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Performance assessment of an optimization strategy proposed for power systems

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ABSTRACT

In the present article, the selection process of the topology of an artificial neural network (ANN) as well as its configuration are exposed. The ANN was adapted to work with the Newton Raphson (NR) method for the calculation of power flow and voltage optimization in the PQ nodes of a 10-node power system represented by the IEEE 1250 standard system. The purpose is to assess and compare its results with the ones obtained by implementing ant colony and genetic algorithms in the optimization of the same system. As a result, it is stated that the voltages in all system nodes surpass 0,99 p.u., thus representing a 20% increase in the optimal scenario, where the algorithm took 30 seconds, of which 9 seconds were used in the training and validation processes of the ANN.

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1. INTRODUCTION

The integration of power generation, transmission and distribution systems with the progress evidenced in the information and communication technologies (ICT) sector has been encompassed within the development of the concept known as smart grids. It has allowed to unite in a single management system the areas of protection coordination, control, measure and economic dispatch of an electric network. Its main purpose is to achieve integration through the efficient and rational use of energy as well as the increase of reliability, security and flexibility of electric systems [1-3].

The inherent result of the development of smart grids has been the constant search for the implementation of algorithms that optimize power systems based on technical and economic criteria as well as energy quality. Improvement practices are also proposed such as control systems to correct voltage unbalances in power generation units embedded within the network [4-7], multi-agent systems [8-10] to compensate the high variability of the energy supply related to alternative sources of generation, and the forecast of the effects of a massive connection of electric vehicles in the future [11-13]. Other proposals have focused in the effects of environmental conditions in the projection of the economic dispatch based on probability functions delivered by the statistical method Latin Hypercube Sampling [14]. Other strategies have focused on developing algorithms that create usage profiles of the generators linked to a network, according to the consumption demand [15, 16].

The calculation of the voltage values involves solving a system of simultaneous non-linear equations in most cases. To achieve this, the Newton-Raphson (NR) and Gauss-Siedel iterative methods [4]. The NR method consists of an iterative procedure in which non-linear equations are used involving voltage magnitude and angle variables as well as active and reactive power. Since there are only two power equations, the other two variables must be calculated [8]. In [9], the NR method is used to calculate photovoltaic parameters and carry out the modelling process. The Gauss-Seidel method is an iterative method in which the number of unknown variables is equal to the number of equations to solve. It consists on designing a converging succession according to a previously defined criteria [11], the convergence values are the solution of the nodal voltages and powers of the electric system. In [12], the Gauss-Seidel method is used as the main strategy to accelerate the solution of power flow in a high-performance reconfigurable computer.

It is evident that it is the process to be optimized within the smart grid that determines the type of algorithm to be implemented, whether it is a linear system or not. Currently, the algorithms of the iterative [17] (Newton method [18], conjugated gradient, interpolation, etc) and heuristic types [19] (evolutionary algorithms, genetic algorithms, Nelder Mead, among others) are the most commonly implemented. Furthermore, there are computational models that can be used in optimization models such as the Artificial Neural Networks (ANN), a bio-inspired algorithm from 1943 that was relegated to the background due to the computational capacity that it required at the time. However, with the unstoppable development in electronics and semi-conductor materials and the manufacture of increasingly powerful processors, the application of ANN has risen. They can be classified into iterative or heuristic methods depending on their learning process [20, 21].

Since their reintroduction as a computational model, ANNs have been used to simulate different types of processes [22-25], due to their swift prediction of variables. Nonetheless, their use as an optimization model is not yet extended and needs some sort of iterative or heuristic algorithm in order to work. Hence, this article presents the development process of an artificial neural network combined with the Newton Raphson (NR) method for the calculation of power flow and the optimization of nodal voltages in power systems with n nodes. This is subsequently implemented in a 10-node IEEE 1250 standardized power system with the purpose of guaranteeing voltages over 0.98 p.u. in all system nodes. Finally, the performance will be assessed by comparing the results obtained with the bee swarm and ant colony algorithms for the same power system. This helps to determine its potential for implementation in smart grids as an optimization method based on the electric energy criteria.

2. PROPOSED ALGORITHM

The proposed algorithm is developed in its totality in the MATLAB 2018b numerical computing software. Initially, the execution of the NR method is carried out in order to obtain the magnitude and angle of the voltage, based on the impedance matrix and the active and reactive power data. Using the power flow calculations, the algorithm can proceed to assess the voltage in each PQ node through ANN to determine whether the nodes are underpowered in comparison to the optimal value used for training. Thus, a capacitive reactance of 0.1 p.u. is injected if the assessed node does not comply with this optimization parameter. When the ANN completes the assessment of all power system nodes, the algorithm executes the NR method with the purpose of determining the new voltages in the system, which are once again assessed by the ANN. The process is concluded when it is established that all the PQ nodal voltages are equal or above the optimal reference value.

In this manner, the NR and ANN methods enable the optimization of the power system, by giving the user a final report in .xlsx format with the optimized values of voltage magnitude and angle for each node as well as the calculation of generated active-reactive power and the demand. The user is informed on the value of the capacitive correction required by each node to elevate the voltage to optimal values. Figure 1 shows the flow diagram of the developed algorithm.

The neural network proposed in the algorith was developed by implementing the base codes of the MATLAB fitnet function, establishing a structure of three layers: input layer, hidden layer and output layer. This is illustrated in Figure 2 and the components are explained in this section.

2.1. Input variables

It is the information given to the neural network, for the traning phase as well as the validation and testing phases. In this specific case, the nodal voltage in p.u. may vary from 0 to 1. The user is informed on the value of the capacitive correction required by each node to elevate the voltage to optimal values. Figure 1 shows the flow diagram of the developed algorithm.

2.2. Layers

The model has three types of layers: input layer, hidden layer and output layer. The input layer has one neuron, which individually receives the information of the voltage in each node. The hidden layer has 30 neurons, which is a number determined by considering that the number of neurons present in this layer is proportional to the accuracy of the neural network regarding the classification of data but it is also proportional to the time required to perform such task. In terms of the connections, each neuron in this layer is connected with a neuron of the input layer depending oh the weights of the connections. It is important to clarify that there may be more than one hidden layer. The number of hidden layers of a neural network is directly related with how easy it is to classify the desired output according to the input. Figure 3 shows the output vs input diagram with typical values of the optimization process of a power system. According to the diagram, for input variables with values below 0.9, the neural network can generate an output of 0. For input variables over 0.9, the neural network must generate an output of 0.1. This allows the perfect division of the data through a linear curve. In case the output states cannot be linearly separated, the number of hidden layers must keep increasing. The output layer has one neuron, corresponding to the number of output variables with a minimum of 2 states.

2.3. Weights

Weights are coefficients that alter the input value of neurons, starting from the hidden layer, considering the periodicity in which a specific input value is transmitted compared to a desired output value. This strengthens the connection with the transmitted neuron at the expense of the connection with other neurons. Hence, weights also have the functionnality of interconnecting neurons in different layers.

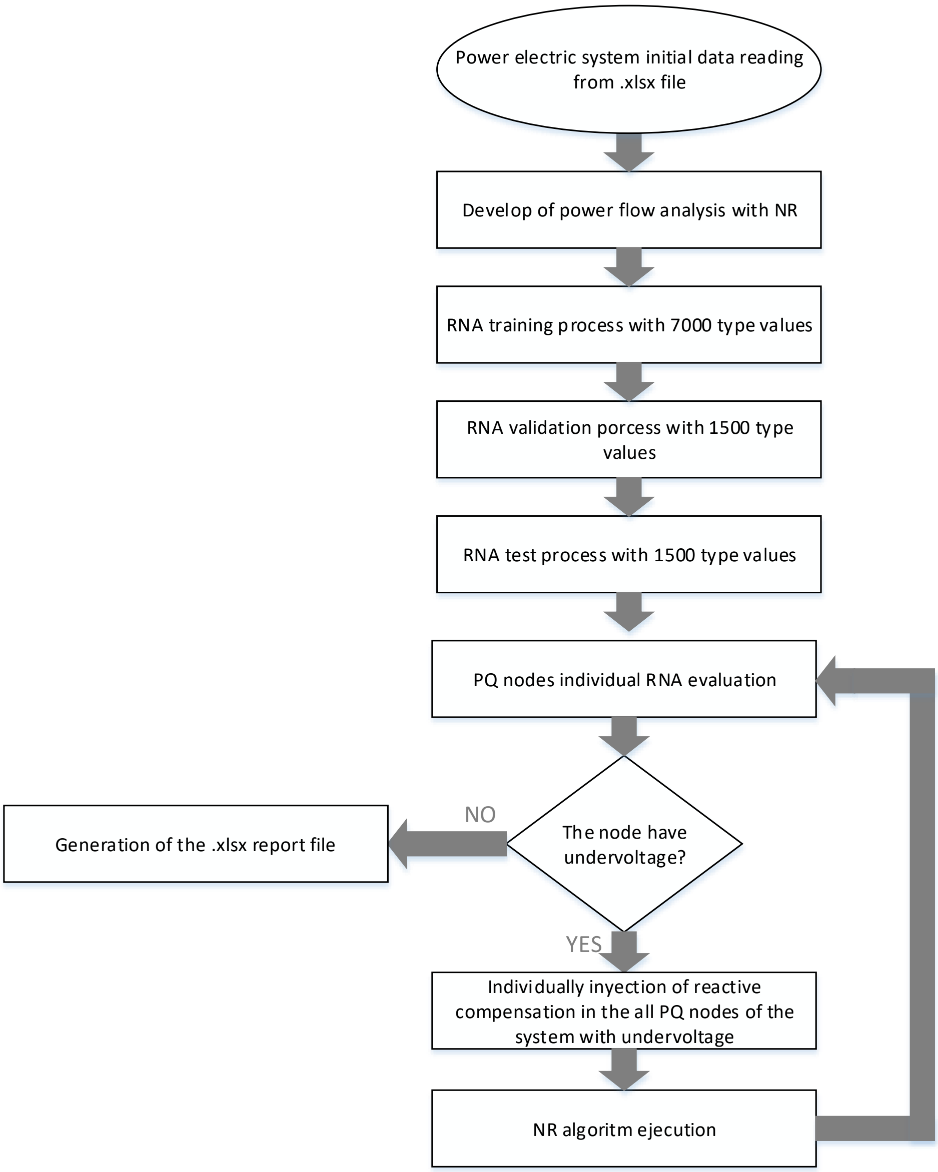

Figure 1. Flow diagram of the developed algorithm

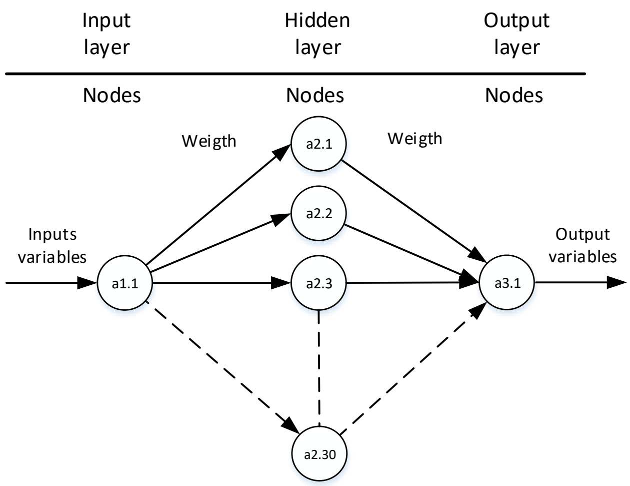

Figure 2. Structure of the neural network implemented in the optimzzation algorithm

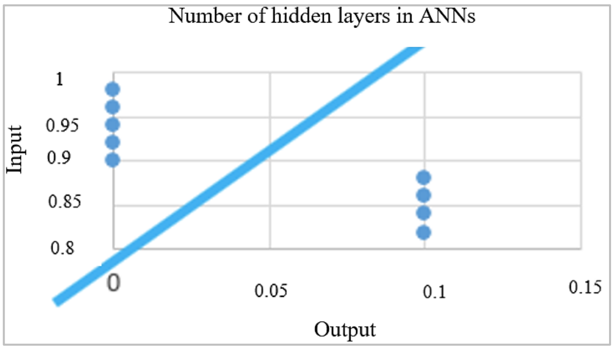

Figure 3. Data classification in a single layer neural network

2.4. Output variables

In (1) is the output of one neuron in the input layer. In (2) is the mathematical model for the output of a neural network and it represents all possible combinations of the connections between the different layers of a neural network from the hidden layer up to the output layer. For the ANN discussed in this paper, the output variable has two states: 0 or 0.1.

$$a_i^k = x_i \tag{1}$$

For k = 1, i > 0, where a is the neuron output and x is the input variable.

$$a_i^{(k)} = f\left(\sum_{j=1}^{nk-1} a_j^{(k-1)} * w_{ji}^{(k-1)}\right) \tag{2}$$

for k > 1, i > 0 and j > 0, where a is the neuron output, w are the weights of the neural connections and f(x) is the limited function.

After establishing the topology of the ANN described in this article, Figure 4 presents the typical results of the training, validation and testing phases, using 7000, 1500 and 1500 typical data respectively. The system implements the Bayesian regularization function as a training function. In order to assess its performance, the geometric mean root is used. A total of 58 iterations were carried out to train the network. The training, validation and testing processes were stopped because the ANN attained the expected minimum gradient in 8 seconds.

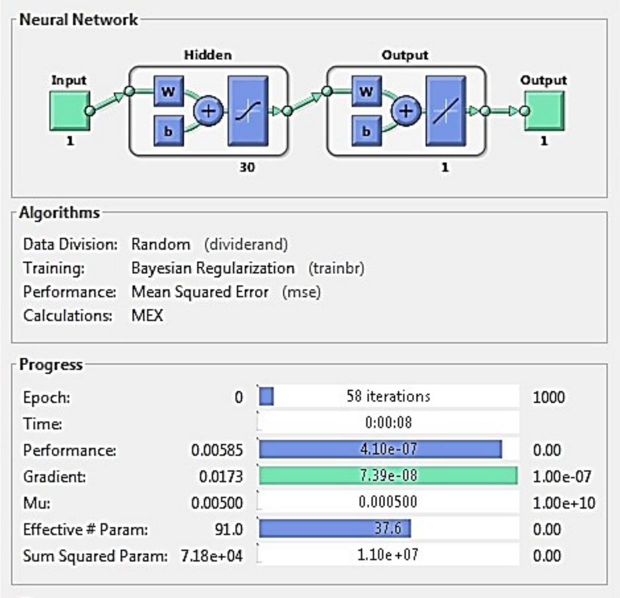

Figure 4. Typical data in the training, validation and testing processes of the implemented ANN

3. RESULTS

The schematic of the system to be optimized is shown in Figure 5. It is comprised of 10 nodes, from which two nodes have a PV type, one node has a slack type and seven nodes have a PQ type. The other characteristics and variables of the electric system are presented in Tables 1 and 2, respectively. In Table 1, the first two columns represent the interconnection of the system nodes, the electric characteristics of these connections are established from the third to the fifth column. In Table 2, the first two columns represent the number of the node and its type. The third column up to the seventh column show the values of the generated active/reactive power, the demanded active/reactive power and the voltage magnitude in each node. The performance of the neural network during the training, validation and testing phases for the optimization process of this specific system is presented in Figure 6. The preliminary result of the nodal voltage after optimization and the total computation time (ANN training time plus optimization time) are shown in Figure 7.

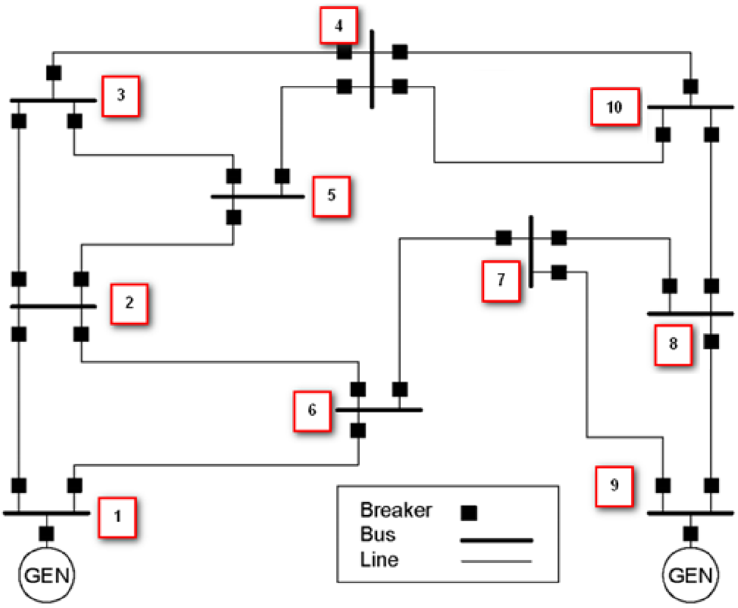

Figure 5. IEEE 1250 power system

Table 1. Characteristics of the IEEE 1250 power system

N start	N finish	R	X	Bsh/2
1	2	0.08379	0.1772	0.00047
1	6	0.1089	0.2304	0.00061
2	3	0.1843	0.3900	0.0010
2	5	0.1508	0.3191	000085
2	6	0.1675	0.3545	0.00094
3	4	0.2346	0.4963	0.0013
3	5	0.2094	0.4432	0.0011
5	4	0.1843	0.3900	0.0010
4	10	0.1675	0.3545	0.00094
6	7	0.1256	0.2659	0.00071
7	8	0.1005	0.2127	0.00056
7	9	0.0670	0.1418	0.00037
9	8	0.1340	0.2836	0.00075
8	10	0.1089	0.2304	0.00061

Table 2. Known system variables of the IEEE 1250 power system

Node	Type	P gen	Q gen	P dem	Q dem	V mag
1	Slack	0.7	0	0	0	1
2	PQ	0	0	0.15	0.2	0.9433
3	PQ	0	0	0.15	0.2	0.8939
4	PQ	0	0	0.15	0.2	0.8666
5	PV	0	0	0.15	0.2	1
6	PQ	0	0	0.15	0.2	0.9353
7	PQ	0	0	0.15	0.2	0.9335
8	PQ	0	0	0.15	0.2	0.8943
9	PV	0.5	0	0	0	1
10	PQ	0	0	0.15	0.2	0.8373

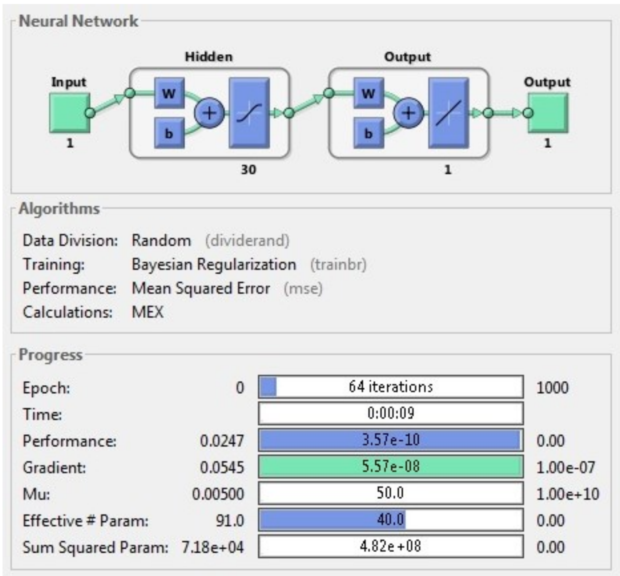

Figure 6. Training, validaiton and testing of the ANN used in the optimization of the IEEE 1250 power system

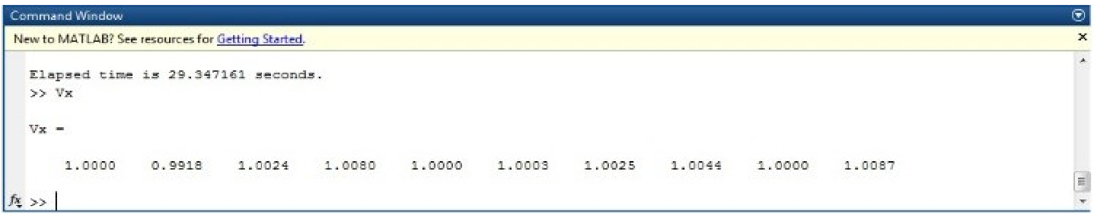

Figure 1. Preliminary results of the nodal voltages and total execution time of the optimization algorithm

4. COMPARATIVE ASSESSMENT

Figure 7 shows the report generated by the algorithm in which the optimization results can be thoroughly detailed for the 10-node IEEE 1250 standard power system. In Table 3, the node type is coded in the second column, with 1 for Slack, 2 for PV and 3 for PQ. Table 4 presents the results of the nodal voltage magnitudes obtained with the genetic algorithm (GA) and the ant colony optimization (ACO). Table 5 shows the optimization percentage of the voltage magnitude for each node of the IEEE 1250 power system. Each column represents one of the algorithms discussed in this section.

Table 3. Report of the optimization results for IEEE 1250

Bus i	Type node	P gen	Q gen	P dem	Q dem	Vmag	Vang
1	1	0.779	-0.28	0	0	1	0
2	3	0	0.2	0.15	0.2	0.992	-5.96
3	3	0	0.3	0.15	0.2	1.002	-1126
4	3	0	0.3	0.15	0.2	1.008	-12.58
5	2	0	0	0.15	0.2	1	-10.99
6	3	0	0.3	0.15	0.2	1	-4.369
7	3	0	0.3	0.15	0.2	1.002	-5.194
8	3	0	0.3	0.15	0.2	1.004	-7.374
9	2	0,5	0	0	0	1	-2.583
10	3	0	0.3	0.15	0.2	1009	-10.996

Table 4. Results in nodal voltage magnitudes for ga and aco

Node	GA	ACO
1	1	1
2	0.9984	0.9566
3	0.9963	0.9109
4	0.9972	0.9038
5	1	1
6	0.9957	0.9722
7	0.9957	0.9735
8	0.9947	0.9513
9	1	1
10	0.9955	0.9075

Table 5. Comparison of the percentages of nodal voltage increase

Node	GA	ACO	ANN
1	0%	0%	0%
2	5.84%	1.4%	5.16%
3	11.45%	1.9%	12.09%
4	15.07%	4.29%	16.31%
5	0%	0%	0%
6	6.45%	3.94%	6.91%
7	6.55%	4.28%	7.33%
8	11.22%	6.37%	12.26%
9	0%	0%	0%
10	18.89%	8.38%	20.5%

5. ANALYSIS OF THE RESULTS

Figures 4 and 6 exhibit the training, validation and testing process of the neural network. It is concluded that the time lapses and iterations of convergence are similar under different performance scenarios. This indicates that the size of the power system to be optimized does not influence the time and quality of the ANN in detecting subvoltages in the system nodes. Going back to Figures 4 and 6, it can be determined that the typical parameters for which the training process is stopped are tied to the minimum learning gradient of the neural network and its performance. This means that the trained neural network guarantees a a high accuracy in the prediction of values depending on the input variable. This is highlighted by the fact that the output has two states only distanced by a 0.01. In case that the neural network is halted after completing the maximum number of iterations, it is recommended to apply once again the learning process since the network may not successfully predict the expected output values.

Table 3 showcases the report of the algorithm after the optimization process of the IEEE 1250 power system. This table also shows that, even if the total non-capacitive reactive powers per node do not exceed the active powers, they are significant enough to affect the power factor associated to the node. This is true not only for the ANN algoritihm but also for the other algorithms. It is recommended to consider this parameters for future versions of the algorithms. Furthermore, Table 3 reveals that the reactive power in the PV nodes or the nodes connected to a generator is increased in order to compensate the capacitive reactive power injected to the system by the ANN. This results in a normal behavior considering that these nodes must remain with a voltage equal to 1 p.u. The results of the optimization of the IEEE 1250 power system exhibited by the genetic algorithm and the ANN are fairly competitive. The minimum difference is 0.46% in the sixth node and the maximum difference is 1.26% in the last node. It is suggested to assess the optimization time to find an arguable difference.

6. CONCLUSIONS

The topology of the implemented ANN in the optimization algorithm has shown a stable behaviour in terms of the parameters used for training, validation and testing, guaranteeing accuracy and swiftness in most cases. A neural network that adopts a number of inputs equal to the number nodes in the power system to be optimized is not viable since it would require a large amount of data to assure a correct training process. The corresponding computing power would need to surpass the capacity of an average computer. It is recommended to include the power factor as an optimization parameter keeping in mind that optimization must be based on the principle of energy quality. The optimization results obtained with both the genetic algorithm and the implemented ANN are similar.

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