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Minimum Degree Reordering Based Graph Partitioning Method for Distributed Fault Section Estimation System in Power Networks

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Abstract In order to make fault section estimation (FSE) in large-scale power networks use distributed artificial intelligence approach, we have to develop an efficient way to partition the large-scale power network into desired number of connected sub-networks such that each sub-network should have quasi-balanced working burden in performing FSE. In this paper, an efficient minimum degree reordering based graph partitioning method is suggested for the partitioning task. The method consists of two basic steps: partitioning the power network into connected, quasi-balanced and frontier minimized sub-networks based on minimum degree reordering and minimizing the number of the frontier nodes of the sub-networks through iterations so as to reduce the interaction of FSE in adjacent sub-networks. The partitioning procedure and characteristic analysis is presented. The method has been implemented with sparse storage technique and tested in the IEEE 14-bus, 30-bus and 118-bus systems respectively. Computer simulation results show that the proposed multiple-way graph partitioning method is suitable for FSE in large-scale power networks and is compared favorably with other graph partitioning methods suggested in references.

Keywords graph partitioning, fault section estimation, large-scale power networks

I. INTRODUCTION

Fault section estimation aims at identifying the faulted element(s) in power networks by using the information of the current status of protective relays and circuit breakers. As the first step to system restoration, FSE is of great importance in enhancing service reliability and reducing power supply interruption. FSE should be implemented quickly and accurately in order to isolate the faulty elements from the rest of the system and to take proper countermeasures to recover normal power supply. It is clear that on-line automatic FSE is significant and crucial to the restorative operations.

Although many techniques have been utilized to solve the problem, such as expert-system-based [1-2], fuzzy-set-based [3], artificial-neural-network-based [4-5], stochastic-optimization-based [6] and logic-based [7] approaches, fault section estimation in large-scale power networks still remains as a difficulty and unsolved issue because of the large amount of information to be dealt with and the FSE speed and accuracy required. The FSE is even more difficult in cases with failure operations of relays and circuit breakers, or multiple faults at the same time.

Since faults and signals from relevant relays and circuit breakers are basically local phenomena, based on the idea of 'divide and conquer', we suggest to use distributed artificial intelligence system for fault section estimation in large-scale power networks, which is more reasonable and more efficient than traditional centralized FSE system. It is clear that in order to implement the task of distributed fault

section estimation system well a good power network partitioning method is essential and crucial.

If we denote the buses and transmission lines in power networks as vertices and edges of a graph, the power network partitioning problem can be easily transformed into a corresponding graph partitioning problem. That is to partition the graph vertices into desired number of connected and quasi-balanced subsets according to the weights of the vertex under the constraint that the number of frontier nodes crossing the different subsets is minimized.

This graph partitioning problem is *NP*-hard [8]. Efficient heuristic algorithms have been investigated for its solution, such as Kernighan-Lin heuristics [9-10], stochastic optimization based methods [11-12] and graph partitioning methods for parallel computation [13-14] etc. The first two methods realize the optimal partition by aggressive and stochastic searches respectively, which partition the graph into balanced subsets under the constraint that the number of edges crossing the subsets is minimized; while the third method puts more emphasis on reducing the nonzero elements in generating balanced partition. Therefore, the common demerit of these methods is that none of them consider the special requirement of the FSE that any obtained sub-network must be connected. It is not easy to modify these methods to adapt this requirement.

In this paper an efficient minimum degree reordering [15-16] based graph partitioning method for distributed fault section estimation system in large-scale power networks is proposed. The partitioning procedure and characteristic analysis is presented. The method has been implemented with sparse storage technique and tested in the IEEE 14-bus, 30-bus and 118-bus power systems. For comparison purpose the graph partitioning method based on depth-first-search algorithm [17] has been realized and tested as well. Computer test results demonstrate that the proposed multiple-way graph partitioning approach is suitable for distributed fault section estimation system in large-scale power networks and has better quality as compared with the graph partitioning method based on depth-first-search algorithm.

II. PROPOSED GRAPH PARTITIONING METHOD

The proposed multi-way graph partitioning method consists of two basic steps: realizing an initial partition by the multi-way graph partitioning algorithm based on weighted minimum degree reordering and further minimizing the number of the frontier nodes through iterations so as to reduce the interaction of FSE in adjacent sub-networks. The two steps with their formulations and theoretical basis are presented in detail below.

A. Multi-way graph partitioning algorithm based on weighted MD reordering

Suppose G is a labeled undirected graph with n vertices. Minimum degree (MD) reordering [15] can be best described in terms of elimination graphs. The number of edges incident on the node x is called *degree* of node x. After eliminating the node x from the graph G, the corresponding elimination graph can be obtained by deleting the node x and its incident edges and then adding edges between any pair of nodes x_j and x_k for which (x, x_j) and (x, x_k) belong to the graph G but (x_j, x_k) does not. The elimination process can thus be modeled by a sequence of graphs, each having one less node than the previous graph, until only one node remains. At each step of the elimination process, MD algorithm selects as the next node to be eliminated a node of minimum degree in the current elimination graph.

A part of the IEEE 118-bus system is taken as the illustrative example (Fig. 1), in which each vertex is denoted by the original subscript and corresponding MD reordering directly. The dotted lines represent the added edges in the elimination process. Using MD algorithm, we could get the reordering is *87 86 84 83 88 85 90 91 89 82 94 92 96 77*.
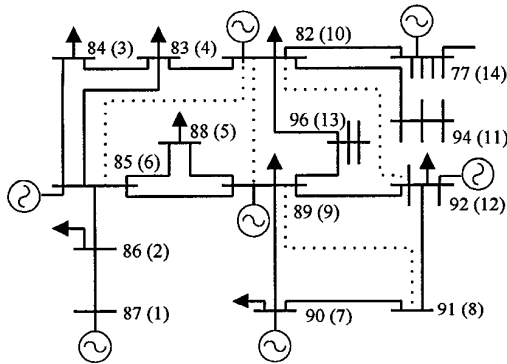

Fig.1 The illustrative power network for MD algorithm

In addition, in order to get the balanced partition, we assign each vertex an integer, called weight, to form the weighted MD reordering. The investigation shows that the calculation burden of a sub-graph is mainly determined by the total number of possible fault elements in the network, hence the weight of a vertex is defined as the number of its incident possible fault elements (bus, lines and transformers).

Suppose Y_n is the bus admittance matrix of the given power network in descent order of the reordering label. For node x_i, we use the number of the nonzero elements in row i of the upper triangular matrix (including the diagonal element) of Y_n as its node weight and denote it as $nodewt(x_i)$. With the weights, the previously formed MD reordering becomes a weighted MD reordering. Then the weighted MD reordering of the illustrative power network is *87* (2) *86* (2) *84* (3) *83* (3) *88* (3) *85* (2) *90* (3) *91* (2) *89* (2) *82* (3) *94* (4) *92* (2) *96* (2) *77* (3).

For graph G with n vertices, let $x_1, x_2, ..., x_n$ be the obtained weighted MD reordering, *Weights* denote the total weights of n vertices and n_g be the desired number of sub-graphs. It can be observe, along the MD reordering, each node will either merge some preceding disjoint subsets into a connected cluster, or exist as a new disjoint subset. If the weight of the emerging connected component is most approaching *Weights*/n_g, then nodes in this component make up the first desired sub-graph C_1. Delete C_1 from the reordering and continue the above process iteratively until all the nodes in graph G have been explored. The completed multi-way graph partitioning algorithm based on weighted MD reordering is described in *Algorithm 1*.

Algorithm 1. Proposed multi-way graph partitioning algorithm

Step 1: Denote the MD reordering of G by S, the node sets of the sub-graphs by C_i, where $i = 1, 2, ..., n_g$, and the preceding disjoint clusters in the partition process by D_j, $j = 1, 2, ..., k$, where k is a variable. Initially, set $S = \{x_1, x_2, ..., x_n\}$, $C_i = \varnothing$, and $D_j = \varnothing$;

Step 2: Set the circulation pointer $p = 1$. The first node x_1 in the reordering composes D_1, that is, $D_1 = \{x_1\}$;

Step 3: $p = p + 1$;

Step 4: For node x_p in the ordering, find all the preceding disjoint connected clusters $\{D_j\}$ which are incident with x_p, that is $\{D_j \mid \exists x_l \in D_j, x_l x_p \in G\}$, and then these clusters and node x_p make up a new connected cluster $D_p = \{D_j\} \cup x_p$. Sort the clusters $\{D_j\}$ in descending order according to their cluster weights $wt(D_j)$. Then test these clusters D_j one by one by this sequence, if D_j satisfies:

$$|wt(D_p) - Weights/n_g| > |wt(D_j) - Weights/n_g| \qquad (1)$$

This means D_j is most approaching *Weights*/n_g, then assign this connected cluster D_j as a sub-graph $C_i = D_j$ and $i = i+1$. At the same time delete all the nodes in D_j from the cluster D_p and the ordering S respectively. If all the preceding disjoint clusters $\{D_j\}$ associated with x_p couldn't satisfy (1), replace all these associated clusters $\{D_j\}$ by D_p;

Step 5: If p equals n, then $S = \varnothing$ means all the nodes of G have been explored systematically, and so the algorithm terminates, else repeat *Step 3* to *Step 5*.

For the weighted MD reordering *87* (2) *86* (2) *84* (3) *83* (3) *88* (3) *85* (2) *90* (3) *91* (2) *89* (2) *82* (3) *94* (4) in Fig. 1, suppose $n_g = 2$ and *Weights* = 29. Then node *85* merges three disjoint subsets: $\{87, 86\}$, $\{84, 83\}$ and $\{88\}$ into one connected component, while the following node *90* makes up a new disjoint subset $\{90\}$. The weight of this new connected component is 15, which is most approaching *Weights*/n_g = 14.5, and thus $\{87\ 86\ 84\ 83\ 88\ 85\}$ makes up C_1. The same way we could get another sub-graph $C_2 = \{90\ 91\ 89\ 82\ 94\}$.

It is obvious that the weighted MD reordering based multi-way graph partitioning algorithm guarantees that the calculation burdens are distributed evenly because all the partitions satisfy (1), but the perceptive reader may question the proposed algorithm in terms of the connectivity and minimization of the frontiers of the sub-graphs. Aiming at these problems, further characteristic analysis is conducted.

It can be observed that the sub-graph C_1 could always be obtained successfully by *Algorithm 1*. However, if the rest part of the graph G becomes disconnected, *Algorithm 1* can not finish the partitioning task as we expected. Therefore the key point of the connectivity of *Algorithm 1* is that the rest part of the graph G must be connected after all the obtained sub-graphs have been eliminated. We'll give proof to this point.

The proof needs the help of a tree structure called the elimination tree [16], whose related concepts and lemma are introduced first. Assume Y_n is the large sparse symmetric positive definite matrix of the graph G, and L is its cholesky factor. If $x_1, x_2, ..., x_n$ is the ordering of the matrix Y_n, the elimination tree of Y_n is defined to be the tree with the same set of n nodes, and x_i is the parent node of x_j if and only if:

$$i = \min\{k \mid l_{kj} \neq 0\} \qquad (2)$$

The structure as defined is a tree with n nodes rooted at the node x_n, which is denoted by $T[x_n]$. The same way, for any node x_j in the elimination tree, the subtree rooted at x_j is denoted by $T[x_j]$. If the elimination tree is produced on the basis of the MD reordering, it has the following desired property.

Lemma 1. [16] For each node x_j in the elimination tree produced by MD reordering of G, the sub-graph of G consisting of nodes in $T[x_j]$ is connected and is given by the connected component C_j in the MD reordering $\{x_1, ..., x_j\}$ containing x_j.

Based on the concepts and *Lemma 1*, we further present and prove *Lemma 2* and *Theorem 3*, which provide a sound theoretical basis for connectivity of the proposed algorithm.

Lemma 2. For each node x_j in the elimination tree produced by MD reordering of G, the sub-graph of G consisting of nodes, $\{x_i \mid x_i \notin T[x_j]\}$, not in $T[x_j]$ is connected too.

Proof. For any node x_j in the elimination tree, the ordering obtained from an elimination tree rotation [16] (actually a composite of basic rotations) at x_j will maintain the relative ordering of the nodes that are not ancestors of x_j. But the ancestor nodes of x_j will be reordered such that the nodes in $Adj(T[x_j]) \cup \{x_j\}$ are numbered last. Since the set $Adj(T[x_j]) \cup \{x_j\}$ is a clique in the elimination graph, they can be renumbered among themselves in any order so long as they are labeled last. Without loss of generality, we pick x_j as the last node, which give a tree rooted at x_j. This operation makes the nodes in $T[x_j]$ be "promoted" up to the root node, which is shown in Fig. 2.

Assume node x_k, one of the ancestors of $T[x_j]$, is the neighboring node of x_j. Then $T[x_k]$ is consisted of the nodes, $\{x_i \mid x_i \notin T[x_j]\}$, not in $T[x_j]$. According to *Lemma 1*, the sub-graph of G consisting of nodes not in $T[x_j]$ is connected too.
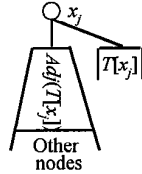

Fig. 2 The elimination tree structure after composite rotations

Theorem 3. For any $k < n_g$, the *Algorithm 1* could guarantee that the rest part of the graph G is connected after all the sub-graphs $\{C_j, j=1, 2, ..., k\}$ have been eliminated from G.

Proof. For any $k < n_g$, without loss of generality, based on *Algorithm 1* and *Lemma 1* we assume that $C_i \cup C_{i+1} \cup \cdots \cup C_k$ $(i < k) = T[x_k]$, in which x_k is the last node of MD ordering in C_k, while $C_1, C_2, ..., C_{i-1}$ are consisted of disjoint subtrees respectively. Since there is no interaction between any pair of the disjoint subtrees, *Lemma 2* could be iteratively used for these disjoint subtrees. Therefore the rest part of the graph G is still connected after eliminating all the disjoint subtrees $C_1, C_2, ..., C_{i-1}, T[x_k]$, which means the rest part of the graph G is connected after all the sub-graphs $\{C_j, j=1, 2, ..., k\}$ have been eliminated from G.

MD reordering still has another favorable property for frontier minimization of the proposed graph partitioning algorithm. Consider a node x_j in the MD reordering $x_1, x_2, ..., x_n$. Let C_j be the connected component in the sub-graph $\{x_1, ..., x_j\}$ that contains the node x_j. If we use $Adj_G(C_j)$ to denote the adjacent set of the node subset C_j, then the property could be expressed as follows:

Theorem 4. [16] The adjacent set {degree} of the node x_j at elimination is given by $Adj_G(C_j)$ $\{|Adj_G(C_j)|\}$.

Theorem 4 assures that the MD reordering based multi-way graph partitioning algorithm could provide a minimum frontier node set $|Adj_G(C_j)|$ for any sub-graph C_j, which is crucial for getting the final optimal partition. This is largely due to the very nature of the MD ordering scheme. At step j of the ordering algorithm, a node x_j is selected with the minimum degree $|Adj_G(C_j)|$. The local minimization of the degree in the elimination graph has the desirable effect of controlling the size of the adjacent set $Adj_G(C_j)$, and hence the size of the corresponding frontier node set.

Hence, the weighted MD reordering based multi-way graph partitioning algorithm, which has a sound theoretical basis, guarantees that any power network can be partitioned into desired number of connected sub-networks with quasi-balanced FSE burdens and local minimum frontier elements.

B. Frontier reduction algorithm

After performing the *Algorithm 1*, the frontier node sets crossing different sub-graphs are determined as well, which will be further minimized to reduce the interaction of adjacent sub-graphs. Joseph has suggested a node separator improving method [14], which is applied to minimize the number of the node separators in 2-way graph partitioning. We extend the node separator improving method to perform the frontier reduction in multi-way graph partitioning.

Let $Adj_G(x, U)$ or $Adj(x, U)$ denote the adjacent nodes of x in U, that is, $Adj(x, U) = Adj(x) \cap U$. The same way, for a subset W, $Adj(W, U) = Adj(W) \cap U$. For any obtained sub-graph C_i $(i=1, 2, ..., n_g)$, the initial value of its corresponding frontier node set is represented by F_i $(i=1, 2, ..., n_g)$ and defined as:

$$F_i = \{u \mid u \in Adj(C_i, U), U = \bigcup_{j>i} C_j, i, j = 1, 2, ..., n_g\} \qquad (3)$$

Consider a subset Y of any given frontier node set F_i, where $Adj(Y, C_i) \neq C_i$. The following simple but crucial results are stated.

Proposition 5: Suppose F_i is the frontier node set crossing C_i and U, then the set $\overline{F_i} = (F_i - Y) \cup Adj(Y, C_i)$ is the frontier node set of the two sets $\overline{C_i} = C_i - Adj(Y, C_i)$ and $\overline{U} = U \cup Y$.

Proposition 6: If $|Adj(Y, C_i)| < |Y|$, then $|\overline{F_i}| < |F_i|$.

It can be observed that the central issue of the frontier reduction algorithm is how to determine a subset Y of any frontier node set F_i so that the size of $Adj(Y, C_i)$ is less than that of Y. This problem is much associated with a well-known combinatorial problem called *bipartite graph matching* [14, 17]. All the necessary material, bipartite graph, matching, saturated or unsaturated vertex, alternating path, augmenting path and other related concepts can be found in [14] and [17]. Then the frontier reduction algorithm is described systematically in *Algorithm 2*.

Algorithm 2. Frontier reduction algorithm

Step 1: $i=1$;

Step 2: For the sub-graph C_i and its frontier node set F_i, construct the corresponding bipartite H_i by $(F_i, Adj_G(F_i, C_i), E)$. At the same time, initialize matching $M=\varnothing$.

Step 3: For each node $x \in F_i$, generating the M-alternating tree rooted at the node x which is defined as: $L_0, L_1, L_2, ..., L_{2j-1}, L_{2j}, ...,$ where:

$L_0=\{x_0\}; j=1, 2, 3, ...;$

For odd levels: $L_{2j-1}=Adj_H(L_0 \cup \cdots \cup L_{2j-2})$;

For even levels: $L_{2j}=\{u \mid \{u,v\} \in M$ for some $u \in L_{2j-1}\}$ (4)

If an M-augmenting path starting from x is found, then
  augment the current matching M by this path;
  repeatedly perform *Step 3* until all nodes of F_i have been tested, then go to *Step 4*.
else
  according to the alternating tree rooted at x, return the desired Y by the union of all the even levels, including L_0. That is,
  $Y=L_0 \cup L_2 \cup \cdots \cup L_{2j}$ (5)
  get the modified $\overline{C}_i$ and $\overline{F}_i$ based on the *Proposition 5*.
  break and restart this algorithm from *Step 2*.

Step 4: $i=i+1$, if $i=n_g$, then this frontier reduction algorithm terminates, else go to *Step 2*.

We still use the simple power network in Fig. 1 as the illustrative example, which has been redrawn in Fig. 3. On the basis of the partition, suppose $C_i=\{87\ 86\ 84\ 83\ 88\ 85\ 90\ 91\ 89\ 82\}$ and then its corresponding frontier node set is $F_i=\{94\ 77\ 96\ 92\}$. Thus two node sets, $I=F_i=\{94\ 77\ 96\ 92\}$, $J=Adj_G(F_i,C_i)=\{82\ 89\ 91\}$, and the edge set E crossing I and J construct a bipartite graph $H=(I, J, E)$. If $M=\{\{77, 82\}, \{96, 89\}, \{92, 91\}\}$ is the matching of the bipartite graph, it can be seen that node 94 is a M-unsaturated node in I, so we could get the alternating tree rooted at node 94 by (4): $L_0=\{94\}$, $L_1=\{82\}$, $L_2=\{77\}$, and thus the expected subset of the frontier node set F_i is $Y=\{94, 77\}$, which has a smaller adjacent set $Adj_H(Y)=\{82\}$.
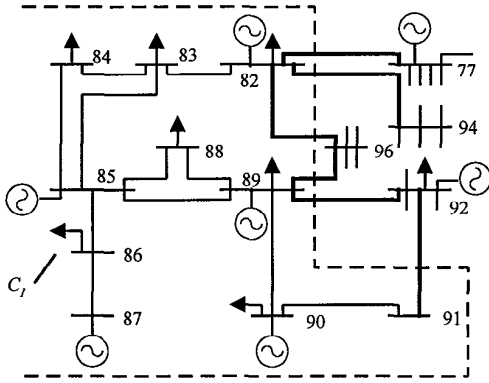

Fig. 3 The illustrative power network for frontier reduction algorithm

In a word, for any large-scale power network, the two steps of the multi-way graph partitioning method described in this section are performed in sequence. Consequently the optimal graph partitioning solution for FSE could be obtained systematically.

III. COMPUTER SIMULATION RESULTS

The proposed multi-way graph partitioning method has been implemented with sparse storage technique. The sparse storage technique only stores and operates nonzero elements and this could improve the calculation efficiency greatly.

IEEE 14-bus, 30-bus and 118-bus systems are used as the test systems respectively. The case, IEEE 118-bus system and $n_g=12$, is selected as an example to show the working process of the proposed multi-way graph partitioning method systematically. After forming the weighted MD ordering, *Algorithm 1* is performed to get $n_g = 12$ sub-networks. The corresponding initial value of the sub-networks and frontier node sets are listed in Table 1. In addition, the initial frontier and the reduction results of the *Algorithm 2* are displayed in Table 2. However, it only reduces the frontier node sets by one frontier node, which is mainly due to the simplicity of the test system.

From this case, it can be concluded that the proposed multiple-way graph partitioning method works effectively and could satisfy all the requirements of FSE problem simultaneously. Other cases in IEEE 14-bus, 30-bus and 118-bus systems could get the similar results. We list these results in Table 3. In this table, we will not display every element in sub-network sets and frontier node sets. On the contrast, because the expected weights of each sub-network, denoted by $aver\_wt$, can be calculated by $aver\_wt=$(the total weights of the whole network)$/n_g$, we use $max\{|wt(C_i)|- aver\_wt|\}/aver\_wt$ to represent the unbalance degree of the partition. The smaller the unbalance degree, the more balanced the obtained sub-networks.

Table 1. Obtained sub-networks of IEEE 118-bus system after partition

$i=[1, n_g]$	Obtained sub-networks $C_i=\{x\|x \in C_i\}$	$wt\ (C_i)$
1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	25
2	50, 51, 52, 53, 54, 55, 56, 57, 58	25
3	82, 83, 84, 85, 86, 87, 88, 89, 90, 91	25
4	103,104, 105, 106, 107, 108, 109, 110, 111, 112	25
5	92, 93, 94, 95, 96, 97, 101, 102	22
6	24, 70, 71, 72, 73, 74, 75, 76, 118	24
7	25, 26, 27, 28, 29, 31, 32, 113, 114, 115	26
8	11, 12, 13, 14, 15, 16, 17, 18, 33, 117	25
9	19, 20, 21, 22, 23, 34, 35, 36, 43, 44	22
10	59, 60, 61, 62, 63, 64, 66, 67	22
11	30, 37, 38, 39, 40, 41, 42, 45, 46, 47, 48, 49	30
12	65, 68, 69, 77, 78, 79, 80, 81, 93, 99, 100, 116	26

Table 2. The frontier node sets of IEEE 118-bus system

$i=[1, n_g-1]$	F_i before reduction	F_i after reduction
1	11, 12, 30	No change
2	49, 59	No change
3	77, 92, 96	92, 82
4	100	No change
5	80, 100	No change
6	23, 69, 77	No change
7	17, 23, 30	No change
8	19, 30, 37	No change
9	37, 45	No change
10	49, 65	No change
11	65, 69	No change

Table 3. The test results of IEEE 14-bus, 30-bus and 118-bus systems

	14-bus ($n_g=2$)	30-bus		118-bus		
		$n_g=2$	$n_g=3$	$n_g=2$	$n_g=3$	$n_g=8$
Unbalance degree %	11.7	12.6	31	19.2	12.1	13.1
Before reduction (no.)	2	3	4	3	7	20
After reduction (no.)	2	3	4	3	7	20

The results in Table 3 have demonstrated that the proposed method could not only work effectively but also succeed in all the test power networks. In addition, it

should be pointed out that the reduction effect of *Algorithm 2* is not obvious for the above test cases, which is caused by the simplicity of the test systems.

For comparison purpose the graph partitioning method based on depth-first-search (DFS) algorithm [17] has been realized and tested as well. Compared with the proposed graph partitioning method, though the DFS based graph partitioning method can satisfy all the requirements of FSE, it can not effectively minimize the number of the frontier nodes since DFS tree has no effect on minimization of the frontiers. Table 4 compares the number of the frontier nodes between these two methods. The results show that the proposed multiple-way graph partitioning method has better quality than DFS based graph partitioning method.

Table 4. The comparison between MD reordering and DFS based method

	14-bus (n_g=2)	30-bus		118-bus		
		n_g=2	n_g=3	n_g=2	n_g=3	n_g=8
No. of F_i based on DFS	2	3	5	5	10	21
No. of F_i based on MD	2	3	4	3	7	20

IV. CONCLUSIONS

In this paper an efficient MD reordering based graph partitioning method for distributed fault section estimation system in large-scale power networks is proposed. The partitioning procedure and characteristic analysis is presented. The analysis demonstrates that the proposed method can effectively satisfy all the requirements of the FSE. The method has been implemented with sparse storage technique and tested in the IEEE 14-bus, 30-bus and 118-bus systems. For comparison purpose the graph partitioning method based on DFS algorithm has been realized and tested as well. Computer test results show that the proposed multiple-way graph partitioning approach is suitable for distributed fault section estimation system in large-scale power networks and has better quality as compared with the graph partitioning method based on DFS algorithm.

V. ACKNOWLEDGMENTS

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