An Evolved Skeleton-Network Reconfiguration Strategy Based on Topological Characteristic of Complex Networks for Power System Restoration

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Abstract

The restoration of a power system following large-scale blackouts is a key issue to the safety of power systems. Reconstructing the reasonable skeleton-network is an effective means of establishing the main network and restoring loads quickly. Based on the topological characteristic of complex networks, an evolved skeleton-network reconfiguration strategy is proposed in this paper. Employing line betweenness as well as node importance degree and clustering coefficient, the evolved strategy refines the index named network reconfiguration efficiency, which aims to select key nodes and key lines into the target network while keeping its sparseness in order to alleviate the burden of reconfiguration. Then, discrete particle swarm optimization is used in realizing the evolved strategy. Application to the IEEE 57-bus power system verifies that skeleton network derived from the evolved strategy includes not only all critical nodes but also most critical lines thereby highlighting the main task of reconfiguration.

1. Introduction

The power systems around the world are intrinsically subjected to interruptions in the energy supply, despite all the efforts towards mitigating the risks of failures occurrence. Typical examples of large-scale blackouts are those took place in the United Kingdom, Italy, Denmark, Sweden and the USA in 2003 and in China in 2008 [1-3]. Recognizing the negative effects of great blackouts on the economy and the society, it is prudent to investigate necessary measures to restore the system as quickly as to be consistent with operation security.

A general procedure of system restoration is composed of three temporal stages, which are preparation, network reconfiguration and load restoration [4]. In the second stage, the overall goal is reintegration of the bulk power network, as a means to achieving the goals of load restoration in the third stage. To this end, skeleton transmission paths are energized, subsystems defined in the first stage are resynchronized, and sufficient load is restored to stabilize generation and voltage. Larger, base-load units are prepared for restart. In general, network reconfiguration includes two sequential steps: the first step is to determine a relative optimal configuration as a restoration target and the second to organize a sequence of switching operations to bring the faulted system into the target system state defined in advance while all the restoration constrains are satisfied. Among methods proposed so far for developing restoration plans, many of them are related with network reconfiguration. The optimal target network is organized when the loads with the higher priority is restored as much as possible during network reconfiguration [5]. Identification of restoration paths after blackout is thoroughly studied in [6], in which the network reconfiguration is divided into series process and parallel process. Further, corresponding sequences of restoration paths are solved by the adapted Bellman-Ford method and the minimum spanning tree respectively. Employed the weighted complex network model, the global optimal sequence and corresponding optimal target network are achieved at the same time [7]. Based on topological characteristics of scale-free networks, a skeleton-network reconfiguration strategy is proposed in [8], in which network reconfiguration efficiency is defined to achieve restoration targets and evaluate their effects.

In this context, an evolved skeleton-network reconfiguration strategy is proposed in this paper. Based on complex network theory, the concept of line betweenness is introduced in power network to screen key transmission lines. Furthermore, line betweenness, coordinated with node importance and clustering coefficient, is employed to reconstruct network reconfiguration efficiency. Being different from the...
original reconfiguration method proposed in [8], the evolved strategy will not choose transmission lines randomly but select them into the target network according their priority. Application examples verify that target network achieved from the evolved strategy can highlight the main task of reconfiguration and alleviate the workload of the corresponding stage more effectively. Consequently, it is practical and helpful for dispatchers to guide field restoration.

2. Introduction of topological characteristic of complex networks

Networks could be used to represent many complex systems. Understanding of network structure and its topological characteristic is helpful to research on complex systems. Watts and Strogatz put forward the model of small-world networks in 1998 [9]. Barabasi and Albert found scale-free property of complex networks in 1999 [10]. These characteristics reveal some important traits of complex networks different from regular networks and random networks. Characteristics of many real networks have been justified to be consistent with those of complex networks. Existing results indicate that small-world effects are notable in a power system, though its node degree distribution doesn’t follow exponential law strictly [11]. Therefore, power systems can be investigated as complex networks and some characteristics can be employed to guide operation and restoration following blackout.

In order to identify key nodes and transmission lines and balance their distribution in the target network, three main topological characteristics of complex networks, namely, node importance degree, line betweenness and clustering coefficient, are introduced in this part.

2.1. Node importance degree

Traditionally, the concept of node degree is employed to scale the importance of nodes when the network topological structure is studied. That is to say, the node with more branches connected is comparatively more important in whole network. However, the fact is that some key nodes are not with larger node degrees. In order to solve the inconsistency, node importance degree \( \alpha_i \) defined in [8] is introduced to assess the importance of nodes.

As shown in Fig.1, when the \( \alpha_i \) of node 12 is considered, the original network in Figure 1(a) should be treated with node contraction corresponding to node 12 firstly. It means that nodes directly connected with node 12 will merge into one node. As a result, node 9, 10, 11 and 12 in Figure 1(a) are replaced by the node 9' in Figure 1(b) after node contraction. Then, the definition of \( \alpha_i \) is given by (1).

\[
\alpha_i = \frac{1}{n_i \cdot I_i} \sum_{i,j \in V_i} d_{\min,ij} \\
I_i = \frac{\sum_{i \neq j} d_{\min,ij}}{n_j (n_j - 1)/2}
\]

Where

- \( n_i \) the total number of nodes in new network after node \( i \) contraction;
- \( I_i \) the average of the shortest distances in new network after node \( i \) contraction;
- \( d_{\min,ij} \) after node contraction, the shortest distance between node \( i \) and node \( j \) denoted with the number of branches;
- \( V_i \) the set consisting of all nodes in new network after node contraction.

From (1), it's more likely for the node with more branches connected, namely the larger node degree, to hold larger \( \alpha_i \) because its contraction will reduce the number of nodes considerably. Beside, the node at pass location may take larger \( \alpha_i \). This kind of node is necessary in the shortest path of many node pairs so that the average shortest distance \( I_i \) will be decreased greatly after its contraction. Generally, \( \alpha_i \) is less than 1. As a special case, \( \alpha_i \) takes 1 (the maximum value) when \( n_i \) takes 1 after node contraction.
2.2. Line betweenness

The concept of line betweenness was first proposed by Freeman in 1979. Line betweenness indicates the frequency that certain line can be passed through by the shortest path between any two nodes of network. The definition of line betweenness of branch $k$, namely $G_k$, is denoted by (2).

$$G_k = \frac{\sum_{i \neq j \in V_0} N_{ij}(k)}{\sum_{i \neq j \in V_0} N_{ij}}$$

(2)

Where, $\sum_{i \neq j \in V_0} N_{ij}$ is the total number of the shortest path between any two nodes of the original network $V_0$. $\sum_{i \neq j \in V_0} N_{ij}(k)$ is the number of the shortest path passing through branch $k$. The definition can show the effect of branch $k$ on the connectivity of network.

![Figure 2. The demonstration of calculation of line betweenness](image)

Take Figure 2 as an example. If the weights of all lines are set to be 1, the number of shortest paths of the network is 45. Simultaneously, line betweenness can be calculated according to (2) and results are shown in Table 1. Obviously, the betweenness of line 4-6 is far higher than that of any other line because line 4-6 is the hub of the total network. As a result, line betweenness can be viewed as an indicator of line importance.

<table>
<thead>
<tr>
<th>Table 1. Line betweenness regarding Figure2</th>
<th>Line Betweenness($G_k$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line No.</td>
<td></td>
</tr>
<tr>
<td>4-6</td>
<td>0.556</td>
</tr>
<tr>
<td>1-4, 2-4, 3-4, 4-5, 6-7, 6-8, 6-9, 6-10</td>
<td>0.178</td>
</tr>
<tr>
<td>1-5, 2-3, 7-8, 9-10</td>
<td>0.022</td>
</tr>
</tbody>
</table>

2.3. Clustering coefficient

Clustering coefficient is a property of a node in a network. Roughly speaking it tells how well connected the neighborhood of the node is. The definition of clustering coefficient of node $j$, namely $\beta_j$, is denoted by (3).

$$\beta_j = \frac{t_j}{k_j(k_j-1)/2}$$

(3)

Clustering coefficient of node $j$ is the ratio of number of connections in the neighborhood of a node and the number of connections if the neighborhood was fully connected. If there are total $k_j$ nodes in the vicinity of node $j$, a fully connected group has $k_j \times (k_j - 1)/2$ connections. $t_j$ denotes number of connections existing in fact.

![Figure 3. The demonstration of calculation of clustering coefficient](image)

Take Figure 3 as an example. Here neighborhood of node 3 includes node 1, 2, 4 and 5, which mean the nodes that are connected to node 3 but does not include node 3 itself. The fully connected group of 4 nodes has 6 connections. Besides, the number of connections in the neighborhood of node 3 is 1, namely, only the connection between node1 and node 2. Therefore, clustering coefficient of node 3 is 1/6. If the neighborhood of certain node is fully connected, the clustering coefficient is 1 (such as node 1) and a value equal to 0 means that no connection exists in the neighborhood (such as node 5).

The clustering coefficient relates to the local “cliqueness” and the higher it is the better the network can withstand the effect of link removal, which tends to fragment the network thereby making it less stable.

3. An evolved skeleton-network reconfiguration strategy

In general, network reconfiguration following large-scale failure of power supply consists of two consecutive phases: the determination of a target system and the construction of a feasible operation sequence leading to the target system. In order to determine the target system efficiently, reference [8] proposed the concept of skeleton network, which is the desirable target system composed by power sources, important loads and transmission lines capable of coordinating and distributing the power reasonably.
Accordingly, an index named network reconfiguration efficiency is put forward to justify skeleton network. Whereas, only the importance of power sources and loads is evaluated and taken into account in reconfiguration efficiency. By comparison, the importance of transmission line can not be scaled thereby being selected randomly. The practice influences the performance of the reconfiguration to some extent. Therefore, line betweenness is introduced here to screen key transmission lines and employed in constructing network reconfiguration efficiency. 

Network reconfiguration efficiency \( \eta \) newly defined is shown in (4).

\[
\eta = (\bar{\alpha} + \mu \bar{G}) / \bar{\beta}
\]

\[s.t. \quad l_b < l_{B_{\text{max}}}
\]

\[
\gamma_{\Delta U} < \gamma_{\Delta U_{\text{max}}}
\]

\[
\gamma_{\Delta P} < \gamma_{\Delta P_{\text{max}}}
\]

\[
\bar{\alpha} = \frac{\sum_{i=1}^{n} \alpha_i}{n_{IC}}
\]

\[
\bar{G} = \frac{\sum_{j=1}^{n} G_k}{N_{IC}}
\]

\[
\bar{\beta} = \frac{\sum_{j=1}^{n} \beta_j}{n_c}
\]

Where

\( \bar{\alpha} \) average node importance degree of total \( n_{IC} \) load nodes selected in the target network. The value of \( \alpha_i \) is that normalized in terms of maximum \( \alpha_i \) of all nodes. Only load nodes are considered here because all power source nodes must be included in the target network and they can’t make the reconfiguration efficiency different;

\( \bar{G} \) average line betweenness of total \( N_{IC} \) transmission lines in reconfiguration network. The value of \( G_k \) is that normalized in terms of maximum \( G_k \) of all lines.

\( \bar{\beta} \) average clustering coefficient of total \( n_c \) nodes in reconfiguration network. Both power source nodes and loads are considered because all connections of whole target network are concerned here;

\( \mu \) regulatory factor. Its value will affect the selection of key lines.

\( n_{\Delta U} \) total number of nodes breaking voltage limits concerning power flow of reconfiguration network;

\( N_{\Delta P} \) total number of transmission lines breaking transmission capacity constraints concerning power flow of reconfiguration network.

From (4), it is obvious that \( \eta \) is determined mainly by parameters concerned with network structure, which are \( \bar{\alpha} \), \( \bar{G} \) and \( \bar{\beta} \). \( \bar{\alpha} \) and \( \bar{G} \) reflect the extent to that important loads and transmission lines are involved in the reconfiguration. \( \bar{\beta} \) represents whether transmission lines distribute evenly in reconfiguration network. The smaller \( \bar{\beta} \), the smaller the workload of reconstructing network is. The main reason is that it is difficult to form the local cliqueness under the condition of smaller \( \bar{\beta} \), in which there exist relative fewer connections around nodes of reconfiguration network. The feature is helpful to control the ratio of the number of transmission lines selected in target network and total number of transmission lines existing in the original network thereby reducing the reconfiguration burden. Beside, smaller \( \bar{\beta} \) is beneficial to choose transmission lines evenly from the original network so that it is convenient to enlarge network frame subsequently.

From (4), \( \eta \) is also subjected to some inequality operation constrains of power system. When energizing empty transmission line, over-voltage is notable with line’s length increasing. Consequently, the length of transmission line selected, i.e. \( l_b \) must be limited corresponding to different voltage level in order to maintain prescribed over-voltage limit. The other two unequal constrains in (4) are about operation performance when power flow analysis is made with regard to reconfiguration network. Inequality operation constrains make reconfiguration network more feasible in practice.

It should be noted that the calculation of the shortest distance is necessary for both node importance degree and line betweenness. The shortest distance between any two nodes is determined by the weights of lines. When node importance degree is calculated, weights of lines are set to be 1. However, the sum of nominal reactance and nominal susceptance with the same base are set to the weight of each line when line betweenness is calculated. The main reason is explained as follow. When node importance degree is used to find key nodes for the target network, the topological trait is mainly concerned and it is convenient for node contraction. By comparison, the
electrical reliability should be taken into account as well as the topological characteristic when line betweenness is employed in finding key transmission lines for the target network. The reactance can represent the electrical distance and loss of restoration path and the susceptance can indicate the risk of energizing corresponding transmission lines.

4. Realization of the evolved skeleton-network reconfiguration strategy

4.1. Introduction of DPSO

In order to realize the evolved skeleton-network reconfiguration strategy, DPSO being same as reference [8] is employed here. DPSO is the discrete binary version of particle swarm optimization (PSO), which is basically developed through simulation of bird flocking in two-dimensional space. DPSO finds the optimal solution using a population of particles. Each particle initialized randomly, with current position \( x_{id} \) and current velocity \( v_{id} \), represents a candidate solution to the problem. Where, \( i \in 1,2,\ldots,N \), \( N \) represents the population of particle swarm, \( d \in 1,2,\ldots, N_i \), \( N_i \) represents the dimension of search space. Each individual particle \( i \) has a fitness value determined by optimization function to justify its performance and retrieve its direction and distance for updating. (10) shows how each particle pursues the optimal particle and updates itself at iteration \( t \) in order to find optimal solution.

\[
v_{id}(t+1) = v_{id}(t) + c_1 r_1(t) [ p_{id}(t) - x_{id}(t)] + c_2 r_2(t) [ p_{gd}(t) - x_{id}(t)]
\]

if \( (S(v_{id}(t+1)) > E) \) then \( x_{id}(t+1) = x_{id}(t) \)

else \( x_{id}(t+1) = x_{id}(t) \)

Where, \( p_{id} \) and \( p_{gd} \) denote the personal best position and the global best position. The personal best position means where particle \( i \) presents the smallest error and the global best position means where the lowest error among all the \( p_{id} \)’s yields. The update of each particle is accomplished through tracing \( p_{id} \) and \( p_{gd} \). Two pseudorandom sequences \( r_1, r_2 \sim U(0,1) \) are used to affect the stochastic nature of the algorithm. Acceleration coefficient \( c_1 \) and \( c_2 \) control how far a particle will move in a single iteration. Typically, they are both set to a value of 2.0. When the question such as network reconfiguration needs to be solved in discrete space, only 0 or 1 value is allowed for \( x_{id} \), \( p_{id} \) and \( p_{gd} \). \( S(v) = \frac{1}{1 + e^{-v}} \) denotes the probability of particle evolution and \( E \) is the threshold set for particle evolution. Therefore, current position \( x_{id} \) takes 1 from 0 or takes 0 from 1 if its current velocity \( v_{id} \) is bigger than the threshold \( E \). Otherwise, \( x_{id} \) remains unchanged.

4.2. Algorithm flow

![Algorithm Flow](image)
According to the nature of DPSO described above, the steps of the evolved skeleton-network reconfiguration realized with DPSO are shown as Figure 4. In order to highlight the traits of DPSO used in network reconfiguration of power system, certain steps are explained specially as follow.

Step 1, the original power network must be simplified and converted to equivalent topological network before the evolved strategy can be used for reconfiguration. After that, buses and transmission lines of power network are represented by nodes and lines respectively.

Step 5, initialization is the base for following iteration and optimization of DPSO. Hence, we define the particle with the state sequence denoting which group of lines in original network is selected to take part in reconfiguration. When certain line is selected, corresponding position in state sequence takes 1 value. Otherwise, 0 value is taken. Presented with a series of value 0 and value 1 whose bit number is \( N_t \) (total number of transmission lines in original network), a state sequence represents a reconfiguration scheme.

Step 6, for practical purpose, particles representing different reconfiguration schemes must be connected totally in topological structure. However, the requirement can not be met naturally because particles are initialized or updated randomly. Consequently, verification of effective particle is necessary in order to achieve more feasible particle. Verification of effective particle means the merge application, in which several isolated sub-networks in the original particle are connected through changing the value of one or several bits in state sequence.

Step 8, the performance of each individual particle is justified by its fitness value determined by optimization function. For network reconfiguration, the performance of each particle means the reconfiguration effect of corresponding target network. Generally, the smaller the fitness, the better the particle is. Hence, the inverse of network reconfiguration efficiency \( \eta \) is adopted as fitness function.

\[
f = \frac{1}{\eta} \quad (11)
\]

Step 11 and step 13, updating of particles is attained through retrieving its direction and distance continuously. During each iteration, the personal best position \( p_{id} \) and the global best position \( p_{gd} \) are found out first and then particles are updating according to (10).

Step 14, power flow check is necessary in order to obtain feasible particles put in practice. The main content of the check is confirming whether the operation condition is consistent to security restrictions represented with inequality operation constrains in (4).

5. Application example

To test the validity of strategy proposed in this paper, the algorithm has been programmed with MATLAB. The IEEE 57-bus test system is taken as an example. Its diagram is shown as Figure 5, in which total 80 transmission lines are included. Note that power flow calculations of algorithm are carried out with a power system simulation package, MATPOWER [12].

![Figure 5. IEEE 57-bus power system diagram](image)

According to the practical state of thermal unit in the stage of network reconfiguration and boiler’s technical minimum load, the output of unit takes 25% rated power, which is the basic requirement for boiler’s stable operation.
Based on (1) and (2), node importance degree of all nodes and line betweenness for all lines could be solved and normalized, as shown in the ascending order in Figure 6 and Figure 7 respectively. The first eight nodes taking the bigger node importance degree and the first eight lines taking the bigger line betweenness are listed in Table 2.

![Figure 7. Distribution of nominal line betweenness](image)

### Table 2. Nominal node importance degree of key nodes and nominal line betweenness of key lines

<table>
<thead>
<tr>
<th>Node No.</th>
<th>Normal node importance degree</th>
<th>Line No.</th>
<th>Nominal line Betweenness</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>1.0</td>
<td>38-48</td>
<td>1.0</td>
</tr>
<tr>
<td>38</td>
<td>0.975</td>
<td>14-46</td>
<td>0.931</td>
</tr>
<tr>
<td>9</td>
<td>0.966</td>
<td>46-47</td>
<td>0.913</td>
</tr>
<tr>
<td>49</td>
<td>0.939</td>
<td>47-48</td>
<td>0.909</td>
</tr>
<tr>
<td>11</td>
<td>0.910</td>
<td>37-38</td>
<td>0.765</td>
</tr>
<tr>
<td>15</td>
<td>0.907</td>
<td>22-38</td>
<td>0.625</td>
</tr>
<tr>
<td>22</td>
<td>0.898</td>
<td>36-37</td>
<td>0.615</td>
</tr>
<tr>
<td>37</td>
<td>0.893</td>
<td>13-14</td>
<td>0.607</td>
</tr>
</tbody>
</table>

Furthermore, DPSO is employed to reconfigure network skeleton. The dimension of particle $N_I$, the population size $N$ and maximum iteration step $t_{max}$ take value of 80, 30 and 150 respectively. Through regulating the value of $\mu$, the performance of corresponding optimal reconfiguration schemes achieved from evolved strategy is shown in detail in Table 3. Obviously, average line betweenness $\bar{G}$ increases notably with $\mu$ increasing. The bigger $\bar{G}$ means that there are more key transmission lines are organized in the target network. Because key lines are located in centralized area of network, average clustering coefficient $\bar{\beta}$ increases with more key lines being selected. Note that $\bar{G}$ could not increase any more if $\mu$ is set to a value bigger than 4. The main reason is that the number of relative important lines is limited and the overall performance of reconfiguration is affected by $\bar{\alpha}$ and $\bar{\beta}$ as well as $\bar{G}$. In order to show the advantage of evolved strategy, the result retrieved from the original strategy proposed in [8] is listed in Table 3 as well. The smaller $\bar{G}$ is due to the practice of selecting lines randomly.

### Table 3. The comparison of performance of skeleton-network reconfiguration strategy

<table>
<thead>
<tr>
<th>reconfiguration strategy</th>
<th>$\bar{\alpha}$</th>
<th>$\bar{G}$</th>
<th>$\bar{\beta}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evolved strategy</td>
<td>$\mu = 1$</td>
<td>0.8947</td>
<td>0.2807</td>
</tr>
<tr>
<td></td>
<td>$\mu = 2$</td>
<td>0.8982</td>
<td>0.3179</td>
</tr>
<tr>
<td></td>
<td>$\mu = 4$</td>
<td>0.8995</td>
<td>0.3436</td>
</tr>
<tr>
<td>Original strategy</td>
<td></td>
<td>0.8937</td>
<td>0.2113</td>
</tr>
</tbody>
</table>

In order to highlight the effectiveness of evolved strategy, the optimal reconfiguration scheme, in which $\mu$ takes 4, has been investigated carefully. Firstly, there are total 20 nodes and 20 lines being included in the target network. The considerable difference of node number and line number justify that the target network is the skeleton of the original network and thereby alleviating the workload in the stage of network reconfiguration. Secondly, composition of nodes and lines selected in the target network should be paid close attention. Figure 6 and Figure 7 show that both nominal node importance degree and nominal line betweenness distribute centralized in several intervals. After total node number and total line number of the original network are viewed as the base value, the percentage of node number and line number in the target network are calculated regarding each interval, as shown with dark red bars in Figure 8 and Figure 9 respectively. In order to make comparison, the same statistics are conducted regarding the original network, as shown with blue bars in Figure 8 and Figure 9 respectively. It’s evident that the percentage of relative important nodes and lines is higher, which is consistent with the objective of skeleton-network reconfiguration. Furthermore, the selection of nodes and lines mentioned in Table 2 is checked. The first eight nodes taking the bigger node importance degree are chosen in the target network totally. However, three of the first eight lines taking the bigger line betweenness are omitted due to the requirement of smaller clustering coefficient, as shown in Table 4. Meanwhile, the selection of these nodes and lines is studied according to the original strategy proposed in [8]. The result is
that all eight nodes are also selected but only two of lines are included in the target network, as listed in Table 4. It definitely demonstrates the considerable improvement of selecting key lines by adopting the evolved strategy.

6. Conclusions

The paper proposes an evolved strategy to reconstruct skeleton network. Different from the original strategy, the evolved strategy views line betweenness as an indicator of the priority for selecting lines into the target network thereby introducing it into the definition of network reconfiguration efficiency. By employing DPSO, reconfiguration of network skeleton based on the evolved strategy is accomplished. The application to IEEE 57-bus power system verifies that the evolved strategy is more favorable to identify the genuine target network because not only nodes but also lines are chosen according to their importance instead of selecting lines randomly in original method. Meanwhile, the lower ratio of nodes and lines selected into the target network is maintained so that the burden of reconfiguration is alleviated, which is beneficial to conducting restoration smoothly.

7. References


Table 4. The comparison of selection of key lines

<table>
<thead>
<tr>
<th>Line No.</th>
<th>Evolved strategy</th>
<th>Original strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>38-48</td>
<td>√</td>
<td>×</td>
</tr>
<tr>
<td>14-46</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>46-47</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>47-48</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>37-38</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>22-38</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>36-37</td>
<td>√</td>
<td>×</td>
</tr>
</tbody>
</table>

Figure 8. Interval statistics of percentage of node number

Figure 9. Interval statistics of percentage of line number


