Learning and Nonlinear Models - Journal of the Brazilian Society on Computational Intelligence (SBIC), Vol. 21, Iss. 1, pp. 36-46, 2023

A HYBRID META-HEURISTIC APPROACH FOR OPTIMAL METER ALLOCATION IN ELECTRIC POWER DISTRIBUTION SYSTEMS

Thales Schuabb de Almeida
Lucas Eduardo Silva Braga
Leonardo Willer de Oliveira
Edimar Jose de Oliveira
Federal University of Juiz de Fora, Brazil
{thales.schuabb,braga.lucas}@engenharia.ufjf.br, {leonardo.willer,edimar.oliveira}@ufjf.edu.br

Julio Cesar Stacchini de Souza
Federal Fluminense University, Brazil
julio@ic.uff.br

Abstract – The number of nodes present in Electric Power Distribution Systems (EPDS) is a complicating factor for carrying out the State Estimation (SE) and the choice of allocation of available meters affects the quality of observability obtained by the SE. Thus, it is necessary to use optimization methods that evaluate the positions of meters in the system that can contribute to an optimal SE. Artificial Neural Networks (ANN) can perform SE, processing the information obtained by the available meters in an agile way. Meta-heuristics techniques apply to the optimal allocation problem but can be slow processing. Thus, the work seeks to evaluate the potential of a hybrid method that associates the meta-heuristic technique, Artificial Immune System (AIS), with ANNs for evaluating several allocation options in an agile way to find an optimal solution for the allocation of meters.

Keywords – Meta-heuristic; Artificial Immune System. Artificial Neural Network; Distribution Network; State Estimation.

1 Introduction

For the real-time operation of Electric Power Distribution Systems, it is necessary to have appropriate observability of the system in terms of voltage levels. This information is crucial in order to perform maneuvers to ensure quality in energy supply and reliability, as well as other EPDS key functions like fault location, distributed generation dispatch and management of electric vehicle charging. Thereby, State Estimation (SE) techniques estimate voltage magnitudes and phase angles of an electrical network, from a limited set of available measurements.

Electric Power Distribution Systems contain a high number of buses, which brings different possibilities for the set of meters positions. The combinatory nature of the solutions of the meter placement problem produces an unfeasible number of possible solutions, which requires the use of meta-heuristics in order to provide a near-optimal solution while reducing the search space. Due to the high cost of this equipment, mainly Phasor Measurement Unit (PMU), studies in the literature seek to determine the best locations for installation. In [1] proposes a multi-objective approach associated with the Modified Monkey Search meta-heuristic. The reference [2] uses an aleatory key genetic algorithm to allocate meters with economic criteria. At [3] approach, the efficiency of SE increases considering the factors: multiple uses of loads, correlation of measures, and precision evaluation of the SE without the Monte Carlo Simulation. Also, EPDS networks are represented by large dimension matrices, and thus, require a vast volume of data for processing. These characteristics are disadvantages for iterative SE methods, making Artificial Neural Networks (ANN) potential for SE application due to their fast processing. In [4], the method presented for the ANN is carried out with training phasors, obtained through PMU, available in buses of the network, to estimate load margins of the EPDS, increasing the precision in the evaluation of the stability of the system. In [5], an ANN is trained with pseudo-measures and historical data, to learn how to map available measures to SE. As [6], a trained ANN with known database can respond to unknown data and this generalization is important for topological variations and operational conditions, common in such as [7] and [8]. In [9] the Estimation of States with an ANN is proposed in which, an admission matrix is embedded in the matrix of weights that map as iterations of the ANN to obtain how much information cites how to connect the network physics during training.

In this study, the application of meta-heuristics for optimal meter allocation problems will evaluate the setup that offers the best SE for an Electric Power Distribution System, whose difficulty consists of the computational time to perform the SE due to the size of the EPDS networks. So, the present work proposes the association of the Artificial Immune System (AIS) technique with ANN. The hybrid method SE process for the evaluation of candidate solutions to the optimization problem during the execution of the meta-heuristic will have the execution time reduced due to the agility of action of artificial neural networks. The training of ANN embedded in the AIS meta-heuristic uses pseudo-measures to ensure the observability of the electrical network even with a reduced number of measurements.

The main contributions of the proposed methodology on this study are:

- Optimal meter allocation in Distribution Systems assembling the meta-heuristic Artificial Immune System with Artificial Neural Networks;
- Quick evaluation process of the numerous AIS candidate solutions with the use of previously trained ANNs, regardless of the EPDS size;
- Use of pseudo-measurements on unsupervised buses during the evaluations process in order to require a single previously trained ANN for each EPDS;

Beyond this section, there are four further sections. Section 2 presents the theoretical foundation of AIS and SE, showing the indices used to evaluate the method. The systems that make up the proposed methodology are presented in section 3. The tests and results, as well as the comparison with methods known in the literature, are described in section 4. Finally, in section 5 the conclusions are presented.

2 Background

2.1 Estimation Indices

The State Estimation problem is widely evaluated by the quadratic error, formulated in (1), called SEE (State Estimation Error) [10]. In addition to the SEE index, the present work also evaluates three more indices proposed by [8]:

- IVM (Voltage Magnitude), formulated in (2);
- IPA (Phase Angle), as in (3);
- OBF (Objective Function), given by the sum of the metrics SEE, IVM and IPA, according to (4).

The OBF index is the one which the AIS aims to minimize. The use of these metrics is necessary so that the results obtained can be directly compared with the results of [8].

$$SEE = \sqrt{\sum_{i=1}^{Nb}(V_i^\star - \widehat{V}_i)^2 + \sum_{i=1}^{Nb}(\theta_i^\star - \widehat{\theta}_i)^2} * 100 \tag{1}$$

$$IVM = max_k|\frac{|V_k^\star| - |\widehat{V}_k|}{|V_k^\star|}| * 100 \tag{2}$$

$$IPA = max_k||\theta_k^\star| - |\widehat{\theta}_k|| * 100 \tag{3}$$

$$OBF = SEE + IVM + IPA \tag{4}$$

Where:

- $V_i^\star$ is the real value of the voltage magnitude of the bus i;
- $\widehat{V}_i$ is the estimated value of the voltage magnitude of the bus i;
- $\theta_i^\star$ is the real value of the voltage phase angle of the bus i;
- $\widehat{\theta}_i$ is the estimated value of the voltage phase angle of the bus i;
- Nb is the total number of buses in the system.

In the tests, OBF result of the proposed methodology is compared with the results obtained by the optimal meter allocation of [8]. The IVM and IPA metrics represents the sensitivity to the result on the individual errors of each state since it indicates the magnitude of the largest error, something that the SEE metric is not able to detect, since it computes all the deviations between real and estimated values, according to (1).

2.2 The Artificial Immune System (AIS)

Artificial Immune Systems consist of a set of methods that blend the fields of immunology, data science and engineering [11]. By emulating the behavior of the Immune System cells identifying infectious agents, the methods are used to solve optimization problems, mainly when the problem has solutions of combinatorial and discrete nature.

One of these methods is the Clonal Selection Algorithm (CLONALG), proposed by [12], which is based on clonal selection and affinity maturation principles. The main steps of the algorithm consist on generation of candidate solutions, evaluation, cloning, random mutation and reevaluation of the new generated solutions until a convergence criterion is met. By iteratively cloning and mutating the best suited solutions, the algorithm is capable of finding a local optimal point. And by constantly generating new random solutions that replace the worst evaluated solutions, the algorithm guarantees that the search does not settle for the fist local optimal point, instead, iterates through possible new global optimal solutions.

The motivation for using the CLONALG technique is the ability to combine global and local search processes, through mechanisms such as receptor editing and affinity maturation, as in [13]. This capability is interesting for combinatorial optimization problems in an attempt to try to avoid premature convergence in sub-spaces with sub-optimal low quality solutions.

3 Proposed Methodology

3.1 Coding the candidate solution in AIS

The buses in which there is measurement allocation must be coded to serve as input in the AIS algorithm. The coding used in the work is exemplified in Figure 1, in which a fictitious 5-bus network demonstrates the coding of a solution, which consists of allocating meters (M) in buses 3 and 5. A vector containing the number of the measured buses is the representation of a a possible solution on the AIS algorithm.

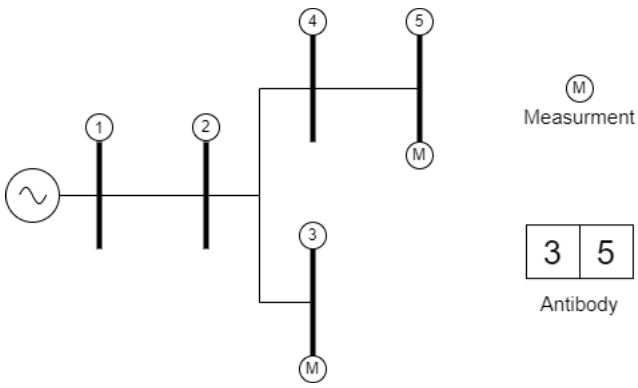

Figure 1: 5-Bus Example Network and Candidate Solution Coding

3.2 The AIS Algorithm

The CLONALG version of the AIS algorithm, proposed in [12], and later used by [14], is suited to solve to combinatorial optimization problems. The algorithm used in this work follows the steps represented by the flowchart in Figure 2. The steps consist mainly on generating a initial random set of solutions, and then iteratively cloning the best ones, replacing the worst ones with new random generated solutions, and mutating some of them until the convergence criterion is met. The steps are individually detailed as follows:

(1) Initial Generation of Antibodies from Repertoire P^*: The initial set of obtained candidate solutions by a random process. Note that P^* represents a matrix $[NAb \times L]$, where NAb is the number of antibodies, and L is the number of attributes of each antibody. At the end of this step, the current population P receives P^*.

(2) Affinity evaluation of f of antibodies from P: The affinity of an antibody is given by the inverse of the OBF evaluated by the ANN.

(3) Selection of the best antibodies from P: In this step, the best antibodies from P are selected to compose the P_n repertoire.

(4) Cloning antibodies from P_n: Antibodies that were previously selected in P_n are cloned, forming the population C.

(5) Hypermutation: In this step, the antibodies from the C repertoire undergo mutation, forming the set of mature clones M.

(6) Affinity evaluation fM of M antibodies.

(7) Selection of the best antibodies from M: In this step, the process described in Step-3 takes place, forming the population M_n.

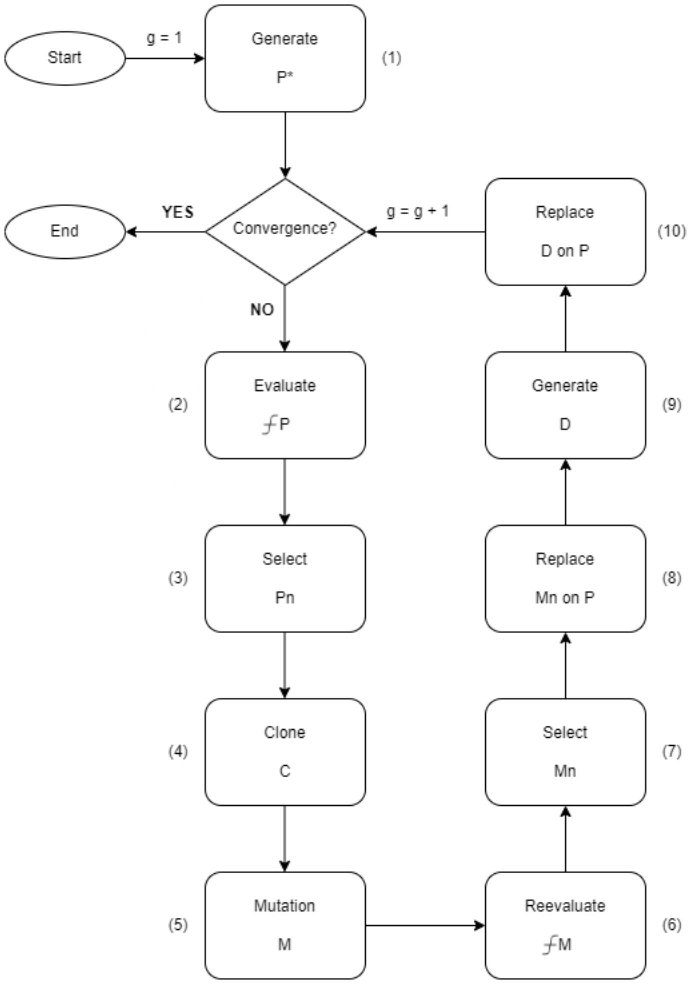

Figure 2: AIS Algorithm Flowchart

(8) Replacement of the worst antibodies from P by antibodies from M_n.

(9) Edition of receptors: A pre-defined amount of "d" of antibodies is generated randomly, forming the set D. These antibodies replace the lower affinity "d" antibodies in the P population.

(10) Replacement of P antibodies by D antibodies.

After **(10)**, the generation counter (g) is incremented and the convergence criterion is evaluated. This criterion is satisfied when the number of generations reaches a threshold value given by $gmax$.

If there is no convergence, the algorithm returns to Step-2.

3.3 The Artificial Neural Network

This work proposed the use of a ANN to evaluate the possible solutions generated by the Artificial Immune System. This ANN uses the MultiLayer Perceptron (MLP) supervised learning. The data used as the input set is the set of measurements coming from the meters associated with the errors of the meters. The output set consists of vectors with $2 * N_b$ elements, where N_b is the number of system buses, which values include the estimated voltage magnitudes ($\widehat{V_i}$) and estimated phase angles ($\widehat{\theta_i}$) on the N_b buses i of the EPDS.

The figure 3 represents the architecture of the proposed ANN, where V_{mi} and θ_{mi} are the voltage magnitude and phase angle measurements, respectively, of bus i. During ANN training, these convergence criteria were checked: the maximum number of cross-validations N_{cv} and the maximum number of iterations or epochs N_{gm}. Training is finished when at least one of these criteria is met. The ANN configuration, as described above, is summarized in Table 1.

The ANN associated with the proposed Artificial Immune System has, as both its inputs and outputs, the voltage magnitudes and phase angles of every bus. Therefore, the number of inputs and outputs is two times the number of buses (N_b) as in Equation 5. As previously depicted by Figure 3, the ANN also contains a certain number of Hidden Layer Neurons (N_h), which is defined as the same number of inputs and outputs, according to Equation 6.

$$NI = NO = 2 * N_b \tag{5}$$

$$N_h = NI = NO \tag{6}$$

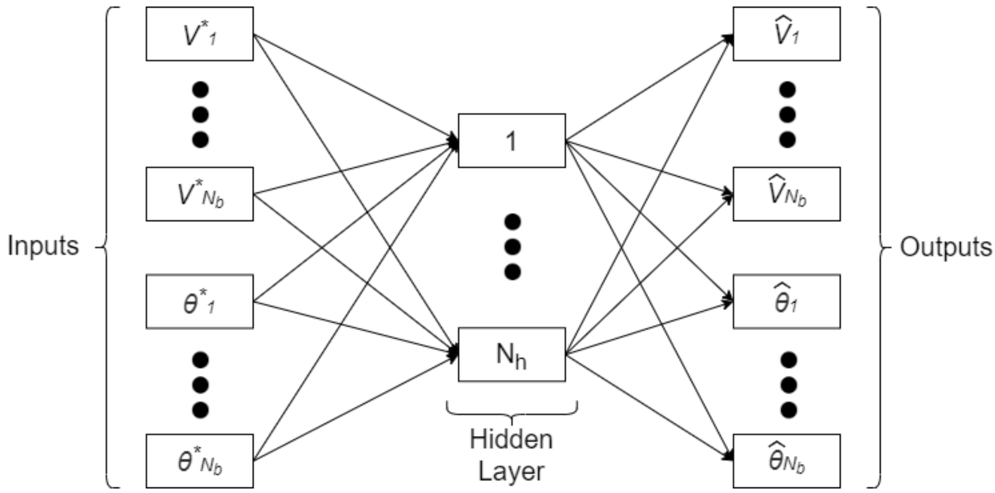

Figure 3: Artificial Neural Network MultiLayer Perceptron

Table 1: ANN Configuration

Parameter	Configuration
Learning Algorithm	Backpropagation
Output Activation Function	Hyperbolic Tangent (tansig)
Hidden Layer Activation Function	Hyperbolic Tangent (tansig)
Learning Rate	10^{-2}
Maximum Number of Validation Checks (N_{cv})	20
Maximum Number of Iterations or Epochs (N_{gm})	10^5

The dataset used by the ANN was generated by the authors using a Power Flow algorithm. For each load bus, a normal distribution is used to model the load variation. The distribution is centered at the bus active power base value, and a standard deviation of ±13.33% is considered, in order to allocate 99.7% of the samples within the range of ± 40% of the mean value, as it is the range utilized by [8] to set uncertainty of the pseudo-measurements. The reactive power of each bus is then adjusted as to maintain the power factor of each bus constant. For each scenario, a different random sample from the normal distribution is taken for each bus, and the Power Flow is run in order to determine the voltage magnitudes and phase angles of the scenario.

3.4 Proposed AIS/ANN Hybrid Method

The Proposed AIS/ANN Hybrid Method consists of a minimization problem regarding the Objective Function OBF formulated on Section 2.1. For a given EPDS, the only changing parameter is the location of the fixed number of available measurement units. For the execution with the AIS, the ANN training considers measurements in all buses, since the location of the meters is variable during the meta-heuristic convergence process.

The set of scenarios obtained from the power flow calculation contains 5000 load scenarios for each test network, and is divided into three groups: 50% of the scenarios for the training set; 25% for the validation set; 25% for the test suite. The cross-validation criterion considers N_{cv} as the limit of times in which the ANN precision, during training, depreciates for the validation set.

During AIS execution, for a candidate solution evaluation, the provided data-set contains 25% of the total destined for ANN tests representing the randomness of the load. In these tests, the inputs to the buses indicated by the AIS candidate solution correspond to the measurements of the allocated PMUs, considering the voltage module accuracy, δ_V, as phase angle, δ_θ as ±0.4%, as per [15]. In the other buses, pseudo-measures V_{pi} and θ_{pi} are used, which consist of the voltage magnitudes and phase angles of the unmonitored buses for a scenario with the loads adjusted to the respective average values of the EPDS historic data.

In this approach, the buses indicated by the solution are provided with accurate measurements, while the buses without meters are represented by pseudo-measurements considering an average load scenario, which does not accurately portray the system in all test scenarios. For each candidate and coded solution as shown earlier in the 3.1 section, the previously trained proposed ANN was sampled and the objective function (OBF) was calculated. The process repeats for all test scenarios and the average of the OBF values for the test scenarios is considered the final metric for the candidate solution.

In order to compare the AIS/ANN hybrid algorithm optimal solution with the optimal solutions found in the literature, both solutions are considered on another ANN responsible solely on State Estimation of the EPDS. This new ANN's inputs are only the measured buses' states. Thus, a new ANN is trained considering the AIS/ANN optimal solution as its inputs, and another one is trained considering the literature optimal solution buses as its inputs. This approach allows for a comparison regarding the SE quality between both optimal solutions.

4 Case Studies

4.1 Case Studies Description

The proposed methodology was applied to four different distribution networks, containing 14, 33, 84 and 119 buses each. The first two ones are well known test networks proposed by [16] and [17], respectively. For these two networks, a meter allocation comparison is possible using the optimal location proposed by [8], where an Extended Optimal Power Flow algorithm is used to find the best meter allocation on both of these two networks. In order to perform this comparison, four meters were considered for both networks, according to the optimal solution found by [8].

For the 84-bus network [18], eight meters were considered across the network, and twelve were utilized for the 119-bus network [19]. For these two other networks, no comparison is possible, as none of them is featured on a similar meter allocation work in the literature.

The proposed AIS has its parameters summarized in Table 2. β is the parameter responsible for controlling the cloning process, and ρ is the antibodies mutation probability., while n is the share of antibodies selected for the cloning process. The methodology was developed on MATLAB, using an Intel(R) Core(TM) i3-3110M CPU @2.40GHz 8.00 GB RAM machine.

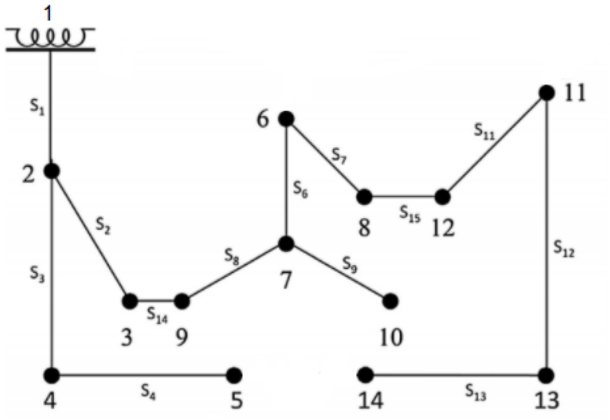

Figure 4: 14 bus network

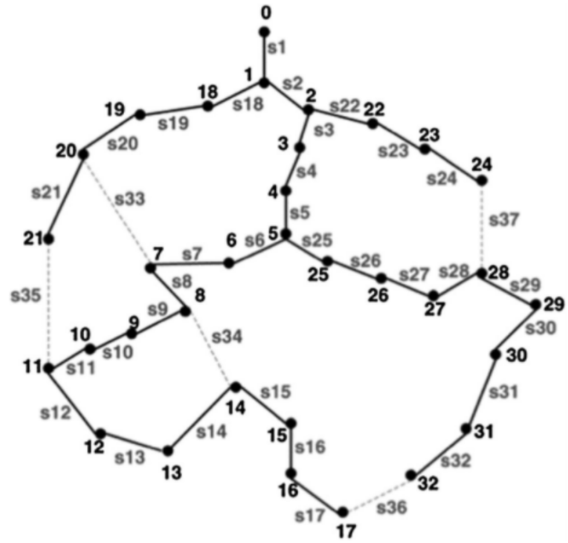

Figure 5: 33 bus network

Table 2: AIS Parameters

Parameter	NAb	β	ρ	d	$gmax$	n
Value	50	20	0,05%	3	50	20%

For every test network, the ANN convergence criterion was the maximum number of validation checks, which is set at 20. The other possible criterion, maximum number of epochs (10^5), was never met during the training process.

4.2 Results

The proposed algorithm was run 100 times for each test network in order to produce a set of optimal solutions. As the AIS is a meta-heuristic, it can produce different results each time it is used. Hence, the need to run the algorithm multiple times and analyze the distribution of the obtained results. The running time for the 100 uses of the AIS/ANN algorithm can be seen in Table 3, which shows the running times for each test network, along with the mean, maximum, minimum and standard deviation values for the proposed objective function OBF. It is possible to see that the total running time did not significantly increase for the bigger networks, which is expected, due to the ANN's response to the evaluation of each solution being fast and not heavily dependent on the ANN's inputs and outputs dimensions. Thus, as the AIS creates a set of possible solutions, the ANN is capable of evaluating them on a similar timeframe for both small networks, such as 14-bus, and bigger ones, such as the 119-bus network. The results also show that the solutions were not sparsely distributed, as the standard deviation values OBF_σ were small when compared with the mean values OBF_μ, the highest of them being only $7,7351\%$ of the mean value, which happened for the 33-bus network.

Table 3: Results

Network	Time (s)	OBFμ	OBFmax	OBFmin	OBFσ
14-bus	26084	2.1574	2.5094	2.1078	0.0939
33-bus	33310	8.8817	10.6005	7.8006	0.6870
84-bus	19410	6.3923	6.8388	5.5477	0.2400
119-bus	23738	5.0361	5.9555	4.1230	0.3576

As the algorithm was run multiple times to evaluate each network, a boxplot for each network was produced and depicts the distribution of the obtained OBF during the simulations. For the 14-bus network, Figure 6 shows that most of the results fall close to the mean value of $OBF_\mu = 2.1574$, while a couple of outlier results yielded OBF around the maximum value of 2.5094. The 33-bus network boxplot, presented in Figure 7 contains more variation regarding the OBF values, which matches its standard deviation OBF_σ, the highest among all test networks. The 84-bus and 119-bus networks had similar results in regards to the distribution of the obtained OBF values. The boxplots can be seen, respectively in Figures 8 and 9. Both figures show that the results were not wide spread around the mean value, having each just a couple of outliers.

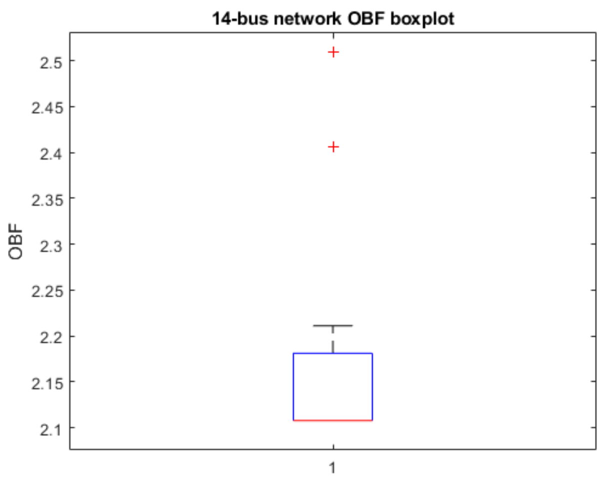

Figure 6: 14 bus network OBF boxplot

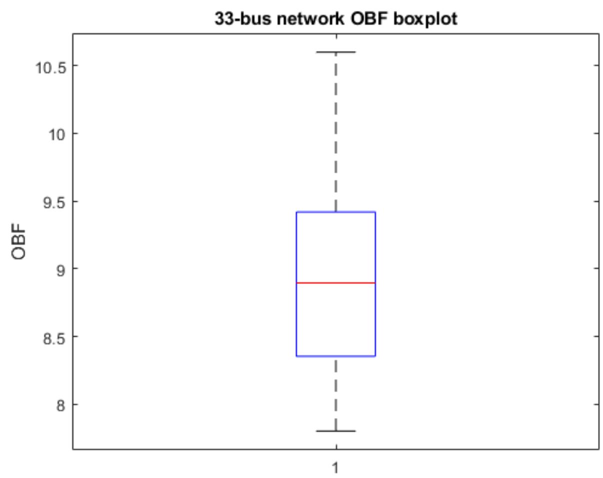

Figure 7: 33 bus network OBF boxplot

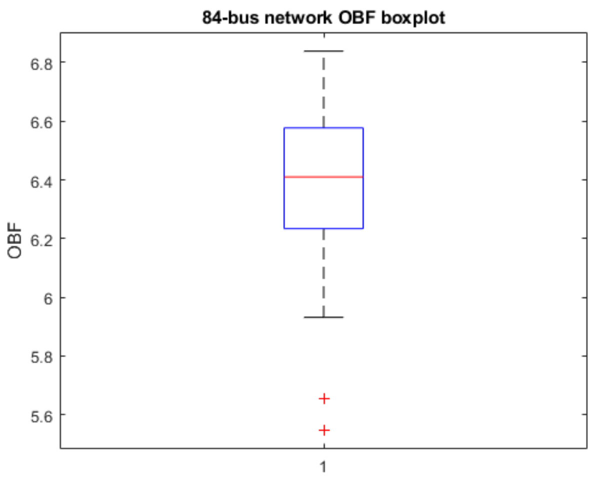

Figure 8: 84 bus network OBF boxplot

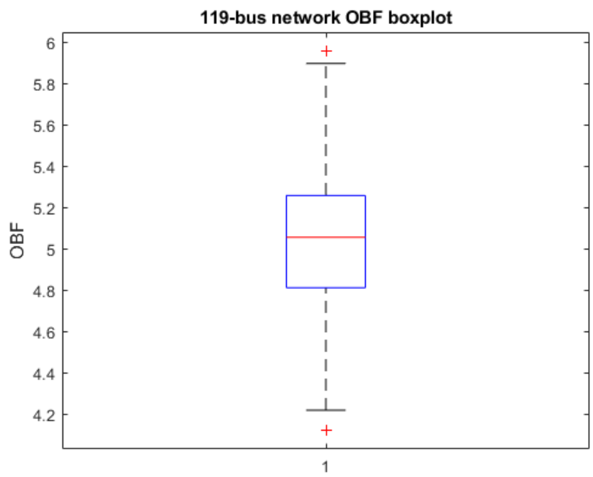

Figure 9: 119 bus network OBF boxplot

In order to define the selected meter allocation that will be tested over the final ANN, the criterion used was to select the solution which OBF is closest to the mean value OBF_μ of each network. The measured buses for the 14-bus and 33-bus networks are shown by Table 4, which brings as a comparison the optimal meter allocation defined by [8]. For the 84-bus and 119-bus networks, the measured buses are presented by Table 5.

As previously mentioned, another ANN was used to estimate the networks' states for several load scenarios. This ANN's inputs are only the measured states of each network, while the outputs consist of the states of all buses. For the 14-bus and

Table 4: Meter Allocation Comparison

Algorithm	Monitored Buses	
	14-bus network	33-bus network
AIS/ANN	5-6-7-12	10-15-28-32
[8]	2-10-12-13	7-14-26-27

Table 5: Meter Allocation

Algorithm	Monitored Buses	
	84-bus network	119-bus network
AIS/ANN	7-17-25-50-53-69-70-78	1-37-48-59-63-71-72-88-89-97-102-104

33-bus networks, two tests were considered, the first one using the optimal meter allocation found by the proposed AIS/ANN methodology, and the second one using the optimal meter allocation found by [8]. Table 6 shows the mean value of the 1250 test load scenarios for each of the four state estimation indexes, while comparing the results obtained by both meter allocations on each network. For both networks, the calculated indexes were smaller for the AIS/ANN optimal meter allocation. For the 84-bus and 119-bus networks, Table 7 presents the mean value of the indexes. Once again, the calculated indexes were smaller for the AIS/ANN solution, showcasing the improvement on state estimation quality for all four test networks.

Table 6: Final Results Comparison

Algorithm	OBF_μ	IVM_μ	IPA_μ	SEE_μ
	14-bus network			
AIS/ANN	0.4358	0.1358	0.0614	0.2386
[8]	0.5486	0.1779	0.0796	0.2910
	33-bus network			
AIS/ANN	2.3499	0.8058	0.1844	1.3597
[8]	3.5132	1.1172	0.2829	2.1130

Table 7: Final Results

Algorithm	OBF_μ	IVM_μ	IPA_μ	SEE_μ
	84-bus network			
AIS/ANN	1.8366	0.3597	0.2031	1.2738
	119-bus network			
AIS/ANN	0.8293	0.1977	0.0513	0.5803

A visual representation of the improvement in the state estimation quality is presented by Figures 10 and 11, which show the real and estimated values of Voltage Magnitude of the same load scenario of the 33-bus network for the AIS/ANN optimal solution and [8] optimal solution, respectively. Figures 12 and 13 bring the same comparison for the Voltage Phase Angles. It is possible to visually infer that the estimated values by the AIS/ANN optimal solution are closer to the real values on both curves, which was expected, as the calculated state estimation indexes were smaller for the AIS/ANN optimal solution.

For the 84-bus network, the real and estimated states are shown by Figures 14 and 15, respectively featuring Voltage Magnitude and Phase Angles. Similarly, for the 119-bus network, Figures 16 and 17 show the real and estimated states. It is possible to see that, even though the 119-bus system is larger, its states are more easily estimated than the 84-bus network, as not only the real and estimated values are closer to one another, but also the mean OBF_μ value on Table 7 is smaller for the bigger network.

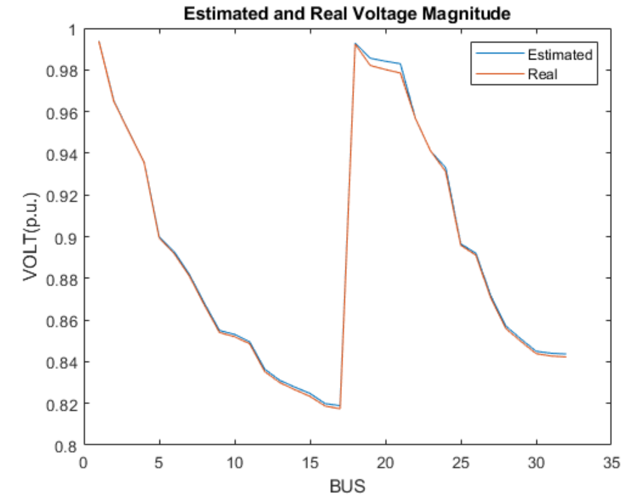

Figure 10: 33-bus network Voltage Magnitude Estimation with AIS/ANN optimal meter allocation

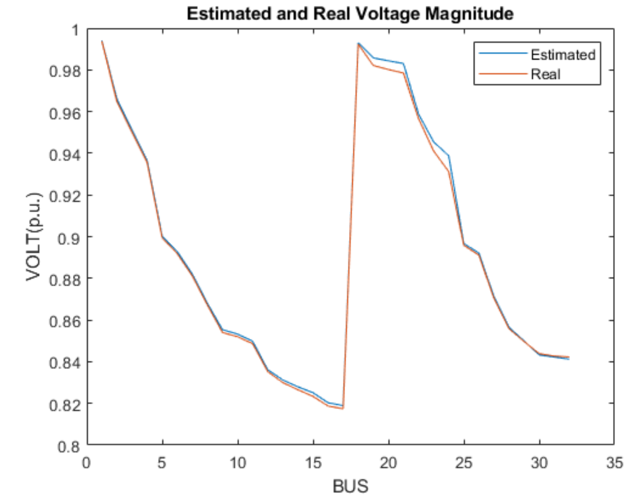

Figure 11: 33-bus network Voltage Magnitude Estimation with optimal meter allocation found by [8]

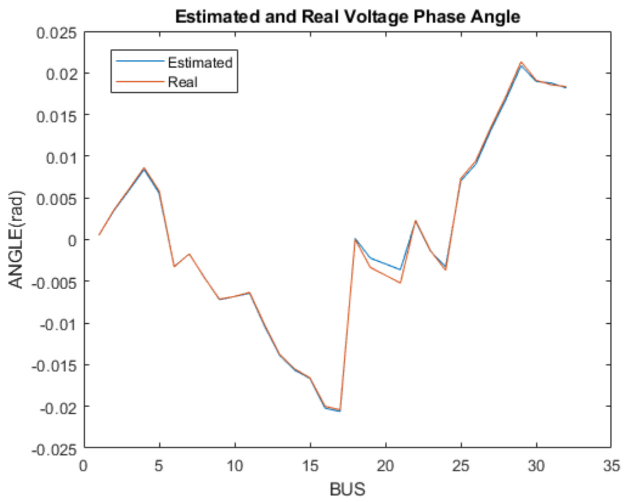

Figure 12: 33-bus network Voltage Phase Angle Estimation with AIS/ANN optimal meter allocation

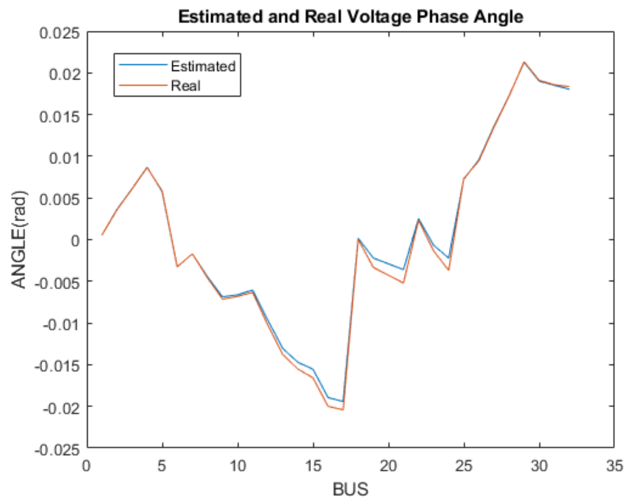

Figure 13: 33-bus network Voltage Phase Angle Estimation with optimal meter allocation found by [8]

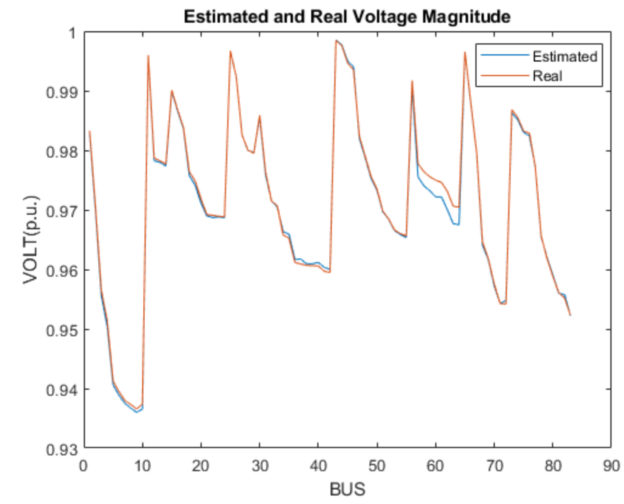

Figure 14: 84-bus network Voltage Magnitude Estimation with AIS/ANN optimal meter allocation

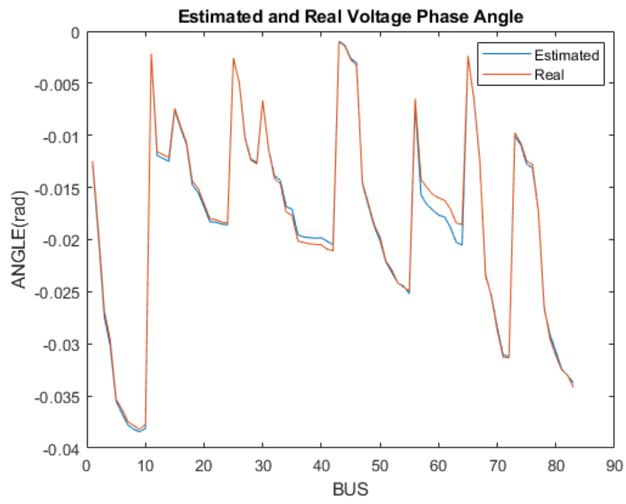

Figure 15: 84-bus network Voltage Phase Angle Estimation with AIS/ANN optimal meter allocation

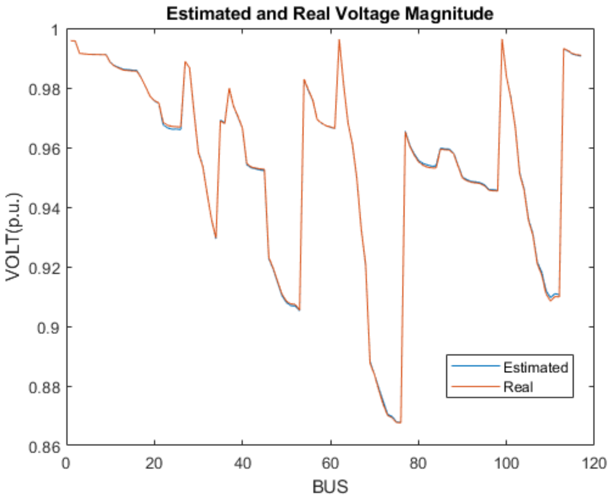

Figure 16: 119-bus network Voltage Magnitude Estimation with AIS/ANN optimal meter allocation

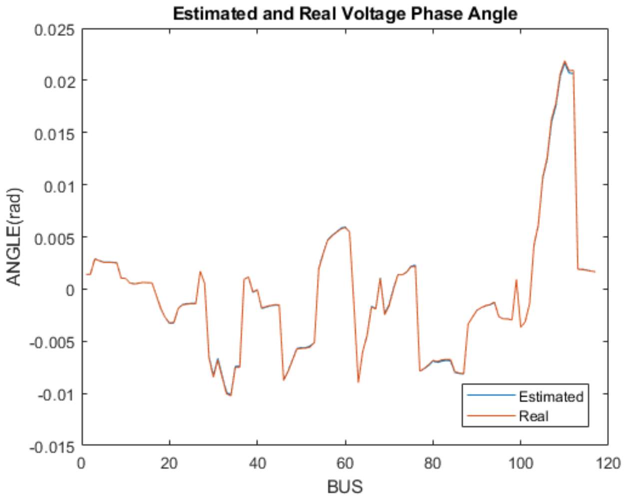

Figure 17: 119-bus network Voltage Phase Angle Estimation with AIS/ANN optimal meter allocation

5 Conclusion

This work proposed a Hybrid Meta-Heuristic approach for optimal meter allocation in Distribution Systems. By combining the Meta-Heuristic Artificial Immune System with an Artificial Intelligence approach in Artificial Neural Networks, the methodology focuses on finding the optimal placement for Phasor Measurement Units in different test networks. The fast computational time response of the previously trained ANNs provides enough flexibility for the AIS's solutions evaluation to be performed on networks of different sizes without drastically increasing the total simulation time required. The results show that the AIS/ANN methodology is capable of evaluating a big number of possible solutions and determining the optimal meter placement using the State Estimation indexes as the Objective Function of the minimization problem. The comparisons made with optimal meter allocations found in the literature showcased that the AIS/ANN is able to find a new solutions that enhance the quality of the ANN performed State Estimation. Future works include the consideration of different types of meters along with the PMUs, such as Smart Meters; the consideration of the networks as three-phased with unbalanced loads; and also the inclusion of Distributed Generation along the buses of the EPDS. Thus, by allowing different types of measurements on three unbalanced phases, with intermittent DG power outputs, the higher complexity of the combinatorial solutions will present a more extensive challenge for the AIS/ANN hybrid methodology to solve.

6 Acknowledgments

The authors of this article are grateful for the support of CNPq, FAPEMIG, CAPES, INERGE, and the groups SMART4GRIDS and GOHB - Group for Heuristic and Bioinspired Optimization.

References

[1] F. G. Duque, L. W. de Oliveira, E. J. de Oliveira and J. C. de Souza. "A cost-benefit multiobjective approach for placement of meters in electrical distribution systems". *Electric Power Systems Research*, vol. 191, pp. 106897, 2021.

[2] A. B. Antonio A.M.Raposo and M. G. da Silva. "Robust meter placement for state estimation considering Distribution Network Reconfiguration for annual energy loss reduction". *Electric Power Systems Research*, vol. 182, 2020.

[3] A. A. Raposo, A. B. Rodrigues and M. d. G. da Silva. "Optimal meter placement algorithm for state estimation in power distribution networks". *Electric power systems research*, vol. 147, pp. 22–30, 2017.

[4] S. M. Ashraf, A. Gupta, D. K. Choudhary and S. Chakrabarti. "Voltage stability monitoring of power systems using reduced network and artificial neural network". *International Journal of Electrical Power & Energy Systems*, vol. 87, pp. 43–51, 2017.

[5] A. S. Zamzam, X. Fu and N. D. Sidiropoulos. "Data-driven learning-based optimization for distribution system state estimation". *IEEE Transactions on Power Systems*, vol. 34, no. 6, pp. 4796–4805, 2019.

[6] S. Haykin. *Neural networks: a comprehensive foundation*. Prentice hall, 1999.

[7] J.-H. Menke, N. Bornhorst and M. Braun. "Distribution system monitoring for smart power grids with distributed generation using artificial neural networks". *International Journal of Electrical Power & Energy Systems*, vol. 113, pp. 472–480, 2019.

[8] F. G. Duque, L. W. de Oliveira, E. J. de Oliveira and A. A. Augusto. "State estimator for electrical distribution systems based on an optimization model". *Electric Power Systems Research*, vol. 152, pp. 122–129, 2017.

[9] Y. Zhang and J. Wang. "Towards highly efficient state estimation with nonlinear measurements in distribution systems". *IEEE Transactions on Power Systems*, vol. 35, no. 3, pp. 2471–2474, 2020.

[10] P. P. Tecchio, R. A. Benedito and L. F. Alberto. "The behavior of WLS state estimator near the maximum loadability point of power systems". In *IEEE PES General Meeting*, pp. 1–6. IEEE, 2010.

[11] D. Dasgupta, S. Yu and F. Nino. "Recent advances in artificial immune systems: models and applications". *Applied Soft Computing*, vol. 11, no. 2, pp. 1574–1587, 2011.

[12] L. N. De Castro and F. J. Von Zuben. "Artificial immune systems: Part I–basic theory and applications". *Universidade Estadual de Campinas, Dezembro de, Tech. Rep*, vol. 210, no. 1, 1999.

[13] L. N. De Castro and F. J. Von Zuben. "The clonal selection algorithm with engineering applications". In *Proceedings of GECCO*, volume 2000, pp. 36–39, 2000.

[14] L. W. De Oliveira, E. J. de Oliveira, F. V. Gomes, I. C. Silva Jr, A. L. Marcato and P. V. Resende. "Artificial immune systems applied to the reconfiguration of electrical power distribution networks for energy loss minimization". *International Journal of Electrical Power & Energy Systems*, vol. 56, pp. 64–74, 2014.

[15] A. Abur and A. G. Exposito. *Power system state estimation: theory and implementation*. CRC press, 2004.

[16] S. Civanlar, J. Grainger, H. Yin and S. Lee. "Distribution feeder reconfiguration for loss reduction". *IEEE Transactions on Power Delivery*, vol. 3, no. 3, pp. 1217–1223, 1988.

[17] M. E. Baran and F. F. Wu. "Network reconfiguration in distribution systems for loss reduction and load balancing". *IEEE Power Engineering Review*, vol. 9, no. 4, pp. 101–102, 1989.

[18] J.-P. Chiou, C.-F. Chang and C.-T. Su. "Variable scaling hybrid differential evolution for solving network reconfiguration of distribution systems". *IEEE transactions on power systems*, vol. 20, no. 2, pp. 668–674, 2005.

[19] D. Zhang, Z. Fu and L. Zhang. "An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems". *Electric power systems research*, vol. 77, no. 5-6, pp. 685–694, 2007.