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Grey relational clustering associated with CAPRI applied to FPGA placement

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Grey relational clustering is used to minimise wire length during field programmable gate arrays (FPGA) placement and routing. The proposed Grey Relational Clustering Apply to Placement (GRAP) algorithm combines grey relational clustering and convex assigned placement for regular ICs method to construct a placement netlist, which was successfully used to solve the problem of minimising wire length in an FPGA placement. Upon calculating the grey relational grade, GRAP can rank the sequence and analyse the minimal distance in configuration logic blocks based on the grey relational sequence and combined connection-based approaches. The experimental results demonstrate that the GRAP effectively compares the Hibert, Z and Snake with bounding box (BB) cost function in the space-filling curve. The GRAP improved BB cost by 0.753\%, 0.324\% and 0.096\% for the Hilbert, Z and Snake, respectively. This study also compares the critical path with the space-filling curve. The GRAP approach improved the critical path for Snake by 1.3\% in the space-filling curve; however, the GRAP increased critical path wire by 1.38\% and 0.03\% over that of the Hilbert and Z of space-filling curve, respectively.

Keywords: grey relational clustering; FPGA; minimal wire length; routing; GRAP; CAPRI; space-filling curve

1. Introduction

An field programmable gate arrays (FPGA) chip is a reprogrammable logic chip that can be configured to implement various digital circuits. Physical placement is a pivotal step in FPGA CAD flow because it determines how logic block circuits in the netlist are mapped onto physical locations. The placement directly affects routing performance in an FPGA design. The placement is an no polynomial time-complete problem in which most CPU time is spent on FPGA CAD design flow. Therefore, high-quality CAD tools are needed to execute the FPGA within a reasonable CPU time. Thus, various placement approaches have been proposed. Generally, these approaches can be divided into three categories: partition-based, improvement heuristics and analytic methods.

Recently, the objective of FPGA placement has been to use heuristics to find optimal solutions, such as Min-Cut by Maidee, Ababei, and Bazargan (2003), Simulated Annealing (SA) by Betz and Rose (1997, 2000), Genetic Algorithm by Yang, Almaini, Wang, and Wang (2005), Quadratic by Yonghong and Khalid (2005), Tabu Search by

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This study associates grey relational analysis technology with the matrix projections of convex assigned placement for regular ICs (CAPRI) heuristic technique to construct Grey Relational Clustering Grade Apply to Placement (GRAP) for improving performance in FPGA placement. The grey relational grade uses the wire length of logic block locations for grading estimation. Experimental results show that the GRAP effectively minimises wire length.

The remainder of this paper is organised as follows. The bounding box (BB) cost function model, delay cost model and the CAPRI expressing metric-space of graph are reviewed in Section 2. Then, the proposed grey relation grade analysis is introduced in Section 3. Section 4 presents the proposed algorithm. Experimental results are presented in Section 5. Finally, conclusions and suggestions for future research are given in Section 6.

2. Preliminary

2.1. The BB cost function model

The objective of FPGA placement is to assign a unique location for each module so that the circuit can be routed with the signal within timing constraints. The bb cost function of a net routing is estimated by the semi-perimeter of the smallest rectangle of bounded region. The BB cost functional form in Pritha Banerjee, Bhattacharjee, Sur-Kolay, Das, and Nandy (2005) is

$$\text{Cost} = \sum_{n=1}^{N_{\text{nets}}} q(n) \left[ \frac{bb_x(n)}{C_{\text{av},x}(n)} + \frac{bb_y(n)}{C_{\text{av},y}(n)} \right],$$

where the summation cost is over all nets $N$ in the circuit. For each net $n$, $bb_x(n)$ and $bb_y(n)$ show the horizontal and vertical spans of their BB, respectively. The $q(n)$ factor compensates for the fact. The $C_{\text{av},x}(n)$ and $C_{\text{av},y}(n)$ are over the BB of the net $n$ the average channel routing tracks in the $x$ and $y$ directions, respectively.

2.2. The delay cost model of partitioning-based placement for FPGAs

In Maidee et al. (2003), the delay assignment during recursive partitioning was to cut the edges to a minimum distance spanned by a determined cut net. The estimated delay value for a net is the average of all delays of all spans a minimum nets distance in the final placement. Figure 1 presents a cut edge spanning a minimum distance at partition level. The net cut at level 5 spans a minimum distance of $3\delta$, where $\delta$ is the width of the smallest placement region. The $(x,y)$ coordinates of this net cells are the centres of the placement regions one and two.

2.3. Metric space CAPRI graph

As described in Andreu, Bidarte, Astarloa, Martinez de Alegría, and Ibáñez (2008), Chrzanowska-Jeske and Her (1994), Abbasi and Abbasi (2007) and Gopalakrishnan, Li, and Pileggi (2006), let $G$ be a graph with $n$ vertices. Each vertex is assigned a unique ID between 1 and $n$. The $d_{ij}$ represents the length of the shortest path between vertices with IDs $i$ and $j$ in $G$. The distance matrix $D_G$ is an $n \times n$ matrix, where $D_G(i,j) = d_{ij}$. Figure 2 illustrates the $n \times n$ distance matrix $D_G$ and the delays with respect to a single location on
3. Grey relational clustering analysis

The pioneering study by Deng (1989) was the first to use grey systems theory to solve uncertain system problems. The theory has been utilised for various applications in Wu,
Equations (2)–(10) are typically used to analyse the grey relational effect. The steps of the grey relational analysis are as follows:

First, define a reference order and sequential order data arrays.

\[ X_i(k) = (x_i(1), x_i(2), \ldots, x_i(k)) \in X, \]

where \( i = 1, \ldots, n \) and \( k = 1, \ldots, m \).

For example,

\[
\begin{align*}
X_1(1) &= (x_1(1), x_1(2), \ldots, x_1(m)) \\
X_2(2) &= (x_2(1), x_2(2), \ldots, x_2(m)) \\
X_3(3) &= (x_3(1), x_3(2), \ldots, x_3(m)) \\
&\vdots \\
X_n(m) &= (x_n(1), x_n(2), \ldots, x_n(m)).
\end{align*}
\]

Second, define three effect measures Youxin (2001), the upper effect measure, lower effect measure and medium effect. Three effect measurement methods are analysed as follows:

(a) The upper effect is measured for the maximum target. A high value indicates that the value is appropriate for the decision:

\[ x_i(k) = \frac{x_i(k) - \min_{all,j} x_i(k)}{\max_{all,j} x_i(k) - \min_{all,j} x_i(k)}. \]

(b) When the lower effect measurement for the minimum target is used, the smallest derived value is the most appropriate for the decision:

\[ x_i(k) = \frac{\max_{all,j} x_i(k) - x_i(k)}{\max_{all,j} x_i(k) - \min_{all,j} x_i(k)}. \]

(c) When the medium effect measurement for the nominal effect weighting of the effect sample is used, the nominal derived values are the most appropriate:

\[ x_i(k) = \frac{|x_i(k) - OB|}{\max_{all,j} \{ \max_{all,j} |x_i(k) - OB|, OB - \min_{all,j} |x_i(k)| \}}, \]

where \( i = 1, \ldots, n \) and \( k = 1, \ldots, m \).

Third, calculate the grey relational coefficients of a reference point \( X_i(k) \) to other points \( X_j(k) \), which are defined as follows:
\[ \gamma(X_i(k), X_j(k)) = \frac{\Delta \text{min} + \zeta \cdot \Delta \text{max}}{\Delta y(k) + \zeta \cdot \Delta \text{max}} \]

where \( i = 1, 2, \ldots, n, j \in i, \) and \( k = 1, 2, \ldots, m. \) Moreover, \( \Delta_y(k) \) is the difference between reference point \( X_i(k) \) to other points \( X_j(k), \) that is,

\[ \Delta y(k) = |X_i(k) - X_j(k)|, \]

where \( \Delta \text{min} \) and \( \Delta \text{max} \) denote minimum and maximum differences among \( \Delta y(k), \) respectively, that are:

\[ \Delta \text{min} = \bigvee_{j \in i} \bigwedge_{k} |X_i(k) - X_j(k)|, \]

\[ \Delta \text{max} = \bigvee_{j \in i} \bigwedge_{k} |X_i(k) - X_j(k)|. \]

The relationship between the reference point and the other points is defined using the distinguishing coefficient \( \zeta. \) Typically, \( \zeta \) is referred to as \([0,1].\)

Finally, grey relational grades are calculated by averaging all grey relational coefficients to determine the relational order:

\[ \gamma(X_i, X_j) = \frac{1}{m} \sum_{k=1}^{m} \gamma(X_i(k), X_j(k)). \]

Since different grey relational coefficients have different weighted actions that affect the grey relational grade, Equation 10 can be rewritten as

\[ \gamma(X_i, X_j) = \sum_{k=1}^{m} \beta_k \gamma(X_i(k), X_j(k)), \]

where \( \beta_k \) denotes the weight of each grey relational coefficient and \( \sum_{k=1}^{m} \beta_k = 1.\)

After using grey relational analysis to cluster pairs of logic block locations, the CAPRI algorithm is used to construct a topological circuit netlist with the minimal wire lengths for an FPGA placement design.

### 4. The GRAP algorithm conclusions

After using grey relational grade, the fixed locations of logic elements on the FPGA netlist are transformed into the distance matrix Gopalakrishnan et al. (2006) to obtain an FPGA placement with the minimum wire lengths. Figure 3 shows how the GRAP algorithm is applied in a set of \(|S|, |S| = n,\) distributed on island-style FPGA with two dimensional array of configuration logic blocks (CLBs) and programmable input/output blocks (IOB). The netlist was transformed into the distance matrix of the undirected graph. Each edge in the graph then connects each net with its source to sinks, and is given unit weights. The CLBs relation value \( (S) \) is calculated, and data are assigned into initial arrays from the distance matrix where \( T_i(k) = (x_i(1), x_i(2), \ldots, x_i(k)) \) is the connection between each edge and in
each net. Finally, all netlists are performed by FPGA placement, and the optimal netlist format of the CLB output is constructed with a minimal wire length.

Given an $n$-CLBs array of $S$, transform the netlist into the minimal distance matrix of the undirected graph takes $O(n^3)$ in GRAP algorithm. For each iteration, calculate CLBs netlist grey relation value $(S)$ is $O(n^2)$. The netlist is then used to perform the FPGA placement. The Hilbert space filling curve is $O(1)$. In the worst case, annealing must be performed a maximum of $K$ times for relocation $O(1)$ and evaluation $O(N)$. Thus, SA takes $O(N)$. Therefore, the time complexity of the proposed GRAP algorithm is $O(n^3)$.

5. Experimental results

The proposed GRAP algorithm was used to perform CAPRI heuristic technique in C++ Builder on a note-book PC with a 2.8 GHz-clock Intel Core™ 2 Duo P9700 CPU. The following experiments used the circuit netlist for ant colony optimisation placement (Xu, Xu, & Xu, 2007). Figure 4(a) shows the FPGA circuit netlist, and Figure 4(b) shows the mapped FPGA placement.

The first experiment transforms the FPGA mapped placement into the distance matrix based on the internal CLB netlist Gopalakrishnan et al. (2006). Vertices correspond to the fixed locations of logic elements on the FPGA. Edges represent direct routing connections between CLB locations, and longer connections are assigned appropriate positive weights to account for their relative delays to unit weight edges. Figure 4(b) shows that, after the blocks are mapped to the FPGA placement, data are assigned to the distance matrix in Figure 5. In the distance matrix, edges represent direct routing connections between CLB locations.

In Table 1, the initial arrays distance matrix is $X_i(k) = (x_i(1), x_i(2), \ldots, x_i(k))$. Table 2 shows the normalised lower effect measure.
Figure 4. The FPGA circuit netlist and mapped placement. (a) Netlist. (b) Mapped FPGA placement.

Figure 5. The netlist into the distance matrix.
Table 3 shows grey relational coefficients of reference array $X_1$ to other array $X_j(k)$. The grey relational grades are calculated by averaging all grey relational coefficients to determine the relational order. Finally, the vertex $C$ is clustered in $X_1$. In Figure 7(a), the $C$ is nearly vertex.

Next, a pair of clustering arrays in vertex $C$ is removed from set $X$ for use as a reference array. The procedure is repeated for all pairs of clustering arrays in reference array $C$ to other array $X_j(k)$. Table 4 shows the relational coefficients in reference array $C$ to other arrays $X_j(k)$. Figure 7(a) shows how the vertex $D$ was used to draw array $C$.

As Table 5 shows, the next step is to remove array $D$ in initial arrays, and repeat all pairs of clustering array in reference array $D$ to other arrays $X_j(k)$. Use vertex $B$ to draw an approximate array $D$. The locations are determined via space filling curves Pritha Banerjee et al. (2005) that exhibited FPGA placement methods in Hibert curve. Finally, use vertex $E$ to draw an approximate array $B$ in Figure 7(a).

Figure 6(b) shows how the FPGA mapped placement is transformed into an undirected design graph. Edges in the design graph connect the driver of each net with its sinks and are given unit weights. The FPGA placement is used to build the undirected graph with unit wire length, and the total wire length is 20 units in FPGA original placement Figure 6(b). Figure 7(b) shows the revised placement modification based on the grey relational grade. The total wire length is 16 units.

Next, GRAP was used for benchmarking. Table 6 summarises of the Microelectronics Center of North Carolina (MCNC) benchmark circuit Banerjee et al. (2005) in terms of number of CLBs and IOB. Table 7 shows the results of the performance comparison between the GRAP algorithm and the placement described in Banerjee et al. (2005), which used BB-cost using space filling curves with the same construction. In comparison with Hibert, Z and Snake, the proposed GRAP approach reduces average BB-cost by 0.753%, 0.324% and 0.096%, respectively.

Table 8 compares the GRAP algorithm and Banerjee et al. (2005) placement in critical path length when the placement is performed by versatile place and route. The proposed GRAP approach improved the critical wire path by 1.3% for Snake in the space-filling
<table>
<thead>
<tr>
<th>Vertices</th>
<th>Array</th>
<th>Grey relational coefficient</th>
<th>Relational coefficients of A and other vertices</th>
<th>Relational coefficients of B and other vertices</th>
<th>Relational coefficients of C and other vertices</th>
<th>Relational coefficients of D and other vertices</th>
<th>Relational coefficients of E and other vertices</th>
<th>Average in grey relational</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Reference array $X_1$</td>
<td>$\gamma_{1-2}$</td>
<td>0.7778</td>
<td>0.3333</td>
<td>1.0000</td>
<td>0.8333</td>
<td>0.5000</td>
<td>0.6889</td>
</tr>
<tr>
<td>B</td>
<td>$X_2$</td>
<td>The most related array</td>
<td>$\gamma_{1-2}$</td>
<td>The most related coefficients</td>
<td>0.7778</td>
<td>0.5000</td>
<td>1.0000</td>
<td>0.5556</td>
</tr>
<tr>
<td>C</td>
<td>$X_3$</td>
<td>$\gamma_{1-3}$</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.0000</td>
<td>0.7143</td>
<td>1.0000</td>
<td>0.7429</td>
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<tr>
<td>D</td>
<td>$X_4$</td>
<td>$\gamma_{1-4}$</td>
<td>0.7778</td>
<td>0.5000</td>
<td>1.0000</td>
<td>0.5556</td>
<td>0.6000</td>
<td>0.6867</td>
</tr>
<tr>
<td>E</td>
<td>$X_5$</td>
<td>$\gamma_{1-5}$</td>
<td>0.7778</td>
<td>0.5000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.3333</td>
<td>0.7222</td>
</tr>
</tbody>
</table>

Note: Bold values indicate the best value.
Table 4. The grey relational coefficients in reference array $X_3$ to other array $X_j$.

<table>
<thead>
<tr>
<th>Vertices</th>
<th>Array</th>
<th>Grey relational coefficient</th>
<th>Relational coefficients of $A$ and other vertices</th>
<th>Relational coefficients of $B$ and other vertices</th>
<th>Relational coefficients of $C$ and other vertices</th>
<th>Relational coefficients of $D$ and other vertices</th>
<th>Relational coefficients of $E$ and other vertices</th>
<th>Average in grey relational</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$B$</td>
<td>$X_2$</td>
<td>$\gamma_{3-2}$</td>
<td>0.7494</td>
<td>0.6662</td>
<td>0.5553</td>
<td>1.0000</td>
<td>0.8330</td>
<td>0.7608</td>
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<tr>
<td>$D$</td>
<td>$X_4$</td>
<td>$\gamma_{3-4}$</td>
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<td>1.0000</td>
<td>0.8834</td>
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<td>$X_5$</td>
<td>$\gamma_{3-5}$</td>
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<td>0.5553</td>
<td>0.6677</td>
<td>0.5553</td>
<td>0.7056</td>
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</table>

Note: Bold values indicate the best value.

Table 5. The grey relational coefficients in reference array $X_4$ to other array $X_j$.

<table>
<thead>
<tr>
<th>Vertices</th>
<th>Array</th>
<th>Grey relational coefficient</th>
<th>Relational coefficients of $A$ and other vertices</th>
<th>Relational coefficients of $B$ and other vertices</th>
<th>Relational coefficients of $C$ and other vertices</th>
<th>Relational coefficients of $D$ and other vertices</th>
<th>Relational coefficients of $E$ and other vertices</th>
<th>Average in grey relational</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$B$</td>
<td>$X_2$</td>
<td>$\gamma_{4-2}$</td>
<td>0.000</td>
<td>0.3333</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.6667</td>
</tr>
<tr>
<td>$E$</td>
<td>$X_5$</td>
<td>$\gamma_{4-5}$</td>
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<td>1.0000</td>
<td>0.8331</td>
<td>0.5002</td>
<td>0.6667</td>
</tr>
</tbody>
</table>

Note: Bold values indicate the best value.
curve; however, the GRAP increased the critical wire path by 1.38% and 0.03% over that of the Hibert and Z of space-filling curve, respectively.

6. Conclusions
This study proposed a GRAP placement methodology based on grey relational grade and mapped CLB netlist technology of the CAPRI algorithm. Various space-filling curves were then used to obtain the minimal wire length for island-style FPGA placement. The experimental results indicate that the GRAP performs as well as the Hibert, Z and Snake with BB cost function in space-filling curve. The GRAP improved BB cost by 0.753%, 0.324% and 0.096% for the Hibert, Z and Snake, respectively. The GRAP approach also improved the critical path by 1.3% for Snake in the space-filling curve. The critical path length also tends to smaller when using the proposed approach.

Objective functions that satisfy various placement constraints in new FPGA architectures and take advantage of space filling curves are needed to produce high-quality
placement solutions. In future works, we will investigate routing construction with minimal delays, minimal critical path and minimal power for FPGA routing in FPGA CAD.

Figure 7. The Revise circuit netlist of FPGA placement. (a) Revise FPGA placement. (b) Revise FPGA placement in undirected graph with total edge wire length is 16 units.

Table 6. The MCNC benchmark circuit.

<table>
<thead>
<tr>
<th>Circuit.net</th>
<th>Input number</th>
<th>CLB number</th>
<th>Output number</th>
</tr>
</thead>
<tbody>
<tr>
<td>ex5p</td>
<td>8</td>
<td>1064</td>
<td>63</td>
</tr>
<tr>
<td>apex4</td>
<td>9</td>
<td>1262</td>
<td>19</td>
</tr>
<tr>
<td>alu4</td>
<td>14</td>
<td>1522</td>
<td>8</td>
</tr>
<tr>
<td>Seq</td>
<td>41</td>
<td>1750</td>
<td>35</td>
</tr>
<tr>
<td>apex2</td>
<td>38</td>
<td>1878</td>
<td>3</td>
</tr>
<tr>
<td>apla</td>
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<td>3690</td>
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<tr>
<td>pdc</td>
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<td>4575</td>
<td>40</td>
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<tr>
<td>ex1010</td>
<td>10</td>
<td>4598</td>
<td>10</td>
</tr>
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Disclosure statement
No potential conflict of interest was reported by the authors.

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References

Table 7. Comparison results of the GRAP algorithm and Banerjee et al. (2005) placement in BB-cost.

<table>
<thead>
<tr>
<th>Benchmarks</th>
<th>(Banerjee et al., 2005) Final BB cost</th>
<th>Our GRAP</th>
<th>Reduction in BB cost (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hibert</td>
<td>Z</td>
</tr>
<tr>
<td>ex5p</td>
<td>161.769</td>
<td>162.449</td>
<td>162.183</td>
</tr>
<tr>
<td>apex4</td>
<td>179.476</td>
<td>181.293</td>
<td>181.062</td>
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<tr>
<td>alu4</td>
<td>191.858</td>
<td>191.866</td>
<td>190.848</td>
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<tr>
<td>Seq</td>
<td>246.935</td>
<td>246.905</td>
<td>246.879</td>
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<tr>
<td>apex2</td>
<td>271.769</td>
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<td>271.204</td>
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<td>spla</td>
<td>608.071</td>
<td>592.415</td>
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<tr>
<td>ex1010</td>
<td>649.046</td>
<td>654.104</td>
<td>656.093</td>
</tr>
<tr>
<td>Aver</td>
<td>− − −</td>
<td>− − −</td>
<td>− − −</td>
</tr>
</tbody>
</table>

Table 8. Comparison results of the GRAP and Banerjee et al. (2005) placement in critical path length.

<table>
<thead>
<tr>
<th>Benchmarks</th>
<th>(Banerjee et al., 2005) Critical path(10⁻⁷ s)</th>
<th>Critical path(10⁻⁷ s)(Our)</th>
<th>Gain in quality(Q%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hibert</td>
<td>Z</td>
</tr>
<tr>
<td>ex5p</td>
<td>1.14784</td>
<td>1.27898</td>
<td>1.22130</td>
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<tr>
<td>apex4</td>
<td>1.23240</td>
<td>1.62950</td>
<td>1.18536</td>
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<td>alu4</td>
<td>1.19603</td>
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