherence as the ratio of the geometric to the corresponding arithmetic mean [31]. A natural generalization of clustering coefficient in the case of weighted networks (the so-called weighted clustering coefficient) is defined as follows:

$$C_{ij}^w = \frac{1}{k_i(k_i-1)} \sum_{j,k} (w_{ij}^w \cdot w_{jk}^w \cdot w_{ki}^w)^{\frac{1}{2}}$$  \hspace{1cm} (3)

The average clustering coefficient $C = \frac{1}{N} \sum_{i=1}^{N} C_{ij}^w$ expresses the statistical level of cohesiveness when measuring the global density of interconnected vertex triplets in the weighted network.

C. DISTANCE AND BETWEENNESS
The distance $d_{ij}$ between two nodes in unweighted networks is defined as the minimum number of edges spanning from node $i$ to node $j$. Similarly, distance $d_{ij}$ in a weighted network is represented as the sum of the weights of the shortest paths between node $i$ and node $j$.

The average distance $L$ shown in the following formula represents the average degree of separation between nodes in the network:

$$L = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} d_{ij}$$  \hspace{1cm} (4)

Betweenness is another important centrality measure based on shortest paths and is defined as follows:

$$B_i = \sum_{j \neq i \neq k} \frac{N_{ij}(i)}{N_{jk}} .$$  \hspace{1cm} (5)

where $N_{ij}$ represents the number of shortest paths between nodes $v_j$ and $v_i$, and $N_{ij}(i)$ represents the number of shortest paths passing through node $v_j$ between node $v_j$ and $v_i$. In a sense, betweenness reflects the influence of a node over the spread of information through the network.

III. EXPERIMENT
A. EXPERIMENT SCHEME
In the experiment, we use a Lenovo workstation platform with a 2.20 GHz CPU and 16.00GB memory. The operating system is Red Hat Enterprise Linux 6. A number of EDA tools are used for comparison. For instance, circuit format conversion tool DATC RDF [32]; placement tools Capo10.0 [33], Fastplace3 [34], Dragon3.0 [35], MPL6 [36], NTUplace3 [37], and FengShui2.6 [38]; routing tools BoxRoute2.0 [39], FGR [40], NCTU-GR2.0 [41], and NTHU-Route2.0 [42]; and complex network modeling and analysis tools MATLAB, PAJEK, and R.

We use the benchmark suite TAU 2017 Benchmark for the experiment. This benchmark originated for the timing contest [43]. It includes 17 circuits which will be run and
TABLE 1. The number of modules and nets in each circuit in TAU 2017 Benchmark.

| Number | Benchmarks          | Nets  | Modules |
|--------|---------------------|-------|---------|
| 1      | ae97_ctrl           | 8683  | 8898    |
| 2      | aes_core            | 16055 | 16185   |
| 3      | b19_icecad          | 118612| 118637  |
| 4      | des_perf            | 95748 | 96232   |
| 5      | des_perf_ispd       | 104413| 104553  |
| 6      | flt_ispd            | 45860 | 47844   |
| 7      | matrix_mult_ispd    | 176890| 178490  |
| 8      | mge_edit_dist_icecad| 129039| 129051  |
| 9      | mge_matrix_mult_icecad| 176807| 178407  |
| 10     | pci_bridge32        | 14784 | 15063   |
| 11     | systemcaes          | 7363  | 7492    |
| 12     | systemcdes          | 3296  | 3361    |
| 13     | tv80                | 5306  | 5338    |
| 14     | ush_funct           | 12181 | 12305   |
| 15     | ush_phy_ispd        | 469   | 488     |
| 16     | vga_lcd_icecad      | 90919 | 91018   |
| 17     | wb_dma              | 3524  | 3739    |

The experiment scheme is outlined in Figure 1. We place and route circuits in TAU 2017 Benchmark in the phase of “physical design by multi-tools”, placements and layouts with different performance are obtained due to different p/l tools. In the phase of “complex network abstraction”, placements and layouts of the circuits are transformed into weighted networks to extract characteristics parameters. In correlation analysis, the Pearson correlation coefficient is computed to evaluate the correlation between circuit performance and characteristic parameters.

1) PHYSICAL DESIGN BY MULTI-TOOLS

In the physical design, circuits in the benchmark are placed and routed to obtain designs with different performances. The designs will be used to form complex networks to extract various characteristics in the next phase.

First, we run the DATC circuit format conversion tool to convert the benchmark circuit into bookshelf format. Then the placement tools (i.e., Capo10.0, Fastplace3, Dragon3.0, MPL6, NTUplace3, and FengShui2.6) are completed to obtain placement designs of the circuits. The performances of the resulting placements may differ from each other due to the qualities of the tools. In the end, we also run the routing tools (i.e., BoxRoute2.0, FGR, NCTU-GR2.0, and NTHU-Route2.0) to obtain different layout designs.

2) COMPLEX NETWORK ABSTRACTION

In this phase, we first convert the formed placement into the weighted complex network. In each circuit placement, modules are regarded as nodes, and links between modules are regarded as edges. The weight of the edge between two connected nodes is approximated as the half-perimeter wire-length (HPWL) of the bounding box. The average strength, betweenness, average distance and clustering coefficient of the weighted complex network are also extracted by the analysis tools.

After the placement designs are routed, the structure of the layout design becomes clear and concrete. The nodes in the layout design are connected by horizontal and/or vertical links. Unlike placement, virtual nodes such as vias are added into the layout design. We use the nodes (include virtual nodes) and links to form complex networks. The average strength, betweenness, average distance and clustering coefficient of the weighted complex network are extracted by the analysis tools.

B. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we introduce the correlation analysis method and analyze the correlations of both placement design and layout design.

1) CORRELATION ANALYSIS

In correlation analysis, we use the Pearson correlation coefficient to compute the correlation between circuit performance and characteristic parameters. The coefficient is defined according to the following formula:

$$r = \frac{N \sum x_i y_i - \sum x_i \sum y_i}{\sqrt{N \sum x_i^2 - (\sum x_i)^2} \sqrt{N \sum y_i^2 - (\sum y_i)^2}}$$

where $N$ is the number of total nodes, and $x_i$ and $y_i$ display two data series, where one indicates the circuit performance and another represents the characteristic parameter of the complex network.

When the correlation coefficient $r$ is larger than 0, the two data series are positively correlated. In contrast, when $r$ is smaller than 0, the correlation is negative. When $r$ is equal to (or approximately) 0, it is uncorrelated.

TABLE 2. Kruskal-Wallis test on correlations.

|          | p-value   | B      | D      | C      |
|----------|-----------|--------|--------|--------|
| Placement| 2.09 e-12 | 2.85 e-14| 3.06 e-13| 1.49 e-13 |
| Routing  | 1.57 e-05 | 5.87 e-08| 2.35 e-07| 0.204 e-13 |

FIGURE 1. The experiment scheme.
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TABLE 3. Correlation between average strength and circuit performance under different placement tools.

| benchmark | Capo | Dragon | FastPlace | FengShui | MPL | NTUPlace |
|-----------|------|--------|-----------|----------|-----|----------|
| HPWL      | HPWL | HPWL   | HPWL      | HPWL     | HPWL| HPWL     |
| 1         | 617.53 | 861963 | 628.00    | 1030686  | 762.78 | 1155152  |
| 2         | 530.94 | 1472879 | 607.59    | 1545410  | 701.77 | 1626166  |
| 3         | 473.27 | 8827399 | 499.10    | 9655616  | 529.46 | 1069994  |
| 4         | 1285.40 | 9040330 | 1090.00   | 9632846  | 1308.20 | 10765400  |
| 5         | 901.15 | 8043061 | 893.50    | 8458085  | 1148.00 | 9249793  |
| 6         | 1976.60 | 13054034 | 1939.60   | 12846118 | 1741.10 | 12151411  |
| 7         | 1118.30 | 28563022 | 1154.80   | 28797712 | 1107.30 | 27241163  |
| 8         | 1793.80 | 32597097 | 1753.60   | 35828582 | 1761.70 | 33567328  |
| 9         | 1094.20 | 28087879 | 1169.30   | 28887903 | 112.40  | 27395950  |
| 10        | 508.76 | 1485442 | 485.24    | 1573577  | 663.05 | 1822965  |
| 11        | 800.02 | 1134442 | 745.70    | 1175582  | 887.34 | 1429369  |
| 12        | 491.64 | 361362 | 486.22    | 318152   | 730.15 | 464669   |
| 13        | 451.52 | 403401 | 492.96    | 467020   | 641.18 | 608193   |
| 14        | 604.59 | 1230203 | 585.14    | 1323573 | 625.15 | 1394876  |
| 15        | 219.31 | 2196 | 261.01    | 27095   | 336.01 | 328.78   |
| 16        | 2008.40 | 15037538 | 1920.70   | 16478944 | 2034.60 | 18153323  |
| 17        | 698.37 | 609232 | 679.00    | 707314   | 727.30 | 825425   |

Table 3 shows values of different average strength \( <s> \) and circuit performance under different placement tools. The correlations between circuit performance and average strength for different placement tools are 0.60283, 0.71816, 0.68531, 0.78013, 0.62986, and 0.71844. In Figure 2, the scatter plots illustrate the variation of average strength \( <s> \) with HPWL for different placement tools. It can be observed that lower performance of the placement tool correlates with higher average strength.

2) CORRELATION IN PLACEMENT

In the experiment, we show the characteristic parameters and circuit performance under different placement tools for TAU 2017 Benchmark. The characteristic parameters and circuit performance (shown as HPWL) present differences due to the efficiencies of the tools. The performance of placement optimized by MPL is the best, followed by Capo, NTUPlace, Dragon, FastPlace, and FengShui. According to the resulting placement of each circuit, characteristic parameters of the corresponding complex network are calculated. The results are listed in Table 3 to Table 6. The correlations between circuit performance and characteristic parameters are calculated and shown in the last lines of the tables.

Table 3 shows values of different average strength \( <s> \) and circuit performance under different placement tools. The correlations between circuit performance and average strength for different placement tools are 0.78013, 0.62986, and 0.71844. In Figure 2, the scatter plots illustrate the variation of average strength \( <s> \) with HPWL for different placement tools. It can be observed that lower performance of the placement tool correlates with higher average strength.

Table 4 shows values of different betweenness \( B \) and circuit performance under different placement tools. The correlations between circuit performance and betweenness for different placement tools are 0.79586, 0.76652, 0.78811, 0.78120, 0.75062, and 0.75874. In Figure 3, the scatter plots illustrate variations of betweenness \( B \) with HPWL of different placement tools. The data roughly show that lower performance of the placement tool correlates with lower betweenness (except for MPL).

Table 5 shows values of different average distance \( D \) and circuit performance under different placement tools. The correlations between circuit performance and average distance for different placement tools are 0.79586, 0.76652, 0.78811, 0.78120, 0.75062, and 0.75874. In Figure 2, the scatter plots illustrate the variation of average strength \( <s> \) with HPWL for different placement tools. It can be observed that lower performance of the placement tool correlates with higher average strength.
for different placement tools are 0.77501, 0.78489, 0.73827, 0.78911, 0.79854, and 0.77627. In Figure 4, the scatters illustrate the variation of average distance $D$ with HPWL of different placement tools. The data roughly show that lower performance of the placement tool correlates with higher average distance.

Table 6 shows values of different clustering coefficient $C$ and circuit performance under different placement tools. The

![FIGURE 2. The HPWL-<$>$ correlation in placement for TAU 2017 Benchmark.](image1)

![FIGURE 3. The HPWL-B correlation in placement for TAU 2017 Benchmark.](image2)
correlations between circuit performance and clustering coefficient for different placement tools are 0.00413, 0.02595, 0.04227, 0.00199, 0.02922, and 0.01134. In Figure 5, the scatters illustrate the variation of clustering coefficient $C$ with HPWL for different placement tools. The data roughly show that lower performance of the placement tool correlates with higher clustering coefficient (except for FengShui).

We show the placement of the wb_dma circuit in Figure 6 and illustrate the three-dimensional weighted complex network of the circuit in Figure 7.

The correlations between circuit performance of placement and characteristic parameters are listed in the last lines of Table 3 to Table 6. The correlation between circuit performance and average strength averages 0.70210, the correlation between circuit performance and betweenness averages 0.77351, the correlation between circuit performance and average distance averages 0.77702, and the correlation between circuit performance and clustering coefficient is 0.01911. The correlations are illustrated in Figure 8. The data show that circuit performance has the strongest correlation with average distance, followed by betweenness and average strength, and has the weakest correlation with clustering coefficient.

3) CORRELATION IN LAYOUT
In this section, it shows the characteristic parameters and circuit performance under different route tools for TAU 2017 Benchmark. The characteristic parameters and circuit performance (shown as WL) present differences due to the efficiencies of the tools. The layout performance generated by NTHU is the best, those of NCTU-GR and BoxRouter are nearly identical and that of FGR is the worst. We convert the layout design into a complex network and calculate the corresponding characteristic parameters. The correlations between the circuit performance of the layout and characteristic parameters are calculated and shown in the last lines of Table 7 to Table 10.

Table 7 shows values of different average strength $<S>$ and circuit performance under different routing tools. The correlations between WL and average strength for different routing tools are 0.50221, 0.54040, 0.48427, and 0.16201. In Figure 9, the scatters illustrate the variation of average strength $<S>$ with WL for different route tools. This shows that lower performance of the routing tool correlates with higher average strength.

Table 8 shows values of different betweenness $B$ and circuit performance under different routing tools. The correlations between WL and betweenness for different routing tools are 0.87639, 0.91437, 0.88974, and 0.96254. In Figure 10, the
scatters illustrate the variation of betweenness $B$ with WL for different routing tools. This roughly shows that lower performance of the routing tool correlates with higher betweenness (except for BoxRouter).

Table 9 shows values of different average distance $D$ and circuit performance under different routing tools. The correlations between WL and average distance for different routing tools are 0.19266, 0.28472, 0.25067, and 0.55930. In Figure 11, the scatters illustrate the variation of average distance $D$ with WL for different routing tools. This roughly shows that lower performance of the routing tool correlates with lower average distance.

Table 10 shows the values of different clustering coefficient $C$ and circuit performance under different routing tools. The correlations between WL and clustering coefficient for different routing tools are 0.46342, -0.33941, 0.44012, and 0.10439. Notably, the correlation between clustering coefficient and circuit performance for FGR is negative. In Figure 12, the scatters illustrate the variation of clustering coefficient $C$ with WL for different routing tools. For the NTHU, NCTU-GR and BoxRouter tools, it shows that higher performance of the routing tool correlates with lower clustering coefficient. The FGR tool presents a different style due to the negative correlation.

It shows the layout of the wb_dma circuit generated by FGR in Figure 13 and illustrates the three-dimensional weighted complex network of the circuit in Figure 14.

The correlations between layout circuit performance and the characteristic parameters are listed in the last lines of Table 7 to Table 10. The correlation between circuit performance and average strength averages 0.42222, the correlation between circuit performance and betweenness averages 0.91076, the correlation between circuit performance and average distance averages 0.32184, and the correlation

### Table 7. Correlation analysis between average strength and performance under different routing tools.

| benchmark | BoxRouter | FGR | NCTU-GR | NTHU |
|-----------|-----------|-----|---------|------|
|           | $<S>$     | $<S>$ | $<S>$   | $<S>$ |
| 1         | 7.58      | 45754 | 10.44   | 45594 |
| 2         | 19.15     | 121430| 31.41   | 129339|
| 3         | 30.63     | 770772| 30.62   | 772523|
| 4         | 12.22     | 484159| 18.47   | 484307|
| 5         | 14.56     | 500633| 23.08   | 498642|
| 6         | 9.52      | 400461| 13.29   | 400809|
| 7         | 16.12     | 1238533| 24.91  | 1272274|
| 8         | 22.46     | 1702299| 37.07  | 1702773|
| 9         | 16.50     | 1227651| 25.47  | 1241819|
| 10        | 8.76      | 71013 | 12.26   | 70666 |
| 11        | 15.86     | 62396 | 22.22   | 65666 |
| 12        | 15.35     | 23324 | 21.61   | 24116 |
| 13        | 20.88     | 32934 | 35.89   | 34412 |
| 14        | 13.08     | 85960 | 19.69   | 96117 |
| 15        | 5.46      | 1381  | 7.55    | 1353  |
| 16        | 21.15     | 1327184| 35.25  | 1263917|
| 17        | 11.71     | 32020 | 16.76   | 30864 |

| correlation | 0.50221 | 0.54040 | 0.48427 | 0.16201 |

### Table 8. Correlation analysis between average betweenness and performance under different routing tools.

| benchmark | BoxRouter | FGR | NCTU-GR | NTHU |
|-----------|-----------|-----|---------|------|
|           | $<S>$     | $<S>$ | $<S>$   | $<S>$ |
| 1         | 41400     | 45754 | 41001   | 45594 |
| 2         | 68597     | 121430| 60266   | 129339|
| 3         | 446864    | 770772| 349096  | 772523|
| 4         | 379964    | 484159| 382195  | 484307|
| 5         | 361320    | 500633| 331415  | 498642|
| 6         | 158120    | 400461| 165050  | 400809|
| 7         | 594716    | 1238533| 547009 | 1272274|
| 8         | 432625    | 1702299| 507777 | 1702773|
| 9         | 578686    | 1227651| 553575 | 1241819|
| 10        | 63212     | 71013 | 58747   | 70666 |
| 11        | 21747     | 62396 | 22929   | 65666 |
| 12        | 9186      | 23324 | 10164   | 24116 |
| 13        | 10827     | 32934 | 8780    | 34412 |
| 14        | 45124     | 85960 | 41026   | 96117 |
| 15        | 1556      | 1381  | 966     | 1353  |
| 16        | 361796    | 1327184| 344079 | 1263917|
| 17        | 12357     | 32020 | 10980   | 30864 |

| correlation | 0.87639 | 0.91437 | 0.88974 | 0.96254 |
TABLE 9. Correlation analysis between average distance and performance under different routing tools.

| benchmark | BoxRouter D | BoxRouter WL | FGR D | FGR WL | NCTU-GR D | NCTU-GR WL | NTHU D | NTHU WL |
|-----------|-------------|--------------|-------|--------|-----------|------------|--------|--------|
| 1         | 7.07        | 4575        | 7.14  | 45594  | 7.61      | 44688      | 7.23   | 44728  |
| 2         | 4.60        | 121430      | 4.37  | 129339 | 4.43      | 124662     | 4.74   | 128194 |
| 3         | 4.35        | 77077       | 4.49  | 77253  | 4.90      | 758380     | 5.40   | 718138 |
| 4         | 9.04        | 484159      | 9.07  | 484307 | 9.53      | 485923     | 9.21   | 477643 |
| 5         | 8.87        | 500633      | 8.20  | 498642 | 8.83      | 497758     | 8.59   | 491412 |
| 6         | 6.03        | 400461      | 5.81  | 400809 | 6.58      | 400494     | 6.34   | 395864 |
| 7         | 6.57        | 1238533     | 6.28  | 1272274| 6.70      | 1238411    | 6.83   | 1253182|
| 8         | 4.99        | 1702299     | 5.51  | 1702773| 5.46      | 1811269    | 6.69   | 1314700|
| 9         | 6.48        | 1227651     | 6.25  | 1241819| 6.75      | 1253943    | 6.76   | 1241869|
| 10        | 6.30        | 71013       | 6.64  | 70666  | 7.11      | 69948      | 6.66   | 70103  |
| 11        | 5.66        | 62396       | 3.93  | 65656  | 3.65      | 61461      | 3.88   | 58239  |
| 12        | 3.61        | 23324       | 4.12  | 24116  | 4.11      | 23252      | 4.08   | 23180  |
| 13        | 2.70        | 32934       | 2.52  | 34112  | 2.49      | 32976      | 2.39   | 30364  |
| 14        | 4.87        | 85960       | 4.82  | 96117  | 5.03      | 86214      | 5.08   | 88358  |
| 15        | 5.82        | 1381        | 3.65  | 1353   | 4.05      | 1338       | 4.06   | 1338   |
| 16        | 5.24        | 1327184     | 5.44  | 1263917| 5.69      | 1457362    | 8.43   | 1019340|
| 17        | 3.79        | 32020       | 2.84  | 30864  | 4.10      | 30807      | 3.92   | 30817  |

Correlation: 0.19266, 0.28472, 0.25067, 0.55930

TABLE 10. Correlation analysis between clustering coefficient and performance under different routing tools.

| benchmark | BoxRouter C | BoxRouter WL | FGR C | FGR WL | NCTU-GR C | NCTU-GR WL | NTHU C | NTHU WL |
|-----------|-------------|--------------|-------|--------|-----------|------------|--------|--------|
| 1         | 0.0518      | 45754        | 0.0066| 45594  | 0.0453    | 44688      | 0.0570 | 44728  |
| 2         | 0.1108      | 121430       | 0.0216| 129339 | 0.0898    | 124862     | 0.0790 | 128194 |
| 3         | 0.1729      | 77077       | 0.0203| 77253  | 0.1279    | 758380     | 0.1040 | 718138 |
| 4         | 0.0624      | 484159      | 0.0088| 484307 | 0.0641    | 485923     | 0.0661 | 477643 |
| 5         | 0.0748      | 500633      | 0.0111| 498642 | 0.0708    | 497758     | 0.0752 | 491412 |
| 6         | 0.0654      | 400461      | 0.0069| 400809 | 0.0638    | 400494     | 0.0682 | 395864 |
| 7         | 0.1033      | 1238533     | 0.0093| 1272274| 0.0950    | 1238413    | 0.0925 | 1231382|
| 8         | 0.1330      | 1702299     | 0.0092| 1702773| 0.1155    | 1811269    | 0.0685 | 1314700|
| 9         | 0.1046      | 1227651     | 0.0092| 1241819| 0.0957    | 1253943    | 0.0938 | 1241869|
| 10        | 0.0516      | 71013       | 0.0059| 70666  | 0.0524    | 69948      | 0.0548 | 70103  |
| 11        | 0.1160      | 62396       | 0.0167| 65656  | 0.0961    | 61461      | 0.0833 | 58239  |
| 12        | 0.1091      | 23324       | 0.0213| 24116  | 0.0737    | 23252      | 0.0640 | 23180  |
| 13        | 0.1101      | 32934       | 0.0205| 34412  | 0.1126    | 32976      | 0.1015 | 30364  |
| 14        | 0.0939      | 85960       | 0.0106| 96117  | 0.0791    | 86214      | 0.0700 | 88358  |
| 15        | 0.0184      | 1381        | 0.0077| 1353   | 0.0193    | 1338       | 0.0223 | 1338   |
| 16        | 0.1224      | 1327184     | 0.0081| 1263917| 0.0947    | 1457962    | 0.0471 | 1019340|
| 17        | 0.0703      | 32020       | 0.0120| 30864  | 0.0796    | 30807      | 0.0718 | 30817  |

Correlation: 0.46342, -0.33941, 0.44012, 0.10439

FIGURE 9. The WL-<S> layout correlation for TAU 2017 Benchmark.

FIGURE 10. The WL-B layout correlation for TAU 2017 Benchmark.

between circuit performance and clustering coefficient is 0.16713. The correlations are illustrated in Figure 15. The data show that layout circuit performance has the strongest correlation with betweenness, followed by average strength and average distance, and has the weakest correlation with the clustering coefficient.

In Figure 16, we show the transition of correlations between circuit performance and characteristic parameters...
from placement to routing. The orange curve presents the correlation between circuit performance and characteristic parameters in placement, while the blue curve presents the correlation between circuit performance and characteristic parameters in route. After routing, the correlations between circuit performance and average distance and average strength have been weakened, while the correlations between circuit performance and betweenness and clustering coefficient have been strengthened. Notably, the correlation between circuit performance and betweenness has been further strengthened after routing, and it presents a remarkable difference in comparison with other characteristic parameters.

We had a statistical analysis on the experimental data using the Kruskal-Wallis test. As shown in Table 2, there are extreme significant correlations between circuit performance and characteristic parameters (p-value < 0.0001), except no significant correlation between circuit performance and clustering coefficient in routing (p-value > 0.05). The conclusion is consistent with the results shown in Figure 2 - Figure 12.

IV. CONCLUSION

In this paper, we have conducted a study regarding the case of characteristic parameters and circuit performance under different placement and routing tools. The experimental results of TAU 2017 Benchmark show that circuit performance varies due to the efficiencies of the optimization tools. The qualities of the placement tools ranked from best to worst are MPL, Capo, NTUPlace, Dragon, FastPlace, and Feng-Shui; the ranked qualities of the routing tools are NTHU, NCTU-GR, BoxRouter, and FGR. The strength of the correlations between circuit performance and the complex network characteristics in placement follows the order of average distance, betweenness, average strength, and the clustering coefficient; the strength of the correlations with routing follows the order of betweenness, average strength, average distance, and the clustering coefficient. We also show the transition of the correlations from placement to routing. After routing, the correlations between circuit performance, average distance and average strength have been weakened, while the
correlations between circuit performance, betweenness and the clustering coefficient have been strengthened. Notably, the correlation between circuit performance and betweenness has been further strengthened after routing, which presents a remarkable difference in comparison with other characteristic parameters.

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