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OPTIMIZED ALLOCATION OF PHASOR MEASUREMENT UNITS IN TRANSMISSION SYSTEMS USING PARTICLE SWARM OPTIMIZATION

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Abstract – This paper describes a particle swarm optimization-based method of multi-objective optimal phasor measurement unit's allocation in transmission systems. The allocation problem can be modeled in the binary domain and equated in to work with mono objective meta-heuristics without ignoring its multi-objective nature. Although the particle swarm optimization is more suited for continuous domain problems, with some adaptations, it can also perform well in allocation problems using few iterations. The algorithm and problem modeling adaptations, test systems' results and comparison with other algorithms in literature are presented and exhibits promising results for optimal monitor allocation in small and medium sized transmission systems.

Keywords: optimal allocation, phasor measurement unit, swarm optimization, evolutionary algorithm, smart grid

1. Introduction

The complexity of the electric power systems (EPS) generated by the interconnection of distant networks, the inclusion of alternative sources and the expansion of the already existing models has hindered the safe operation and monitoring of these networks by their administrators. This challenge comes from the large number of physical points present in the electrical networks that require different monitoring, and the search for ways to minimize the number of meters to reduce costs is crucial, maintaining the possibility of determining the operational state in which a given system. The correct monitoring of a network is important in the identification of faults, in the control of quality of service indicators and in the planning of concessionaires in general.

Due to its high data sampling capacity and the possibility of GPS communication, which guarantee numerous benefits in state estimation processes, the use of phasor measurement units (PMUs) has become increasingly common. However, the high cost of these devices requires that their implementation be done in a precise manner to ensure the observability of the network at low cost.

In order to solve this problem in an economically viable way, projects for the distribution of monitors that are low cost and yet guarantee observability and are as redundant as possible, which allows for a better estimation of EPS states.

As it is a problem of a combinatorial nature, the application of meta-heuristics is widely used. In recent years, evolutionary algorithms have been proposed for the design of measurement systems with good results [1,2]. Going a step further, it was demonstrated how these algorithms can be easily adapted to different types of systems. In fact, its practicality would allow the operation in real time to restore observability from pseudo-measurements, with just a few small changes [3,4], in which they use an evolutionary algorithm for state estimation.

Still in the allocation problem, a methodology is presented based on network characteristics with good results in the IEEE test systems and uses an approach based on dynamic programming successfully approximated in large systems [5,6].

The publications of [7] and [8] propose an allocation method based on the branch and bound integer programming algorithm. In these works, restrictions for the solutions are imposed, which considered aspects regarding the location and the importance of each bar, as well as the existence of equipment and availability of communication channel. In [9], the allocation methodology for a larger system was evaluated and a sensitivity analysis of the impact of the addition of meters was performed from the minimum number of meters on the accuracy of the estimation results.

Another type of problem present in electrical power systems is the occurrence of faults in certain busbars in the circuit. In [10] it was concluded in a system of 14 bars that when a transmission line failure occurs, the voltage and current value is changed in relation to its nominal value. Thus, in this article, simulations will be carried out for different types of faults in order to analyze the system's behavior for each of the situations.

Given the flexibility of the meta-heuristics and the history of success in the PMU allocation problem, an algorithm based on particle swarm optimization (PSO) is proposed, capable of performing the allocation with the lowest possible cost, ensuring the observability of the system and seeking greater redundancy. This algorithm was tested with IEEE test systems and a brief statistical analysis and comparison with known results from the literature was made.

2. Modeling the problem

The use of phasor measurement units (PMU) allows the problem to be modeled as a covering problem (PR). Each PMU can provide data related to its installation bar and the currents that are coming out of it, that is, each unit will serve its installation point and everyone directly connected to it. Following the modeling proposed by [6], the problem consists in minimizing equation (1), while meeting the conditions imposed by (2), (3) and (4), being:

$$\min z = \sum_{j=1}^{n} c(j) * x(j) \tag{1}$$

$$Sujeito\ a$$

$$\sum_{j=1}^{n} d(i,j) * x(j) \geq b(j) \tag{2}$$

$$0 \leq x(j) \leq 1 \tag{3}$$

$$x(j)\ inteiro\ para\ j = 0,1,2,\ldots,n \tag{4}$$

In the equations, c (j) is the cost of a PMU in a bar j, x (j) is a binary variable that says whether there is PMU installed in that bar j (x (j) = 1) or not (x (j) = 0), in the total number of bars, d (i, j) is a binary value that represents the position (i, j) of the adjacency matrix corresponding to the topology of the analyzed SEP and b (j) is an element of vector B that indicates for at least how many PMUs the bar j must be serviced.

For validation of the method, b is considered a vector with all elements equal to 1, since it is desired to meet all the bars with at least one meter (minimum cost condition that guarantees the observability of the system), as well as the cost vector it is also considered unitary.

The condition of maximizing the sum of the product between the adjacency matrix and the vector of variables is also added, which indicates the total amount of measurements possible to be obtained using all the measurement channels of the system.

Thus, equation (5) must be included in the problem.

$$\max r = \sum_{j=1}^{n} D * x \tag{5}$$

Being the elements d (i, j) of matrix D obtained from equation (6), where Y (i, j) are the elements of the matrix Y of admittances from SEP.

$$d(i,j) = 1\ se\ Y(i,j) \neq 0\ e$$
$$d(i,j) = 0\ se\ Y(i,j) = 0 \tag{6}$$

As it is a multi-objective problem adapted to a mono-objective meta-heuristic, equations (1), (2) and (5), which describe fitness, were ordered in a hierarchical manner, where the priority is to ensure observability (2), then reduce costs (1) and, finally, increase the quantity of measurements provided to have the most redundant system possible (5).

3. Methodology

3.1. Algorithm

A swarm optimization algorithm was implemented based on the proposed model [12]. The evaluation of the solutions or particles is made following the equations presented in the modeling of the problem, considering a hierarchy among the existing objectives.

Thus, in the particle evaluation step, it is considered (i) whether the solution has better observability than the compared solution, given by the best location (in this case the value is compared to the product of the value obtained in the solution with the established tolerance) or global , depending on the stage; (ii) if the values in (i) are equal, the costs are compared and the lowest cost is chosen; and (iii) if the values are equal in (i) and equal in (ii), the most redundant solution is chosen.

For the generation of the initial solutions, solutions with small amounts of elements equal to one were used, seeking to accelerate the convergence because it is a problem where there will always be a solution with minimum cost in which the number of installed PMUs will be equal to or less than half the

number of buses in the system, where each PMU can serve the installation bar and adjacent buses.
New operators were also created to act in the movement of the particle: tolerance constants in the local evaluation of solutions (in cost and observability), where the best location can change to a worse solution, but close to the optimum location, in order to increase the space search for solutions; and
After the changes, the new algorithm is given as follows:

Variables
pop, obj, v, tol, it, objL, objG, inertia, better Start
generating pop for i from 1 to it
for j from 1 to size (pop)
obj (j) = evaluate (pop (j)) if obj (j)> olerance * objL (j)
objL (j) = obj (j) if obj (j)> objG objG = obj (j) best = pop (j) end if
end if
v (j) = rand * (obj (j) -objL (j)) + rand * (obj (j) objG) +
pop inertia (j) = pop (j) + v (j) end to
order to return objGlobal, better
End

Pop being the population of particles, obj the performance of each solution for the objectives, v the speed of each particle, toler the search tolerance of the objectives, it the number of iterations, objL the best historical performance of a particle, objG the best performance general history, inertia caused by the movement of the previous iteration and better the best particle found.

This algorithm was then applied to the IEEE test systems of 14, 30, 57 and 118 busess, using the three combinations of input parameters shown in Table 1, with tolerances of 20% for the worst in cost and observability and always with constant populations 500 individuals (also called solutions or particles). The initial populations were all limited to having up to five elements equal to 1 in their individuals. The stopping criterion adopted was always the number of iterations.
For each combination of input, 30 simulations were performed in each test system considering the uniform cost vector. Thirty simulations were also carried out considering non-uniform costs in 57-bus systems using the best performance combination for the uniform case.

Table 1. Input parameters

Input	Maximum positions with random acceleration	Iterations
1	3	150
2	4	300
3	5	500

3.2. IEEE-14 bus fault analysis

The short circuit can be defined as an intentional or accidental connection between two regions with a potential difference and low impedance, which results in high currents. These operating phenomena are categorized according to their origin, duration and type [13,14].

In this study, we focused on the analysis of asymmetric faults of the phase-to-ground and phase-to-phase-to-ground type, as these have the highest occurrence in the electrical system. In addition, the frequent changes in the characteristics of the loads disturb the balance between generation and consumption, causing the system to vary its operating point considerably.

In these conditions, the elements used as compensators are responsible for monitoring the variation of the system and keeping it stable. The purpose of this study was to improve the transmission of energy and the capacity of the network, a situation that has been fulfilled.

Therefore, aiming at the stability of the electrical system, following the idea presented in [15], a series of capacitor banks was inserted, seeking reactive compensation. Then, the results were analyzed, comparing with the values of the system in normal operation.

4. Results

First, we have the results already known from the literature to take as a basis. Table 2 shows the relationship of the systems with their minimum quantities of PMUs required, reference values for the problem.

Table 2. Reference values

System	Minimum PMUs required
14	4
30	10
57	17
118	32

2.1 Performance considering uniform costs

Assuming that PMU installation costs are equal at any point is useful to demonstrate the performance of the algorithm as there will be no considerable difference that would make the algorithm converge to a minimum point. The cost per PMU of 1 unit of cost (u.c.) is then assumed.

In this situation, at least one of the combinations of input parameters was able to find solutions with the quantities of reference PMUs in each case at least once. Only conditions 1 and 3 for the 118 bus system, which did not meet the expected value. In all cases, the solutions ensured total observability of the system.

The best results found, in terms of the number of PMUs for each entry and systems are shown in Table 3.

Despite having the minimum quantities of PMUs equal, the bars with installed units do not coincide in all cases with what is observed in the literature. This does not mean, however, that they are worse solutions, since there may be more than one combination with the same number of measurements possible, the same cost, but different installation positions. This fact occurs in the systems of 30, 57 and 118 buses, and in the cases of 30 and 57 gains are observed in relation to what some meta-heuristic risks or that do not consider the quantity of measurements in the modeling of the problem found.

Table 3. Best results obtained

Input / System	1	2	3
14	4 PMUs	4 PMUs	4 PMUs
30	10 PMUs	10 PMUs	10 PMUs
57	17 PMUs	17 PMUs	17 PMUs
118	33 PMUs	32 PMUs	33 PMUs

For the 57 bus system, the installation of PMUs on buses 1, 4, 9, 20, 24, 27, 29, 30, 32, 36, 38, 39, 41, 45, 46, 51 and 54 is presented as a solution, which indicates the need for 17 PMUs for up to 68 different measurements. Using the adapted PSO, the best solution obtained also indicates 17 PMUs, but in buses 1, 4, 6, 9, 15, 20, 24, 28, 31, 32, 36, 38, 39, 41, 47, 51 and 53, allowing up to 72 different measurements [5].

Equally, gains were observed for the 30-bus system, which needs 10 PMUs. In this case, its methodology finds the optimal use of buses 2, 3, 6, 9, 10, 12, 15, 19, 25 and 27, capable of providing up to 50 measurements. PSO, on the other hand, finds bars 2, 4, 6, 9, 10, 12, 15, 18, 25 and 27 as a solution, giving the possibility of up to 52 measurements without increasing the quantity of PMUs.

For the 118-bus system, the solution found involves the installation of PMUs on buses 3, 5, 9, 12, 15, 17, 21, 23, 28, 30, 34, 37, 40, 45, 49, 53, 56, 62, 64, 68, 71, 75, 77, 80, 85, 86, 91, 94, 101, 105, 110 and 115. There are 32 units with up to 164 measurements.

For the 14-bus system, its solution can be easily obtained with most of the known methodologies, and the overall optimum for uniform cost is the installation of PMUs on buses 2, 6, 7 and 9, allowing up to 19 measurements. In terms of average performance, the data show that the success rates in the 14, 30 and 57 bus systems are considerable. Considering the most successful input parameters, Tables 4 and 5 show the standard deviations and averages for costs and quantity of measurements over the 30 simulations.

Table 4. Standard deviations after 30 simulations.

System	Deviation in cost	Deviation in measurements	Inputs
14	0	0	3
30	0	0	1, 2 e 3
57	0,556053	3,601564	2
118	0,973204	9,456251	2

Table 5. Averages after 30 simulations.

System	Average cost (u.c)	Average measurements	Inputs
14	4	19	3
30	10	52	1, 2 e 3
57	17,633333	73,833333	2
118	34,466667	187,4	2

Finally, looking at the average performance over the iterations, it is noted that the algorithm finds solutions with total observability in the first iterations and, even the 57-bus system, the cost and quantity of measurements also tend to stabilize quickly. Figures 1, 2, 3 and 4 show the behavior of the algorithm for the combination of input parameters 2 (300 iterations and up to 4 random changes of speed) in the systems of 14, 30, 57 and 118 buses, respectively. In addition, on average, in less than 20 iterations solutions are already found with the observable system and close to the optimal cost. On the one hand, this shows the great efficiency of the PSO in finding solutions quickly, but it indicates the need to create routines that prevent the problem from getting stuck in these minimum points and spend less simulations to find global optimums.

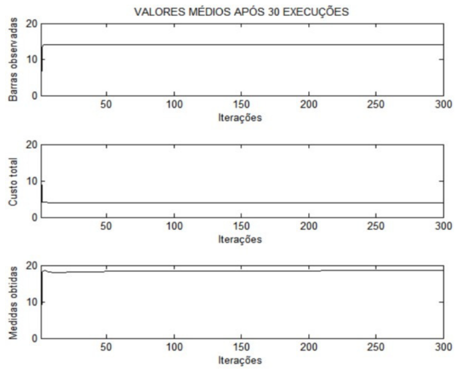

Fig. 1. Behavior in the 14-bus system

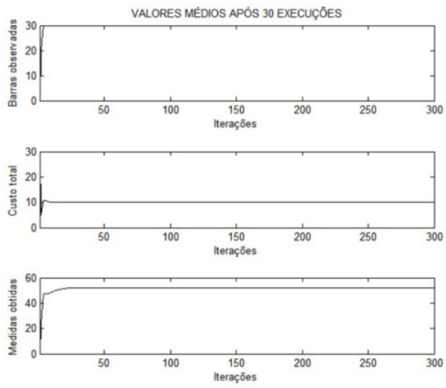

Fig. 2. Behavior in the 30-bus system.

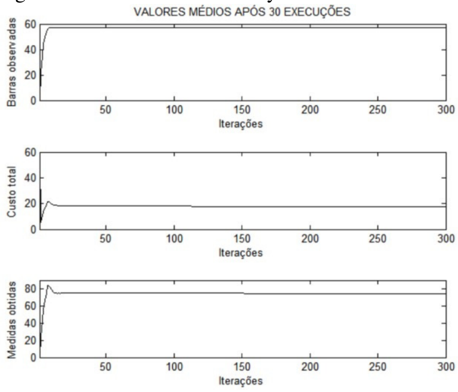

Fig. 3. Behavior in the 57-bus system

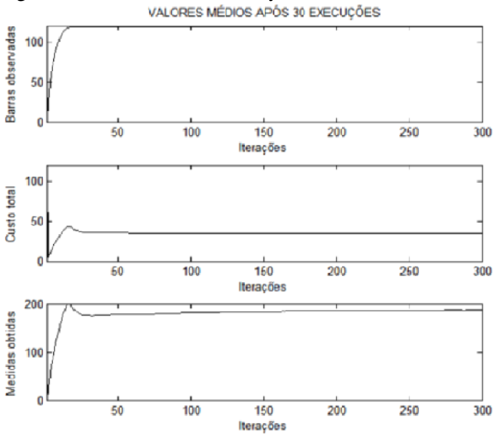

Fig. 4. Behavior in the 118-bus system

2.2 Performance considering non-uniform costs

To test the feasibility of applying this algorithm in cases of non-uniform costs, instead of using random values, which would make it impossible to compare with what is expected from the algorithm, the costs of the 57-bus IEEE system were changed.

As the optimum solution obtained for uniform costs in the 57 bus system and its differences from the solution found by [5] is already known, the installation values of PMUs in buses 15, 28, 31, 47 and 53 were increased by 10 %, to 1,1u.c .. These bars are the ones that appear in the solution found by the PSO, but not in the initial one, it is expected that now a solution similar to this one will be found without the algorithm being stuck in solutions that involve the highest cost buses.

Surprisingly, although identical solutions were found initially and some with fewer measurements, but also using 17 PMUs, different solutions with 70 possible measurements were still found. The first given by bars 1, 6, 13, 15, 19, 22, 25, 27, 32, 36, 38, 41, 46, 51, 52, 55 and 57 and the second by buses 1, 6, 10, 15 , 19, 22, 26, 29, 30, 32, 36, 38, 41, 46, 49, 54 and 57.

Considering the average performance and behavior throughout the iterations, Table 6 and Figure 4 are obtained.

Table 6. System of 57 with changed costs.

	Average	**Standard deviation**
Cost (u.c)	17,623333	0,632828
Measurements	71	3,769204

The fact that optimal solutions were obtained with only two measurements less than the optimum for uniform costs, even with five important bars having their values increased, indicates that the PSO set with the PR modeling are suitable for the optimization problem independently the type of cost considered.

2.3. Analysis of IEEE-14 bus faults

The system used for the fault analysis was that of the IEEE-14 buses and can be seen in figure 5.

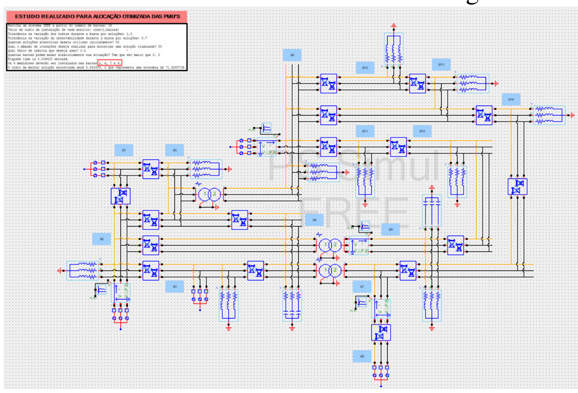

Fig. 5. IEEE-14 buses.

Figure 6 shows the behavior of the voltages of the three phases and their values when the system operates normally, that is, without any interference.

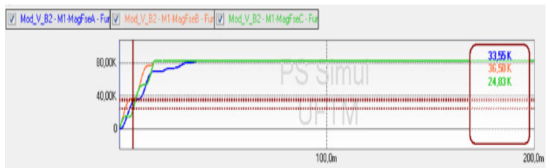

Fig. 6. System voltages.

It is possible to observe that the values of the three phases are close and that the behavior of the waveforms is also similar.

Figure 7 shows the behavior of the voltages and their values when the single-phase fault was applied in phase A of the system.

It is possible to visualize the impact caused both in the value of voltage A, where the fault was applied, which suffers a significant sinking, while the other phases remain with values similar to that of the system in normal operation.

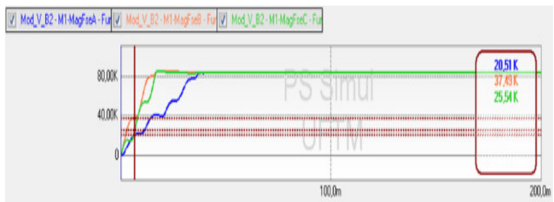

Fig. 7. Single-phase fault.

Figure 8, on the other hand, shows the behavior of the voltages and their values during the application of the phase-phase-to-earth fault in the system.

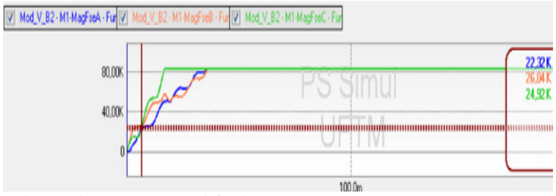

Fig. 8. Phase-phase-to-ground fault.

For this type of fault, a behavior similar to that of a single-phase fault is observed. However, now, the phase-to-ground voltage sinking occurs in the two missing phases, phase A and phase B, which are represented by the colors blue and orange, respectively, where it is possible to notice that the voltage modules have been reduced, while that of the healthy phase, is similar to the value of normal operation.

5. Conclusions

The results for the IEEE test systems of 30, 57 and 118 buses confirm the efficiency of metaheuristics to solve the problem of allocating PMUs in electrical systems, however it may be necessary to perform several implementations of the algorithms to find truly optimized solutions, already that there is no guarantee of achieving optimum in metaheuristics. It is noted that, even if several executions are necessary, the time spent to find very optimized options of measurement systems is much less than what would be used to test all possibilities or apply some deterministic method.

The way the problem is modeled, also ensures that the algorithms developed and validated under uniform cost conditions and with a minimum requirement of only one measurement per bar can work with varied costs and impose a minimum local redundancy different from one, in addition to allowing work with varied topologies of electrical systems.

Regarding the proposed methodology, despite the good results, optimizations are necessary to prevent the PSO from being trapped in local minimums, especially in larger systems so that it is not necessary to have such a high number of simulations to find optimal solutions. There is also the need to establish a stopping criterion that is not based only on the number of iterations in real applications. A better adjustment of the input parameters is also recommended, since only three different combinations were chosen for comparison purposes only, but in practice, this affects the performance of the algorithm.

Finally, different faults in the system were analyzed for the same circuit with the insertion of a capacitor bank in series. As it was possible to analyze, the use of capacitors improved the stability of the system as expected.

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