A HYBRID GENETIC ALGORITHM FOR PARTITIONING OF DATA MODEL IN DISTRIBUTION MANAGEMENT SYSTEMS

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Abstract. In this paper, we propose a Hybrid Genetic Algorithm for data model partitioning of power distribution network. Analytical functions are the core of Distribution Management Systems (DMSs). Efficient calculation of the functions is of the utmost importance for the DMS users; the necessary preconditions for the efficient calculation are optimal load balancing of processors and data model partitioning among processors. The proposed algorithm is applied to different real models of power distribution systems. It obtains better results than classical evolutionary algorithms (Genetic Algorithm and Particle Swarm Optimization). The Hybrid Genetic Algorithm also achieves better results than multilevel algorithm (METIS) in cases of small graphs.

Keywords: graph partitioning, genetic algorithm, Distributed Management System, Common Information Model.

1. Introduction

In order to effectively manage modern adaptive applications within the multiprocessor system, large amounts of data need to be optimally processed in parallel. For optimal calculations to be carried out on certain groups of data, the following conditions must be satisfied: the data are necessarily partitioned across the processors and load balancing of the processors must be achieved. It is necessary to make an optimal distribution of data across the processors in accordance with pre-defined criteria that determine the calculation functions so that the calculations and the overall system functioning is efficient.

The Integrated Smart Grid power system largely increases the amount of data in each of its subsystems. It integrates systems such as [1]: Geographic Information System, Energy Management System, Distribution Management System (DMS), Outage Management System, etc. We treat parallel calculations in the DMS as one subsystem of Smart Grid system. DMSs have the supervision, management, planning and visualization of the distribution network in two modes: on-line (real-time) and simulation. Analytical DMS functions are the central component of the DMS. They allow monitoring and manage the power distribution network.

The most important DMS functions are: Load Flow (LF), State Estimation (SE), Fault Calculation, Performance Indices, Volt/Var Control, etc.

This paper describes the optimal partitioning of power distribution network data model by using the most common DMS functions – Load Flow and State Estimation. Also, the real power distribution networks and the corresponding functions are analyzed. The LF [2] and SE function algorithms are based on the weakly meshed radial data network. SE requires multiple LF execution and will thus not be discussed further. The network architecture makes the data models suitable for partitioning and parallel calculations [3, 4].

Depending on an application context of the DMS, dynamic data can be monitored either on-line by the SCADA system (real-time context), or off-line – defined and analyzed by the user (within the planning, simulation or testing contexts). Calculation time of the functions above becomes critical with increasing amounts of data involved in calculations (the present network contains tens of millions of data). For DMS functions optimization, only real-time (RT) context is critical for time calculation.

The initial partitioning of the DMS data model is studied. The partitioning is based on the initial values of objects’ attributes and the relationships between the data. As a result, groups of data necessary for calculation are made. Dynamic changes of certain attributes (usually the relations among the data objects) can affect the data; and consequently, calculations. Thus we introduce the optimization criterion by which a potential need of using the data stored in other partitions is lowered. The structure of the power distribution network enables the transformation of data into a graph that can be successfully partitioned. In other words, the problem of DMS data model partitioning can be reduced to the problem of graph partitioning.
This paper reports the results of experiments which show that hybrid Genetic Algorithm (HGA) can be successfully applied for initial partitioning and that it always provides better results than simple Genetic Algorithm (GA)[5,12] and Particle Swarm Optimization (PSO)[6] algorithm.

The paper is organized in the following way: next section describes related work on algorithms for partitioning graphs. Section 3 describes the problem and defines terms used in the paper. It also includes the details of data model and definitions of the optimization problem. The HGA for initial partitioning is presented in Section 4. Section 5 describes experimental setup, presents and discusses the results. Section 6 is a conclusion.

2. Related Works

Graph partitioning is classified as an NP hard optimization problem [7]. Many suboptimal graph partitioning solutions have been proposed. Two commonly used classes of algorithms are multilevel and evolutionary algorithms.

Multilevel algorithms [8,9] consist of three phases: coarsening – the matching of vertices per levels, partitioning – the partition graph consisting of matched vertices at a certain level and refinement – improvement of the partitioning at various levels. Most of these algorithms use KL [10] or its variant FM [11] algorithms, which are specialized for local improvement of solutions by exchanging vertices between the individual partitions. In addition, the FM algorithm moves a vertex from one partition to another in each iteration, and the KL algorithm exchanges vertices between partitions. Most commonly used multilevel algorithm is METIS algorithm [9].

In our studies [5,6,12], evolutionary algorithms are used for the initial partitioning. This allows the use of somewhat slower algorithms since it is done prior to startup. However, before the algorithms are applied, the coarsening of data is required in order to reduce the problem dimensionality and make a smaller number of data groups. The aim of the study reported in this paper is to improve previously obtained results and determine the applicability of evolutionary algorithms to large data model partitioning in power distribution systems.

Evolutionary algorithms have been successfully used for graph partitioning. The most commonly used algorithms are PSO[6] and GA[5,13-15].

GA is used for graph partitioning: various size graphs or unweighted ones [13]. Furthermore, parallel GA [14,15] was developed to speed up the algorithm. If the accuracy of a simple GA is not satisfied, then variants of hybrid GA are recommended [16-19]. GA finds a solution close to the optimum and some other algorithm (often KL/FM) is used for local refinement [13].

This paper compares hybrid GA with previously used GA[5, 12] and PSO[6, 12] algorithms for initial graph partitioning.

3. DMS Data Model Partitioning

3.1. DMS data model

Data models in power distribution utilities, based on Common Information Model (CIM) connectivity/topology model (Figure 1) are studied. CIM [20] is a well-known standard established by the International Electrotechnical Commission (IEC). It defines an object-oriented model of electric power systems, represents resources as classes and associations between them.

The distribution network is a weakly meshed radial network. It begins in high-voltage substations (Substation) of the power sources (EnergySource), representing the point of supply from energy transmission networks. The connectivity model is composed of transformer substations (represented by PowerSystem-Resource) connected with power lines (ACLineSegment), which are used to supply groups of consumers with energy (EnergyConsumer). Substations contain various equipment (ConductingEquipment and PowerTransformer) that is connected by various nodes (ConnectivityNode). ConductingEquipment objects are modelled with single- or double-ended (SingleEndedCondEq and DoubleEndedCondEq) conductors, and these are always connected with ConnectivityNode(s). Some of the typical single-ended conductors are EnergyConsumer, EnergySource, and BusbarSection, and double-ended ones are Switchgear (Breaker, Fuse) and ACLineSegment. In essence, the connectivity model is an edge-vertex model suitable for a graph presentation, where edges and vertex are instances of ConductingEquipment and ConnectivityNode, respectively.

![Figure 1. Connectivity CIM based DMS data model](image)

The DMS data model partitioning is described by analyzing the target DMS functions. It is assumed that only one function $\xi$ is running in the system. This is done in order to optimally partition datasets and finish data processing as quickly as possible.
DMS data model \((Q)\) contains all elements \(\alpha_i\) that are included in a calculation. Conducting equipment and transformers are elements usually used for the DMS functions.

If two elements \(\alpha_i\) and \(\alpha_j\) are in a relation \(N(\alpha_i, \alpha_j)\) then it is assumed that the calculation function \(\xi\) uses them together. The elements are connected and they are called neighbors.

The relation between neighbors that depends on the state of an element \((u_{ij})\) could be temporarily inactive. We refer to it as potential connection \(Pot(\alpha_i, \alpha_j, u_{ij})\). When a potential connection is activated, two elements become neighbors
\[
(\forall \alpha_i, \alpha_j \in Q) \; Pot(\alpha_i, \alpha_j, u_{ij} = \text{active}) \Rightarrow N(\alpha_i, \alpha_j)
\] (1)

For example, state of a switch between pieces of equipment could be active (closed) or inactive (open).

The set of mutually connected elements is called calculation region \(R\) (or just region)
\[
(\forall \alpha_i \in R_j) \; N(\alpha_i, \alpha_j) \Leftrightarrow \alpha_i \in R_k,
\]
and it is the smallest data unit that can be processed by calculation function.

All regions create a calculation domain \(D\) (\(D = R_1 \cup R_2 \cup ... \cup R_n\)) and function \(Y_i = \xi(R_i)\) is applied to each region \(R_i\) to produce output result set \(Y = Y_1 \cup Y_2 \cup ... \cup Y_n\).

3.2. Model Partitioning

The process of partitioning large datasets consists of the following phases: 1) formation of the initial graph, 2) topological analysis and creation of the graph for calculations (coarsened graph), and 3) partitioning of the coarsened graph.

1. Formation of the initial graph

The initial graph is derived from the conduction elements and other equipment involved in the calculations. The edges of the initial graph are: (i) double ended equipment, (ii) single ended equipment with one fictive vertex. The transformers with two windings are presented with two edges (primary + derived), and transformers with three windings are presented with three edges (primary + two derived). The vertices are connectivity nodes.

2. Topological analysis and creating of the graph for calculations

Topological analysis is one of the DMS functions. It depends on the status of conducting equipment; for instance, the state of the switches (open / closed). The analysis determines the basic group of elements (calculation regions) necessary for the calculations. The result of the analysis is a calculation domain \(D\) that could be represented by undirected weighted graph \(G = (V, E)\) with vertices \(V\) and edges \(E\).

3. Partitioning of the coarsened graph - definition of optimization criteria

The problem of graph partitioning is based on partitioning of the undirected graph with vertices and edges that have a certain weight. The result of p-way partitioning is a set of \(p\) partitions \(\Pi = \{\pi_1, \pi_2, ..., \pi_p\}\).
where partition \( \pi_i \) contains an optimal set of regions (vertices).

### 3.3. Optimization criterion

In order to define optimization criterion for a partition \( \pi_k \), we need to define the partition weight \( W_{\pi_k} \):

\[
W_{\pi_k} = \sum_{R_j \in \pi_k} W_j
\]

as the sum of all contained regions’ weights. We also need to define a function \( \phi_k \) as:

\[
\phi_k = \sum_{R_p, R_q \in \pi_k} Pot_{R_p, R_q}
\]

This function is an indicator of “good connectivity” between the regions in the partition.

First, it is necessary to group regions into a defined number of partitions \( p \), so that the weights of these partitions are approximately the same. They can never be greater than the maximal partition weight \( M \) defined as:

\[
M = (1 + \varepsilon) \cdot \frac{1}{p} \sum_{\pi_k} W_{\pi_k}
\]

where \( W_{\pi_k} \) is weight of partition \( \pi_k \), \( p \) is the number of partitions, and \( \varepsilon \in [0, (p-1)/p] \) is the tolerance.

The optimization criterion should obtain the maximum connection inside a partition:

\[
\Psi = \sum_{k=1}^{p} \phi_k,
\]

\[
F = \max(\Psi),
\]

where function \( \phi_k \) is given in (4), and all partition weights are constrained by:

\[
W_{\pi_k} \leq M, \forall k \in \{1,2,...,p\}.
\]

It should be noted that the maximal number of connections inside each of the partitions means a minimal number of connections among partitions.

### 4. Algorithms

We apply the HGA to find the best approximate solutions for the optimization problem (7) with respect to the constraints given in (8). HGA consists of the simple genetic algorithm. Its solutions are improved by using FM algorithm.

It is assumed that a graph with the \( n \) regions (vertices) should be divided into the \( p \) partitions. The solution is represented by the vector of the \( n \) elements whose values are indices of the given partitions (integers between 0 and \( p-1 \)).

#### 4.1. Genetic Algorithm (GA)

GA starts from randomly constructed initial solutions, which are considered individuals in a population. The initial partition weight can affect the quality of the solution. After coarsening the graph, the DMS data model partitioning problem becomes the weighted graph partitioning problem. The weighted graph has less than 1000 vertices (realistic estimations are around 500 vertices). Experimental results show that good solutions for this kind of graph partitioning can be obtained when the number of individuals is similar to the number of vertices (regions). The GA execution time is not considered since the algorithm execution time is not critical. The algorithm is executed prior to the start of the system.

GA is an iterative algorithm that consists of selection, crossover and mutation.

Different types of selection (random, tournament and roulette-wheel) are studied. Experimental results show that the best selection type is roulette-wheel.

In addition, different types of crossovers can be used: in one point, in the k-points, etc. For the purposes of our research, we chose the one point crossover. It randomly selects a cut point which is the same on both parent individuals. The cut point divides the individuals into two disjoint parts. Two offsprings are created from opposite parts of parents. If the constraint for partition weights (given by (8)) is not satisfied then a high penalty factor is used to decrease function F. Besides the one point crossover (without preprocessing), we investigate the following crossovers: (i) a crossover with unique partition representation (normalization) in all individuals [22], and (ii) a crossover with the favorite best partition [5]. Our experiments show that the best results are obtained with the crossover without preprocessing ([22], [5]). The probability that a certain individual is involved in a crossover is called crossover rate. Mutation is performed with a probability that is called mutation rate. The choice of mutation rate significantly influences the solution quality.

Also, the results gained from our experiments show good convergence of GA (i.e. good global search). However, inadequately fine solutions indicate the need to combine GA with algorithms for local improvements. FM algorithm is chosen for local improvement.

#### 4.2. Fiduccia-Mattheyses (FM) algorithm

FM algorithm [11] is a group migration heuristic which starts with a partitioned graph and iteratively moves vertices to improve solution. It selects the vertex that should be moved from one partition to another. The criterion for moving vertex \( v_i \) from partition \( \pi_S \) to partition \( \pi_T \) is the maximum value of gain parameter \( g \). The parameter is calculated as:

\[
g(i, J) = FS(i, J) - TE(i)
\]
where $FS(i, J)$ is the number of edges connecting the vertex $v_i$ with vertices in the partition $\pi_i$, and $TE(i)$ is the number of edges incident to vertex $v_i$ and another vertex in the same partition ($\pi_k$) as vertex $v_i$.

In the case of weighted graphs, it is the sum of weights of the corresponding edges that is calculated instead of the number of edges. Fiduccia and Mattheyses [11] propose a method of FM algorithm realization. The method speeds up the execution time of the algorithm by using data structure (bucket list) that reduces computation time (an iteration can be done in $O(|E|)$ time). For multiple-way partitioning, all possible transfers of border vertices (neighbors with vertices from other partitions) are checked.

Pseudo code of a simplified FM algorithm is given below:

```
Input: partitioned graph $G=(V,E)$ -> $\Pi=\pi_1 \cup \pi_2 \cup \ldots \pi_p$
Output: improved partitions of graph $G$ -> $\Pi=\pi'_1 \cup \pi'_2 \cup \ldots \pi'_p$

Repeat
  for each border vertex $v_i$ in graph $G$
    for each partition $\pi_i$ in $\Pi$
      $g(i,J) \leftarrow FS(i,J) - TE(i)$
    end for
  end for

  find $v_b \in \pi_0$ and $\pi_0 \leftarrow (\max(g)=g(b,D))$
  if $(w(\pi_0 \cup \{v_b\}) < M)$
    $\pi_0^+ = \pi_0 \cup \{v_b\}$
    $\pi_0^- = \pi_0 \setminus \{v_b\}$
  end if

  recalculate $g(i,J)$ (for neighbors of $v_b$)
  until $(\max(g) \leq 0)$

In the HGA, we first use the GA to partition a graph; then, we use the FM algorithm to improve this graph.

### 4.3. Hybrid Genetic Algorithm

The HGA utilizes the results of FM algorithm to improve the local optimum. The initial population is generated randomly (for each gene in each individual the partition number is randomly set). Since the FM algorithm moves a vertex from one partition to another (in the GA, this movement presents a value change of a particular gene), hybridization of the genetic algorithm is carried out in a mutation phase. HGA uses mutations from the classical genetic algorithm; but it also introduces FM mutations periodically (every $freq$ iterations).

Pseudo code of the HGA is given below:

```
Input: unpartitioned graph $G=(V,E)$
Output: partitioned graph $\Pi=\pi_1 \cup \pi_2 \cup \ldots \pi_p$

create initial population $X=\{x_1,x_2,\ldots,x_m\}$
$it \leftarrow 0$

repeat
  select pairs $(x_i,x_j)$ for crossover
  $it \leftarrow it+1$
  for each pair $(x_i,x_j)$
    offspring$_{i,j} \leftarrow$ Crossover($x_i,x_j$)
    $X = X \cup \{offspring_{i,j}\}$
  end for
  $X_{mut} \leftarrow$ select individuals for mutation
  for each individual $x_k \in X_{mut}$
    $x_{nk} \leftarrow$ Mutation($x_k$)
    $X = X \cup \{x_{nk}\}$
  end for
  if $it$ % $freq = 0$
    $X_{FM} \leftarrow$ select individuals for FM
    for each individual $x_k \in X_{FM}$
      $x_{nk} \leftarrow$ FM_mutation($x_k$)
      $X = X \cup \{x_{nk}\}$
    end for
  end if

  $X \leftarrow$ choose the best $m$ individuals from $X$
  until (no progress) or $it > maxit$

The algorithm is finished either if there is no improvement or, after a predefined number of iterations ($maxit$) are executed.

### 5. Experimental Results

We tested the models of the real electric power distribution network. The network characteristics are shown in Table 1.

<table>
<thead>
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<th>Graph name</th>
<th>Total number of elements</th>
<th>Size of initial graph (uncoarsened)</th>
<th>Size of coarsened graph</th>
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Models $bg54$ and $bg63$ are different versions of Belgrade (Serbia) power distribution network. $pec$ is a part of North Carolina (United States) power distribution network model; $it206$ is a network model of Milano (Italy); and $bg5x$ is Belgrade network model multiplied five times.

We ran initial partitioning tests using HGA on datasets from Table 1.

The tests were carried out for 2, 3, 4, 5, 6 and 8 partitions. Each test was repeated 100 times. The HGA is applied with the following parameters:
The applicability of the HGA is determined by giving a comparison of the results gained from the HGA and the ones gained from the METIS algorithm.

The METIS algorithm is much faster but this characteristic is insignificant for the practical applications of the model initial partitioning. Thus we conclude that the HGA yields better results for graphs of up to 200 vertices. We recommend specialized multilevel algorithms for partitioning graphs that are over 200 vertices and if there is a large number of partitions required.

6. Conclusions

In this paper, we developed a new HGA for initial partitioning of large data models. The amount of data that need to be processed in the DMSs is increased. The increase calls for parallel calculations of analytical DMS functions. The calculations are executed in different processors; consequently different data are sent to different processors. The DMS network is such that the problem of data partitioning boils down to the problem of graph partitioning.

The algorithm is successfully applied to large scale electricity power distribution data model. Experiments reported in the paper show that HGA always obtains better results than simple GA and PSO algorithms do. Further, HGA is compared with METIS algorithm. The results show that HGA is good for partitioning graphs with up to 200 vertices.

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References


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