APPLICATION OF GENETIC ALGORITHMS FOR PLANNING METERING SYSTEMS IN STATE ESTIMATION

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Abstract – Power system state estimators require a set of redundant measurements properly chosen according to their type, amount and location in the supervised electric network. The metering system planning can be expressed as an NP-hard combinatorial optimization problem and treated by metaheuristic search techniques. This paper presents a solution method for the meter placement problem based on genetic algorithms. A fitness function is formulated in which the cost of the metering system is minimized, while no critical measurements and/or critical sets are allowed in the optimal solution. A fast and reliable method for identifying critical measurements and sets is employed during the evaluation of the fitness function. In the proposed method, there is no need to run the state estimator for the design of the metering system. Simulation results illustrate the performance of the proposed method.

Keywords: genetic algorithms, optimization, state estimation, power systems monitoring.

1   INTRODUCTION

The State Estimation (SE) function [1,2] processes periodically a set of analog measurements of the type: active/reactive power flows and injections, as well as voltage magnitudes. Under normal conditions, there will be more than a sufficient number of measurements (data redundancy) to define the system state completely.

The overall meter placement problem [3] consists of the determination of which measurements—in terms of number, type, and topological distribution— are necessary for SE, considering the following requirements:

- Observability—SE is accomplished for the entire system network;
- Reliability—Gross error detection, identification, and suppression is possible;
- Quality—A certain level of accuracy for estimated quantities is assured;
- Robustness—In the event of network configuration changes or temporary malfunction of the data acquisition system, implying in redundancy deterioration, observability, reliability and quality requirements are still met;
- Cost—Investment cost for data acquisition is minimized.

Hence, meter placement is of primary importance and one of the most difficult problems in SE. This is due not only to the problem dimension itself (number of possible configurations), but also to the need of establishing a trade-off between SE performance and metering system costs.

Data redundancy is crucial for the success of the SE process. Adequate redundancy levels enable SE to efficiently process bad data and also to achieve accurate and reliable estimates, even in case of temporary data loss. Although highly redundant metering systems would be desirable, they are often not achieved due to financial constraints. Besides, during power system operation, topology changes or temporary malfunction of the data acquisition system may reduce measurement redundancy level for SE [4]. Even critical redundancy levels may be reached [5], in which critical measurement and sets occur, leading to inadequate performance of bad data processing routines.

Several methods have been proposed for planning metering systems. In [6] a method that takes into account technical and financial issues is proposed. However, the optimization process involves an exhaustive search procedure. In [7] a method to reinforce a metering system is proposed, based on the topological observability of the supervised network. In [8] an algorithm for the identification of observable islands and selection of additional measurements to restore network observability is also proposed. A method that considers observability, reliability, and robustness requirements is presented in [9]. However, the minimization of investment costs is not evidenced. In [10] investment costs are also taken into account, but an exhaustive search procedure is employed. In [11] a metering system is designed for a basic network and possible occurrence of topology changes and/or measurement losses. However, only the observability requirement is considered.

Methods based on intelligent systems techniques have also been proposed for obtaining optimal metering systems [12,13]. However, the reliability requirement is not explicitly considered and bad data suppression capability can not be assured. In [14] a genetic algorithm is employed to plan metering systems without critical

measurements and sets. Although SE bad data processing capability is enabled, the formulated fitness function does not guarantee that a minimum cost solution is reached.

This paper presents a genetic algorithm-based method for planning metering systems used in real-time power systems monitoring through the SE function. The method extends the concepts presented in [15] to explore the flexibility of the adopted fitness function when it is necessary to obtain limited cost metering systems. Optimal metering systems are obtained in terms of number, location, and type of measurements, considering redundancy requisites, such as network observability and reliability (SE results free of bad data). The consideration of robustness requirement is out of the scope of this paper and will be the subject of a future work. It is worth to mention that the proposed method can be used for planning new metering systems as well as for expanding existing ones. Numerical results with the IEEE-14, 30, and 118 bus systems are included to illustrate the performance of the proposed method.

2   METERING SYSTEM PLANNING

The meter placement is an optimization problem in which investment costs should be minimized, considering some performance requirements in order to guarantee SE success. This problem can be formulated as:

$$\text{Min} \; (C_{met} + C_{RTU}) \tag{1}$$
$$\text{s.t. performance requirements}$$

where C_{met} and C_{RTU} represent, respectively, the cost of meters and remote terminal units (RTUs) to be installed. The performance requirements refer to the SE process.

In the formulation described here, it is possible to establish constraints such as: system observability, absence of critical measurements and absence of critical sets. Each of these constraints progressively enhances the reliability of the SE process. However, more redundant metering systems means higher investment costs. The determination of critical redundancy levels [5] can be done through a linear SE model.

In this section, in view of the construction of an algorithm for identifying data critical redundancy levels, SE basic aspects related to observability, filtering, and residual analysis are presented [1].

2.1 Linear State Estimation

For a given network configuration, the operating state and measurements gathered from around the system are related according to:

$$z = Hx + v \tag{2}$$

where x and z are the (nx1) state and (mx1) measurement vectors; H is the (mxn) Jacobian matrix obtained from the linearization of the load-flow equations for the current network configuration; v is a Gaussian noise vector, with zero mean and diagonal covariance matrix R. The state vector components are bus voltages phase angles

and magnitudes. Active/reactive power flows and injections as well as voltage magnitudes form the measurement vector.

Usually, SE has been formulated as a weighted least-squares (WLS) problem for the overdetermined system in (2). The objective is to find the n-vector $\hat{x}$ that minimizes the index $J(x)$, defined as follows:

$$J(x) = [z - Hx]^t R^{-1}[z - Hx] \tag{3}$$

2.2 Observability Analysis

Usually, a linearized, decoupled state estimator is adopted to perform observability analysis. Hereafter, for the sake of simplicity, the Pθ (active power-angle) model will be used. A system is said to be observable if the gain matrix $G = H^t R^{-1}H$ is nonsingular, which can be verified during its triangular factorization.

2.3 Filtering

The state estimate $\hat{x}$ which minimizes $J(x)$ can be obtained from:

$$H^t R^{-1}[z - H\hat{x}] = 0 \tag{4}$$

$$\hat{x} = G^{-1}H^t R^{-1}z \tag{5}$$

where $G = H^t R^{-1}H$ is known as gain matrix.

2.4 Residual Analysis

The residual vector r, defined as being the difference between z and the corresponding filtered quantities $\hat{z} = H\hat{x}$, is normalized and submitted to a validation test:

$$r_N(i) = |r(i)| / \sigma_E(i) \; \leq \; \text{threshold} \tag{6}$$

$$E = R - HG^{-1}H^t \tag{7}$$

where $\sigma_E(i) = \sqrt{E(i,i)}$ is the standard deviation of the i*th* component of the residual vector. Threshold violations indicate the presence of bad data.

2.5 Critical Measurements and Critical Sets

A critical measurement (Cmeas) is a non redundant measurement, for which SE is useless. A gross error in a Cmeas is undetectable by residual analysis. Numerically, the residual and standard deviation associated with a Cmeas are always zero. Thus, in a dataset received for processing, the ith measurement is identified as a Cmeas if:

$$r(i) = z(i) - \hat{z}(i) = 0 \tag{8}$$

$$\sigma_E(i) = \sqrt{E(i,i)} = 0 \tag{9}$$

Normalized residuals of measurements pertaining to a critical set (Cset) are always equal, and present maximum correlation coefficients. It is impossible to identify bad data among Cset elements by the residual test analysis. Suppose that measurements z(i) and z(j) belong to the same Cset. Then, it follows that:

$$\rho_{ij} = \frac{r_N(i)}{r_N(j)} = 1 \qquad (10)$$

$$\gamma_{ij} = \frac{E(i, j)}{\sqrt{E(i, i)}\sqrt{E(j, j)}} = 1 \qquad (11)$$

An efficient method for identifying critical measurements and sets is detailed in [5].

3   GENETIC ALGORITHMS

Recently, genetic algorithms (GAs) have gained popularity for their easy searching process, solutions near global optimum, independence of searching space, and probabilistic nature. The main advantages of GAs over conventional algorithmic optimization methods are:

- They do not need any prior knowledge, space limitations, or special properties of the objective function such as smoothness, convexity, or differentiability. They only require the evaluation of the fitness function to assign a quality value to every solution produced ;
- Instead of a point-to-point search, they work with a set of solutions from one generation to the next, making the process likely to converge to a global minimum;
- The solutions obtained are randomly based on the probability rate of the genetic operators such as mutation and crossover, thus avoiding that initial solutions state the search direction of the algorithm.

The optimization problem represented by (1) is combinatorial and adequate for the application of global search techniques, such as GAs. These algorithms are based on natural evolution processes [16], where attributes found in biological systems have their correspondence in computational models particularly designed to simulate such processes.

Like in natural systems, evolution in a GA is based on Darwin's postulation of the survival of the fittest, which means that the best individuals will participate with their genetic material in the population of the next generation. This adaptive process can be used to solve optimization problems formulated as:

$$\text{Max } f(x)$$
$$\text{s.t.} \quad g(x) = 0 \qquad (12)$$
$$h(x) \leq 0$$
$$x \in S$$

where:
f(x)—objective function to be optimized;
g(x)—equality constraints;
h(x)—inequality constraints;
x—vector of problem variables;
S—search space.

A population is formed by a set of individuals, each of them representing a proposed solution for the problem; an individual is codified into a string of characters of finite alphabet, denominated chromosome. Each element (character) in a chromosome is called a gene.

A GA search is done by examining at the same time a set of possible solutions, instead of a single one. This strategy allows a better exploration of the solution space during the search for the global optimum. Also, it reduces the probability of being stuck in a local optimum. The success of the optimization process depends on the appropriate design of a fitness function for the problem. The fitness values of individuals in a given population are employed to drive the evolution process. These characteristics enable the GAs to present excellent results even when optimizing complex, multimodal or discontinuous functions.

The evolution process in a GA takes place by performing genetic operations among individuals. The basic genetic operations are: reproduction, crossover and mutation.

Reproduction is employed to copy (select) individuals from the current population to the next one. In such process, individuals with higher fitness values have more probability to be selected to participate with their genetic material in the next generation.

Crossover is a very important operator for GAs. The crossover operator is responsible for the recombination of genetic material (strings of characters) of two individuals to generate new individuals in the next population. Crossover is performed in two steps: first, two individuals of the new generation are selected; then, strings of characters are swapped to create two new individuals. The crossover is a random process, which occur with a pre-defined probability.

Mutation is the operator responsible for the injection of new information. It is implemented by flipping bits at random, generally with a constant probability for each bit in the population. This operator allows the recovering of genetic material that has been lost during the evolution process. It acts as a protection against premature loss of genes. As it happens for crossover, the mutation also occurs with a pre-defined probability.

More details about GAs and genetic operators can be found in [16].

4   METER PLACEMENT METHODOLOGY

4.1 Encoding

The meter placement problem is modeled through GAs considering a binary encoding system in which each individual (chromosome) of a population corresponds to a proposed solution for the problem (metering system).

A chromosome is represented by a vector whose elements are associated with meter types and locations. The chromosome dimension then corresponds to the maximum number of meters that can be installed in a given network (twice the number of branches plus the number of buses). The chromosome elements (genes) assume binary values: equal to 1, if a meter is placed and 0, otherwise. Figure 1 depicts the chromosome representation for a 2-bus system.

It is assumed that all the power measurements are in active-reactive pairs. Therefore, a single gene represents a pair of measurements. Although voltage magnitude

measures are not explicitly considered, they can be placed with little extra cost at any of the RTUs already allocated by the proposed algorithm.

Flows		Injections	
line(1-2)	line(2-1)	bus(1)	bus(2)
0	1	1	0

Figure 1: Meter placement encoding scheme

4.2 Fitness Function

The formulation of the fitness function (FF) is a key aspect of the application of GAs to practical optimization problems. FF assigns a quality value to every member of the population. This value is used as a comparative measure of each solution against other members of the population.

FF is built taking into account the objective, constraints, and search space. In constrained optimization problems, the approach of penalties is largely used and will be adopted here. Observability, absence of critical measurements and critical sets are considered as constraints of the meter placement problem studied in this paper. Thus, the following FF can be formulated:

$$FF = [C_{met} + C_{RTU} + \\ + (k \times p_{obs} + N_{Cmeas} \times p_{Cmeas} + Nmeas_{Cset} \times p_{Cset})] \quad (13)$$

where:
FF—fitness value assigned to a member (metering system) of the population;
C_{met}—cost of meters;
C_{RTU}—cost of RTUs;
k—binary coefficient indicating observability violation (k=1), situation in which a penalty factor p_{obs} is applied. For observable networks, k=0;
N_{Cmeas}—number of critical measurements (Cmeas) in the proposed metering system;
p_{Cmeas}—penalty factor associated with the occurrence of Cmeas;
$Nmeas_{Cset}$—total number of measurements belonging to critical sets (Csets);
p_{Cset}—penalty factor associated with the presence of Csets.
Note that $Nmeas_{Cset}$ is a better weight for indicating the violation of this constraint than the number of Csets, since these may be of different sizes. For the same reason, simply flagging the presence of Csets with a binary coefficient would be inadequate.

The FF in (13) is flexible and allows the consideration of one or all problem constraints by appropriately adjusting the corresponding penalty factor. For example, if p_{Cset} and p_{Cmeas} are made equal to zero, the GA will search for a minimum cost metering system in which only the observability constraint is satisfied.

One should also remark that, as GAs usually solve maximization problems, meter placement can be solved by maximizing the inverse of FF in (13).

5   RESULTS

In this section, the proposed GA solution of the meter placement problem is evaluated using the IEEE-14, 30 and 118 bus systems. Simulations are performed according to the basic aspects of SE presented in Section 2. A FORTRAN program has been developed and results obtained on a Pentium *4*, 2.8 GHz.

During the search procedure, different values for GA parameters (crossover probability, mutation rate, and population size) have been tested. Roulette and tournament selection, as well as single point and uniform crossover, have also been tested. An elitist strategy has been employed in all test cases. The search process stopping criterion is based on a previously defined maximum number of generations.

The relative costs for meters and RTUs were $4.50 and $100.00, respectively. Also, the penalty factors to build FF in (13) were: $p_{obs} = 10^6$; $p_{Cmeas} = 10^4$; $p_{Cset} = 10^2$. These penalties values have been chosen so as to guarantee that the constraints are fully satisfied, in a cumulative way. In all tests it has been assumed that the search process starts with not any meter installed.

Many simulations have been performed with the test systems IEEE-14 (benchmark system for SE studies), IEEE-30 and IEEE-118. Tables 1, 2, and 3 present the obtained results, where metering schemes A, B, and C satisfy, respectively, the following requisites: observability, absence of Cmeas, and absence of Csets.

	Metering System/ Constraint	Number of power meters		No. of RTUs	Cost ($)
		Flows	Injections		
A	Observability	10	3	4	458.5
B	Absence of Cmeas	13	4	4	476.5
C	Absence of Csets	11	7	8	881.0

Table 1: Metering Systems for IEEE-14

	Metering System/ Constraint	Number of power meters		No. of RTUs	Cost ($)
		Flows	Injections		
A	Observability	23	6	10	1130.5
B	Absence of Cmeas	27	10	10	1166.5
C	Absence of Csets	29	16	18	2002.5

Table 2: Metering Systems for IEEE-30

	Metering System/ Constraint	Number of power meters		No. of RTUs	Cost ($)
		Flows	Injections		
A	Observability	95	29	42	4758.0
B	Absence of Cmeas	109	38	43	4961.5
C	Absence of Csets	141	61	71	8009.0

Table 3: Metering Systems for IEEE-118

The results presented in the previous tables show that it is possible to satisfy each constraint with low redundant metering systems. Plans A and B require the same number of RTUs for the IEEE-14 and IEEE-30; for IEEE-118 they differ by only one RTU. These results show that an efficient search was carried out, leading to an optimal location of meters and RTUs, and a more restrictive constraint could be satisfied with little extra cost.

Plan C requires higher redundancy, necessary to allow a reliable performance of the SE function. However, as it has been obtained in an optimal sense, the associated redundancy and cost can still be considered low. It is important to remark that the absence of Cmeas and Csets is not usually observed even in high redundant and expensive metering systems.

5.1 Computational Aspects

The metering system planning is a problem that should be solved offline, where the computing time is not a topic of major concern. Figures 2 to 4 depict the performance of the proposed method for obtaining the optimal solutions presented in Tables 1 to 3. Those results have been obtained when the population size and number of generations were 100 and 1000, respectively, during the GA process.
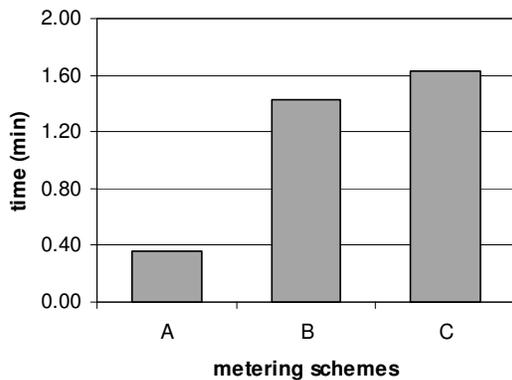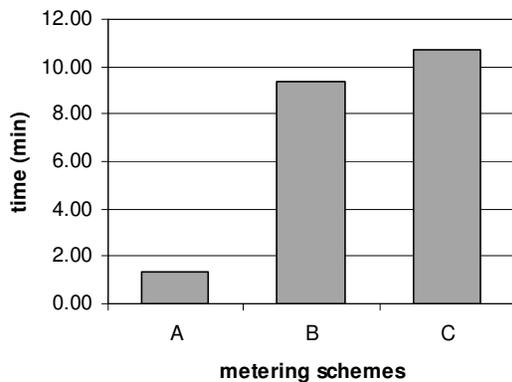
Figure 2: IEEE-14 bus system
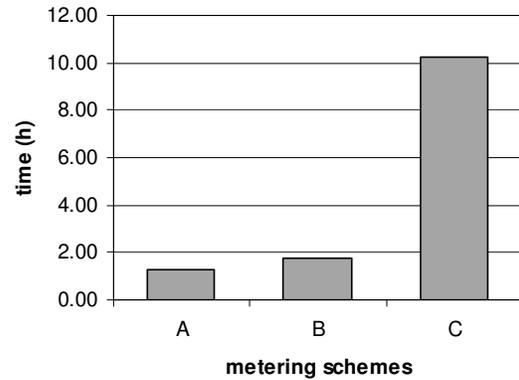
Figure 3: IEEE-30 bus system

Figure 4: IEEE-118 bus system

The proposed method achieved a very good performance, considering the complexity of the problem being solved. This is due to an efficient methodology for detecting/identifying Cmeas and Csets. It is possible to evaluate the fitness function of each individual without explicitly running a SE program.

5.2 Fitness Function Flexibility

As stated in Section 4.2, the FF is flexible, in the sense that it is possible to assure which redundancy constraints should to be met in the meter placement problem and, consequently, the respective metering cost to be invested. This situation is illustrated with the IEEE-30 bus system, assuming that the cost of the optimal metering system C, presented in Table2 and illustrated in Figure 5, should be reduced. One alternative for cost reduction would be to meet only the observability requirement, leading to metering system A of Table 2. However, the proposed method can easily search for intermediate solutions taking into account qualitative information about the network. For example, suppose that from the monitoring point of view there are some portions of the network which are more important than others, requiring stringent redundancy requisites.

In the metering system of Figure 5, the requirement for absence of Csets is satisfied for the whole system, although it is known that monitoring reliability in area 1 is more important than in area 2. This knowledge can be easily employed to reduce the metering system cost in an optimal sense. The FF in (13) can cope with this situation by considering different values for p_{Cmeas} in areas 1 and 2, which are 10^4 and 0, respectively, and p_{Cset} is equal to 0.

The new optimal metering system (plan C1) is shown in Figure 6. Table 4 presents a comparison between metering systems C (requisite of absence of Csets for the whole network) and C1 (requisite of absence of Csets for area 1 and observability for area 2).

According to the results obtained in Table 4, it was possible to reduce the global cost of the metering system while preserving the redundancy requirement for area 1.
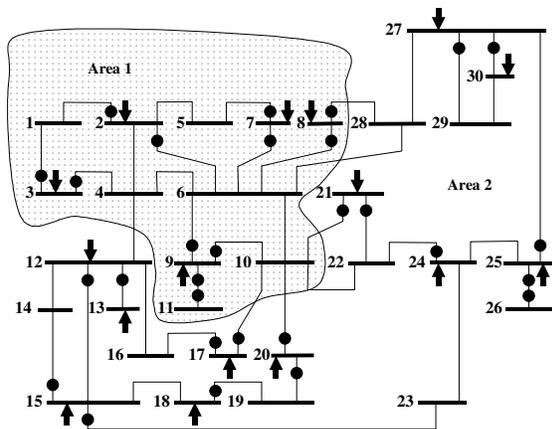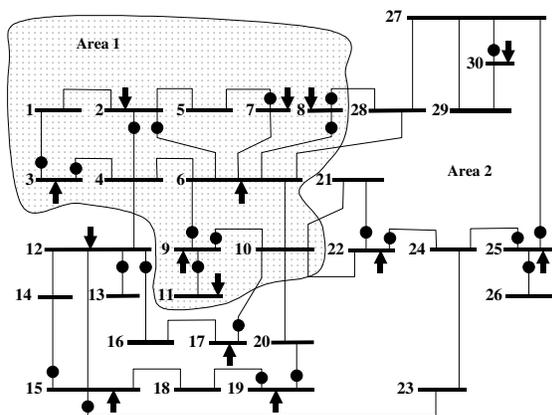
Figure 5: IEEE-30 bus metering system—Plan C

Figure 6: IEEE-30 bus metering system—Plan C1

Meter-ing System	Area 1		Area 2		No. of RTUs	Cost ($)
	Flows	Injec-tions	Flows	Injec-tions		
C	11	5	18	11	18	2002.5
C1	10	7	13	7	12	1566.5

Table 4: Metering Systems for IEEE-30

6   CONCLUSIONS

A genetic algorithm solution to the metering system planning problem has been presented and applied to typical power system networks. The main advantage of the proposed solution relies on its modeling flexibility. An optimization problem has been formulated, where investment costs are minimized, while performance constraints are satisfied to preserve state estimation capabilities. This is achieved by formulating constraints which require a metering system that satisfy conditions such as: system observability, absence of critical measurements and/or absence of critical sets.

A flexible fitness function has been constructed, where it is possible to choose which constraints should be satisfied by the optimal solution. This feature allows the investigation of different trade-offs between investment costs and state estimation reliability. For the proposed approach, it is not necessary to execute a state estimation program during the search for the optimal solution. The proposed methodology can be used for planning new metering systems, as well as for expanding existing ones. The application to distribution networks is also possible and will be subject of a future work. Test results obtained with the test systems illustrate the viability of the proposed approach.

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