A novel methodology for optimal location of reactive compensation through deep neural networks

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ARTICLE INFO

Keywords:
Deep learning
Multi-layer neural network
Reactive compensation
Electrical power system

ABSTRACT

The present investigation proposes a methodology for the optimal location of reactive compensation in an electrical power system (EPS) through deep neural networks for voltage profile improvement. One of the main parameters to consider regarding EPS reliability is the voltage profile, a parameter that can be affected due to unexpected increases in impedance and loads in the system that translate as overloads in the system and an increase in the number of users. A voltage profile below the minimum or above the maximum accepted in the regulations of each country puts at risk the correct operation of equipment connected to the electrical network and, in turn, can cause economic losses and human lives (e.g by not guaranteeing reliability for hospitals and similar institutions).

Economically, one of the most viable alternatives for improving voltage profiles is reactive compensation which in itself is carried out through capacitor banks. Therefore, this work proposes to find the correct location of capacitor banks in an electrical power system (using IEEE 14, 30 and 118 bus-bars systems as cases of study). In each system, the highest reactive load is identified, thus three values for reactive compensation are established as 80%, 50% and 25% of this maximum.

Then, with these values, power flows are generated by locating each one of the reactive compensators' possible values in each one of the bars of the system, hence generating a large number of training data so that finally the neural network is capable of providing a quantitative classification highlighting which compensation and in which bus-bar produces the best result. The result is assessed by applying a modified standard deviation which evaluates the separation of the voltage profiles from the ideal desired value of 1pu.

1. Introduction

The increasing growth in global electrical energy demand has required electrical power systems to expand, forcing energy transmission, the energy market, and network operators to evolve with new technological infrastructures to guarantee service under quality parameters.

This growth forces the construction of long transmission lines, which in themselves introduce problems in the energy power flow over long distances, causing dynamic and voltage instability.

Since the 50s, with the progress of power electronics, microprocessors, and the incorporation of communications in transmission and distribution networks, the inclusion of new technologies in the electrical power system such as Flexible Alternating Current Transmission Systems FACTS started to develop (Karuppiah et al., 2018) (Guo et al., 2021) (Hameed et al. 2020). These devices allow to control and improve voltage profiles, increase transmission capacity, reactive power compensation, and integration of renewable energies.

1.1. Literature review

In recent years, research has been focused mainly on the sizing and placement of FACTS within the transmission and distribution networks, under multiple criteria of quality and economic viability with different heuristics and optimization models, such as reducing voltage deviation at the network nodes, minimizing power losses in the conductors of transmission lines, the minimum cost of location and more criteria, all with the same purpose of placing FACTS devices and improving the operation of the power grid. For example (Mutegi and Nnamdi 2022), shows a meta-heuristic called Filter Feeding Allogenic Engineering (FFAE) algorithm inspired by the filter-feeding and the motile behaviour of Allogenic Engineers that determines the optimal location of the FACTS devices considering as target variables the minimization of active power losses and voltage deviations, also its methodology is compared with the whale optimization algorithm (WOA) in the same test network giving better results in the computation time.

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https://doi.org/10.1016/j.heliyon.2022.e11097
Received 20 May 2022; Received in revised form 22 July 2022; Accepted 11 October 2022
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Neural networks and artificial intelligence have gained great significance in research fields related to electrical power systems, especially because they help to predict the power demand in the short and medium-term, as well as, to improve the performance of FACTS devices with advanced control techniques respectively.

Figure 1 shows the most important works by author related to the application of neural networks to solve and improve compensation techniques.

For example (Guo et al., 2021), discusses three commonly used machine-learning methods used for load forecasting, the support vector machine method, the random forest regression method, and the long short-term memory neural network method to forecast the load in the machine method, the random forest regression method, and the long short-term memory neural network method to forecast the load in the short-term, as well as, to improve the performance of FACTS devices with advanced control techniques respectively.

Also (Alatshan et al., 2020); changes the conventional PI control for one based on Artificial Neural Network (ANN) on a STATCOM to improve its performance giving it adaptability, and robustness, considering the non-linearities of the electrical network.

The importance of this research area can also be noted by analyzing the main countries that contribute to this field as it can be seen in Figure 2.

The work of (Karuppiah et al., 2018) focuses on the optimization of the location, number and nominal capacity of FACTS de-vice (SVC, TCSC, UPFC) using Evolutionary Algorithms like Bacterial Foraging Algorithm (BFOA) and Gravitational search algorithm (GSA) and as decision variables analyze the sensitivity factors related to bus and transmission line voltage stability. The results on an IEEE type network show that the optimization process improves more using the first method (BFOA) than the second (GSA) but both meet the objective of giving the network a better performance.

In (Shehata et al., 2022), a multi-objective optimization algorithm combining the autonomous group particle swarm and grey-wolf (AGPSOGWO) methods is proposed for the localization of SVC, TCSC and UPFC devices minimizing the power system active losses, voltage deviation and operating costs, in addition; the authors perform a comparative analysis of their proposal with other methodologies such as particle swarm optimization (PSO) and simulated annealing (SA) to validate their model and determine that it allows obtaining global optimal solutions with a high convergence rate.

In (Shokouhandeh et al., 2021) the optimal management of re-active power in the network considering the location of the FACTS to improve voltage stability and the reduction of costs associated with power generation and reserves is studied through the modified version of the artificial bee colony (MABC) algorithm and its results are compared with the artificial bee colony (ABC) algorithm, and the genetic algorithm (GA).

Authors in (Hameed et al., 2020) have studied the improvement in voltage stability of an electrical power system under fault conditions with the proper location of FACTS, SVC and STATCOM compensation devices using a fuzzy control system under two criteria and indicators Line Flow Index (LFI) and Voltage Profile Index (VPI).

The research presented in (Shaheen et al. 2019) describes a procedure to solve the reactive power planning (RPP) problem and determine the location as well as the maximum VAR capacity of the devices to be installed in order to optimize energy losses, operating and investment costs and improve the voltage profile in a robust network considering 354 bus-bars with strategies of differential evolution (DE).

The research in (Mohamed et al. 2021) proposes a strategy for the optimal placement of FACTS devices, specifically SVC, to improve the performance of AC transmission networks in terms of losses, voltage profile and reactive power using the simplified Reduced Gradient power flow method (GRG-OPF). Its results on a 57-bus network offer acceptable and scalable efficiency for larger power systems.

Authors in (Mahapatra et al., 2021) work on the Optimal Power Flow solution with the incorporation of thyristor controlled series compensator (TCSC) to reduce the system power losses and improve the voltage profile under overload scenarios, the methodology proposes a sizing of the FACT capacity with the ant-lion Optimizer (ALO) and the optimal location of the TCSC is determined by the Cuckoo Search (CS) algorithm. Its statistical and comparative results with other methodologies in the literature such as the Radial basis function neural network-GSA (RBFNN-GSA) demonstrates its validity.

Authors in (Kumar and Bhowmik 2020) propose a heuristic for STATCOM location to minimize transmission losses and improve the voltage stability index by modifying techniques based on genetic algorithms from the current literature, the variant mainly does not allow the top two chromosomes (which have the highest fitness values) to pair with the other chromosomes. Their study is validated at steady-state and under pre and post-island operation conditions.

(Diab and Rezk 2019) shows the application of grey wolf (GWO), dragonfly (DFO) and moth-flame (MFA) optimization techniques for optimal placement of Mvar reactive compensation in various distribution systems to improve the voltage profile under criteria of total cost minimization and net savings due to losses, the simulation shows accurate convergence to the optimal placement and sizing, as well as, performance compared to other techniques.

Figure 1. Main publications by authors and years regarding neural networks applied to voltage profile compensation.
An algorithm based on fuzzy logic is presented in (Bhowmik and Gaur 2018) as a decision method for determining the optimal location and size of reactive compensation systems to minimize the loss rates and nodal voltage deviations of three tested networks and whose results give high reliability.

In (Malathy and Shunmugalatha 2016), the authors examine the increase of transmission system load-ability with the optimal location of FACTS devices (SVC, UPFC, TCSC) for reactive contribution increase considering single (N-1) and double (N-2) contingencies using the Modified Differential Evolution (MDE) algorithm, the authors evaluate the Contingency Severity Index (CSI), as well as the Fast Voltage Stability Index (FVSI) as decision variables for the optimal location and their results, show an improvement in the system, specifically in minimizing investment costs and increasing social profitability.

In (Dibya and Mala 2018) by using graph theory, the authors establish the centrality index of a distribution network to determine the optimal size and location of reactive power compensation (RPC) based on static compensators. Also, in (Dibya and Mala 2019), a graph theoretical methodology for optimal reactive compensation in systems with high penetration of renewable generation in distribution systems is presented, the work tests a 34-bus radial system and compares it with other methodologies presented in (El-Fergany and Abdelaziz 2014) and, in the latter, the RPC is based on capacitors and the location heuristic uses Accelerated Particle Swarm Algorithm and Artificial Bee Colony verified in 34 and 118- bus systems.

1.1.1. Deep learning

Deep learning is defined as a set of autonomous learning algorithms that attempt to model abstractions or high-level processes in a database defined by employing computational architecture that is related to multiple and iterative nonlinear transformations that are usually expressed in tensorial form, deep learning is currently a type of machine learning that organizes this database so that it is executed through predefined equations, configuring basic parameters on this database, training the computer to learn on its own, recognizing patrons using layers of processing, in today’s world the impact of deep learning is very significant and it is only the beginning, with the continuous collective increase of processing in artificial intelligence, deep learning allows us to collect, locate and detail the information concerning, in this case, a reactive compensation in various scenarios to validate this algorithm.

1.2. Organization

The organization of the paper is as follows: Section 1 discusses an introduction to Reactive compensation in Electrical distribution systems and their main characteristics such as reliability and its relationship with voltage profiles, also this section shows the previous research done in the area involving deep learning neural network and the relationship with compensators voltage control.

Section 2 shows the three IEEE transmission systems that have been analyzed and studied in this research. IEEE 14, 30 and 118 bus-bars are detailed. Each system has its own specific values for the configuration of lines, loads, generators, and capacitor banks.

Section 3 shows the models, simulations and techniques that were used to generate the training data for each transmission system. This section analyses also provides a detailed discussion and analysis of the training data.

Section 4 shows the testing results of the neural network for each transmission system. The voltage profile enhancement and the optimal location of reactive compensation are fully analyzed and explained through data and graphics.

Finally, section 5 summarizes the conclusions from the research done in this work.

2. Methodology

The research methodology is explained throughout the following cases of study:

2.1. Cases of study

2.1.1. IEEE 14 bus-bar transmission system

This research takes as one case study the IEEE-14 bus system, this system was developed for research and to provide tools for the improvement of various electrical parameters involved. The system has specific values for the configuration of lines, loads, generators, and capacitor banks.

A summary of the most important information of this test system is shown in Table 1 by considering system values of generators as a voltage
source per terminal and an impedance of 10Ω, and a power base of 100 MV A.

The load values for the different bus bars in the selected IEEE test system are shown in Table 2.

2.1.2. IEEE 30 bus-bar transmission system

IEEE 30 bus-bar transmission system is the second case of analysis for this research’s work. This system represents portion of the American Electric Power System located in the Midwestern USA. The system has specific values for the configuration of lines, loads, generators, and capacitor banks. A summary of the most important information about this test system is shown in Table 3 in this case a power base of 100 MV A is considered.

The load values for the different bus bars in the 30 bus-IEEE test system are shown in Table 4.

2.1.3. IEEE 118 bus-bar transmission system

IEEE 118 bus-bar transmission system is the third case of analysis for this research’s work. This system also represents a portion of the American Electric Power System located in the Midwestern USA. This case of study consists of 118 buses, 19 generators, and 91 loads, a summary of the most important information about this test system is shown in Table 5 in this case a power base of 100 MV A is considered. The load values for the different bus bars in the 118 bus-bar IEEE test system are shown in Table 6.

2.2. Deep neural network

The self-organizing network (SON) is an unsupervised learning method for the classification of multidimensional data, whose main characteristic is the creation of two-dimensional maps. Self-organizing networks (SONs) are radio access networks (RANs) that automatically plan, configure, manage, optimize, and heal themselves. These SONs can offer automated functions such as self-configuration, self-optimization, self-healing, and self-protection. The SONs strive to make complicated network administration a thing of the past by enabling the creation of a plug-and-play environment for both simple and complex network tasks. This is in stark contrast to the traditional implementation of cellular wireless networks we see in enterprises today, most of which require teams of technicians for maintenance, management, and optimization.

2.2.1. Simple neural network

SIMPLEX is one of the most simple and general optimization methods. It is used to predict the experiments that most quickly lead to an optimum value. This method can be used to optimize the parameters of the counter-propagation neural network model, for the forecasting and reliability models and robotics control.

Below, in Figure 3 the basic architecture of a simple neural network can be seen, which serves as the basis for the construction of a more robust neural network.

2.2.2. Deep learning neural network

Deep Learning can be defined in many ways but mainly it can be defined as a Machine Learning technique that is based on a series of algorithms, where its logical structure is assimilated to the functioning of the human nervous system, in which the majority of Deep Learning methods use neural network architectures that automatically learn and extract features from the data to produce optimal results. An example of a deep learning network is shown in Figure 4.

Deep learning neural networks are organized in layers and can have hundreds of hidden layers of an artificial neural network, hence the term Deep. Generally, all neurons in each layer have a connection to every neuron in the next layer, Figure 5 shows this network characteristics.

3. Neural network training

3.1. Simulations general information

The models have been implemented in Matlab (2021b) computing environment and applied on a 2.80GHz core i7 personal computer with 16GB RAM. The simulation results and discussion corresponding to the voltage enhancement models on IEEE 14, 30 and 118 bus-bars systems are presented in the scenarios as follows.

| Bus | V [pu] | Θ [deg] | P [MW] | Q [Mvar] |
|-----|-------|---------|--------|----------|
| 1   | 0.98  | 0.00000 | 232    | -17      |
| 2   | 0.95  | -4.98960| 40     | 42.4     |
| 3   | 1.01  | -12.7250| 0.0    | 23.4     |
| 4   | 1.07  | -14.2209| 0.0    | 12.2     |
| 5   | 0.95  | -13.3596| 0.0    | 17.4     |

Table 1. Characteristics values IEEE-14 bus system.
3.2. Test system: IEEE-14 bus-bar system

The IEEE-14 bus system main parameters were detailed in Tables 1 and 2. Before any change in this system, Figure 6 shows the voltage profiles in each bus bar before any kind of compensation.

For this case study, the methodology consists in training a neural network with different electrical parameters of the IEEE 14 Bus-bar system considering different scenarios of reactive compensation.

In this system, the highest reactive load is 19Mvar, located in bus-bar 3. Therefore, considering as a threshold 80%, 50% and 25% of this load, this research will consider values of 16Mvar, 10Mvar and 5Mvar respectively for reactive compensation.

3.2.1. Data generated from scenarios with 5Mvar compensation

For this scenario, training data for the neural network was obtained by implementing a reactive compensation with 5Mvar in every single bus bar and then registering all the voltage profiles as it is shown in Figure 7.

This scenario generates a data set of 196 voltage profiles. By analyzing Figure 8 it can be concluded that the best scenarios for reactive compensations are when the reactive compensation (with 5Mvar) is located in bus-bars 3, 6 and 12, which will be reviewed when the neural network is implemented.

It is important to detail that although the 5Mvar reactive compensation improved the voltage profiles in the IEEE 14 bus system, the difference between the different scenarios of compensation (considering each bus bar) is not highly significant. The best way to properly compare this data is by considering a statistical approach. Table 7, shows the 5 best locations for reactive compensation. For this case, the best voltage profile (mean value for all 14 bus bars) is 0.946558pu when the compensation is located at bus-bar 14.

Figure 3. Simplex neural network.

For this case study, the methodology consists in training a neural network with different electrical parameters of the IEEE 14 Bus-bar system considering different scenarios of reactive compensation.

In this system, the highest reactive load is 19Mvar, located in bus-bar 3. Therefore, considering as a threshold 80%, 50% and 25% of this load, this research will consider values of 16Mvar, 10Mvar and 5Mvar respectively for reactive compensation.

Figure 4. Self organized network.

3.2.2. Data generated from scenarios with 10Mvar compensation

The second scenario obtained training data for the neural network by implementing a reactive compensation with 10Mvar in every single bus bar and then registering all the voltage profiles as it is shown in Figure 9.
3.2.3. Data generated from scenarios with 16Mvar compensation

The last scenario obtained training data for the neural network by implementing a reactive compensation with 16Mvar in every single bus bar and then registering all the voltage profiles as it is shown in Figure 11.

This scenario also generates a data set of 196 voltage profiles. By analyzing Figure 10 it can be concluded that the best scenarios for reactive compensations are when the reactive compensation (with 10Mvar) is located in bus-bars 3, 6 and 12 (bus-bars 7, 9 and 10 give good results as well), which will be reviewed when the neural network is implemented.

This scenario generates results that are better than the previous one (5Mvar). Table 8, shows the 5 best locations for reactive compensation. For this case, the best voltage profile (mean value for all 14 bus bars) is 0.947715pu when the compensation is located at bus-bar 14.

This scenario also generates a data set of 196 voltage profiles. By analyzing Figure 12 it can be concluded that the best scenarios for reactive compensations are when the reactive compensation (with 16Mvar) is located in bus-bars 3, 6 and 12 (bus-bars 7, 9 and 10 give good results as well), which will be reviewed when the neural network is implemented.

This scenario provides the best results among the previous data sets. Table 9, shows the 5 best locations for reactive compensation. For this case, the best voltage profile (mean value for all 14 bus bars) is 0.94907pu when the compensation is located at bus-bar 14.

3.3. Test system: IEEE-30 bus-bar system

The IEEE-30 bus system main parameters are detailed in Tables 3 and 4. Before any change in this system, Figure 13 shows the voltage profiles in each bus bar before any kind of compensation.

In this system, the highest reactive load is 50Mvar, located in bus-bar 8. Therefore, considering as a threshold 80%, 50% and 25% of this load, this research will consider values of 40Mvar, 24Mvar and 12Mvar respectively for reactive compensation.

| Location | Voltage [pu] |
|----------|--------------|
|          | Min | Max | Median | Mean     |
| B14      | 0.923404 | 0.98 | 0.949914 | 0.946558 |
| B9       | 0.91842 | 0.98 | 0.949914 | 0.946417 |
| B10      | 0.917536 | 0.98 | 0.949914 | 0.946323 |
| B7       | 0.916941 | 0.98 | 0.949914 | 0.946122 |
| B12      | 0.91553 | 0.98 | 0.95 | 0.945959 |

Table 7. Data analysis for 5Mvar compensation data set.
3.3.1. Data generated from scenarios with 12Mvar compensation

For this scenario, training data for the neural network was obtained by implementing a reactive compensation of 12Mvar in every single bus bar and then registering all the voltage profiles (data is not graphically shown due to its size). This scenario generates a data set of 900 voltage profiles, and by analyzing Figure 14 it can be concluded that several bus-bars generate a significant increase in voltage profiles, although bus-bars 18, 19, 25, and 27 have a better performance. A 12Mvar compensation was able to increase the mean value of the voltage's profiles. Table 10, shows the 5 best locations for reactive compensation considering the highest mean value of all voltage profiles for each case. This table clearly shows that the best voltage profile (mean value for all 30 bus bars) is 0.99693pu when the compensation is located at bus-bar 19.

3.3.2. Data generated from scenarios with 24Mvar compensation

For this scenario, training data for the neural network was obtained by implementing a reactive compensation of 24Mvar in every single bus bar and then registering all the voltage profiles (data is not graphically shown due to its size). This scenario generates a data set of 900 voltage profiles, and by analyzing Figure 15 it can be concluded that several bus-bars generate a significant increase in voltage profiles. Table 11, shows the 5 best locations for a 24Mvar compensation considering the highest mean value of all voltage profiles for each case. This table clearly shows that the best voltage profile (mean value for all 30 bus bars) is 1.002402pu when the compensation is located at bus-bar 19.

3.3.3. Data generated from scenarios with 40Mvar compensation

For this scenario, training data for the neural network was obtained by implementing a reactive compensation of 40Mvar in every single bus bar and then registering all the voltage profiles (data is not graphically shown due to its size). This scenario generates a data set of 900 voltage profiles, and by analyzing Figure 16 it can be concluded that several bus-bars generate a significant increase in voltage profiles. Table 12, shows the 5 best locations for a 40Mvar compensation considering the highest mean value of all voltage profiles for each case. This table clearly shows that the best voltage profile (mean value for all 30 bus bars) is 1.009253pu when the compensation is located at bus-bar 19.

3.4. Test system: IEEE-118 bus-bar system

The IEEE-30 bus system main parameters are detailed in Tables 5 and 6. In this system, the highest reactive load is 113Mvar, located in bus-bar 59. Therefore, considering as a threshold 80%, 50% and 25% of this load, this research will consider values of 90Mvar, 55Mvar and 27Mvar respectively for reactive compensation.

3.4.1. Data generated from scenarios with 27Mvar, 55Mvar and 90Mvar compensation

Three sets of training data for the neural network were obtained by implementing a reactive compensation of 27Mvar, 55Mvar and 90Mvar in
every single bus bar and then registering all the voltage profiles (data is not graphically shown due to its massive size) This scenario generates three data sets, each of 13924 voltage profiles.

Table 13, shows the 5 best locations for 27Mvar, 55Mvar and 90Mvar compensation scenarios considering the highest mean value of all voltage profiles for each case. This table shows that the best voltage profile (mean value for all 118 bus bars) for compensation of 27Mvar is 0.988596pu when the compensation is located at bus-bar 21. Similarly, the best voltage profile for compensation of 55Mvar is 0.989217pu when the compensation is located at bus-bar 21. Finally, the best voltage profile for compensation of 90Mvar is 0.989945pu when the compensation is located at bus-bar 21.

4. Comprehensive result analysis for neural network performance

4.1. Objective function

After obtaining data for all the different optimal scenarios of reactive compensation, all this data needs to be processed as inputs for training in the neural network this paper proposes.

For the IEEE 14 bus-bar System each of the three data sets (5Mvar 10Mvar, 16Mvar) consists of 14 scenarios of reactive compensations, each containing 14 values for each bus bar. Also, for IEEE 30 bus-bar System each of the three data sets (12Mvar, 24Mvar, 40Mvar) consists of 30 scenarios of reactive compensations, each containing 30 values for each bus bar. Finally, for IEEE 118 bus-bar System each of the three data sets (27Mvar, 55Mvar, 90Mvar) consists of 118 scenarios of reactive compensations, each containing 118 values for each bus bar.

Therefore, to obtain the most important characteristics of each scenario, this paper uses a modified approach to the standard deviation.
Standard deviation is characterized by calculating the mean deviation between a group of data and the mean of such data group. However, this concept does not provide much information about the voltage profiles in the IEEE systems (14, 30 and 118 bus-bars), therefore in this research, a modified approach for the standard deviation is used. This criteria from now on will be called objective deviation, having a comparison of each voltage profile against 1.0 pu as it is shown in Eq. (1).

\[ \sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2} \]  

(1)

### 4.2. Objective deviation: 14 bus-bar system

After the objective deviation is calculated, for every data set 14 values are generated. These values represent how close the voltage profiles of the entire system are related to 1pu. Therefore, the closer this objective deviation is to 0, the better the voltages profiles of the compensated system. Figure 17 shows this objective deviation values for each data set.

### 4.3. Objective deviation: 30 bus-bar system

For every data set, 30 values are generated. Exactly as in the previous case the closer this objective deviation is to 0, the better the voltages profiles of the compensated system. Figure 17 shows this objective deviation values for each data set.

### 4.4. Objective deviation: 118 bus-bar system

Finally, for every data set 118 values are generated. Exactly as in the previous case the closer this objective deviation is to 0, the better the voltages profiles of the compensated system. Figures 19 and 20 show this objective deviation values for each data set.

### 4.5. Trained network performance

#### 4.5.1. Results for trained neural network, 14 bus-bar system

After the neural network was developed and trained, the next step consisted of testing the neural network with objective deviation data obtained from different scenarios of reactive compensation with 16Mvar. This value was selected because it gave a greater range of variation in the data than other smaller compensation values, this characteristic provides the opportunity of testing the network performance under a more challenging approach.

The neural network should be able to classify the data and specify which ones are the scenarios with the best voltage profiles.

For this analysis, the objective deviation was scaled by multiplying by a factor of 1000 (as these values are too small and by doing this, they are easier to analyze). As it can be seen in Figure 21, the neural network proposed in this paper was able to successfully classify the different scenarios of reactive compensation according to their performance (lowest objective deviation).

Figure 21 shows the neural network output which can classify the data into four categories, the first category is the one with the best objective deviation values and the fourth is the one with the worst objective deviation values. Figure 21 literal a, shows that the best scenarios for reactive compensation with 16Mvar are located in bus bars 14, 9 and 10 respectively. Figure 21 literal b, shows that the second best scenario is at bus bars 7 and 3, additionally, Figure 21 literal c, shows that the third-best scenario is at bus bars 4 and 6. Finally, Figure 21 literal d, shows that the worst compensation scenarios are located in bus bars 1, 2, 5, 8, 11 and 13 respectively.

#### 4.5.2. Results for trained neural network, 30 bus-bar system

For this scenario, the neural network was tested for a bigger transmission system. After the network was trained for the IEEE 30 bus-bar system. The neural network was analyzed under different scenarios of reactive compensation with 40Mvar. This value was selected because it gave a greater range of variation in the data than other smaller compensation values, this characteristic provides the opportunity of testing the network performance under a more challenging approach.

For this analysis, the objective deviation was also scaled by multiplying by a factor of 1000. As it can be seen in Figure 22, the neural network proposed was able to successfully classify the different scenarios of reactive compensation according to their performance (lowest objective deviation) even with a bigger transmission system.

Figure 22 shows the neural four neural network output categories, the first category is the one with the best objective deviation values and the fourth is the one with the worst objective deviation values. Figure 22 literal a, shows that the best scenarios for reactive compensation with 40Mvar are located in bus bars 10, 22, 21, 24, 15 and 17 respectively. Figure 22 literal b, shows that the second-best scenario is at bus bars 23, 12, 16, 18, 20, 9, 19, 14. Finally Figure 22 literal c and d show the third and fourth categories respectively.

#### 4.5.3. Results for trained neural network, 118 bus-bar system

Finally, the neural network was tested for even a bigger transmission system. After the network was trained for the IEEE 118 bus-bar system. The neural network was analyzed under different scenarios of reactive compensation with 90Mvar. This value was selected because it gave a greater range of variation in the data than other smaller compensation values, this characteristic provides the opportunity of testing the network performance under a more challenging approach.

For this analysis, the objective deviation was also scaled by multiplying by a factor of 1000. As shown in Figure 23, the neural network was successfully able to classify the different scenarios of compensation into the four categories stated before. However, due to the size of the

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**Table 12. Data analysis for 40Mvar compensation data set.**

| Location | Min  | Max  | Median | Mean  |
|----------|------|------|--------|-------|
| B19      | 0.986033 | 1.048298 | 1.006395 | 1.009253 |
| B20      | 0.986442 | 1.046653 | 1.006609 | 1.008797 |
| B18      | 0.985346 | 1.050145 | 1.007357 | 1.008545 |
| B23      | 0.98695 | 1.048192 | 1.005906 | 1.006399 |
| B22      | 0.987301 | 1.04 | 1.005468 | 1.006199 |

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**Table 13. Data analysis for 27Mvar, 55Mvar and 90Mvar compensation data sets.**

| Location | Min  | Max  | Median | Mean  |
|----------|------|------|--------|-------|
| B21      | 0.95 | 1.05 | 0.98608 | 0.988596 |
| B22      | 0.95 | 1.05 | 0.98608 | 0.988541 |
| B44      | 0.95 | 1.05 | 0.986222 | 0.988485 |
| B52      | 0.95 | 1.05 | 0.986057 | 0.988458 |
| B20      | 0.95 | 1.05 | 0.98608 | 0.988444 |
| B21      | 0.95 | 1.05 | 0.986222 | 0.989217 |
| B22      | 0.95 | 1.05 | 0.986222 | 0.989112 |
| B44      | 0.95 | 1.05 | 0.986222 | 0.988998 |
| B52      | 0.95 | 1.05 | 0.98608 | 0.988951 |
| B20      | 0.95 | 1.05 | 0.986222 | 0.988926 |
| B21      | 0.95 | 1.06802 | 0.986222 | 0.989945 |
| B22      | 0.95 | 1.07541 | 0.986222 | 0.989782 |
| B44      | 0.95 | 1.080194 | 0.986222 | 0.989597 |
| B52      | 0.95 | 1.05 | 0.986222 | 0.989534 |
| B20      | 0.95 | 1.05 | 0.986222 | 0.989496 |
transmission system, this research will only focus its study on the first category. Figure 24, shows that the best scenarios for reactive compensation with 90Mvar are located in bus bars 53, 51, 58, 52, 115, 114, 118, 108, 109, 28, and 29 respectively.

4.5.4. Overall neural network performance

The results achieved in this research, show that the neural network is capable of locate the optimal location for reactive compensation in any transmission system, independently of the network size and number of bus-bars.

![Objective deviation calculated for data sets of 5Mvar, 10Mvar and 16Mvar compensation.](image1)

**Figure 17.** Objective deviation calculated for data sets of 5Mvar, 10Mvar and 16Mvar compensation.

![Objective deviation calculated for data sets of 12Mvar, 24Mvar and 40Mvar compensation.](image2)

**Figure 18.** Objective deviation calculated for data sets of 12Mvar, 24Mvar and 40Mvar compensation.

![Objective deviation calculated for data sets of 27Mvar, 55Mvar and 90Mvar compensation.](image3)

**Figure 19.** Objective deviation calculated for data sets of 27Mvar, 55Mvar and 90Mvar compensation.
From similar works analyzed in section 1, as it is shown in Table 14, the optimal location of reactive compensation has been studied under different approaches. Table 14 shows that Filter feeding allogenic engineering, fuzzy control, graph-theoretic methods, particle swarm algorithms and other genetic algorithms have been used as techniques for optimal location of reactive compensation, between these works the different methodologies location times vary from 0.308 to 350 s. It is important to note that most of the works apply their methods to a single transmission system and occasionally to two transmission systems.
As it is shown in results of sections 4.2.1, 4.2.2 and 4.2.3, this research's methodology allows after properly training a neural network to find the optimal location of reactive compensation for any transmission system and this has been tested and demonstrated in three IEEE bus-bars transmission systems. Once the neural network is trained, testing is a process that only takes a single machine cycle of processing having processing times of milliseconds, by far exceeding other methodologies.

5. Conclusions

Training is essential for a neural network's correct performance, for this purpose a large amount of training data is needed. In this investigation, data sets of 196, 900 and 13924 voltages profiles were generated for training in each case of study (IEEE 14, 30 and 118 bus-bars), thus guaranteeing that all possible compensation cases were covered.

By training the neural network with a large number of data and considering all reactive compensation scenarios, neural network was able to correctly classify with 100% accuracy the best scenario for the reactive compensation location. The network's performance is also validated when applying the neural network to bigger transmission systems and obtaining the same accuracy.

Based on this research results, a classification neural network can be used in an electrical power system as an optimization method as long as an objective function is adapted for the output of the network. In this work, the objective function was a modified approach to the standard

Table 14. Different methodologies from literature review used for optimal reactive compensation.

| Author (2022) | Methodology | System Tested | Time [s] |
|--------------|-------------|---------------|----------|
| Mutegi and Nnamdi | Filter Feeding Allogenic Engineering (FFAE) | Kenya’s 87-Bus Engineering | 0.308 |
| Hameed et al., 2020 | Fuzzy Control System | IEEE 24 bus system | 0.300 |
| Dihya and Mala, 2019 | Graph theoretic Method with Average Electrical Cen | 34 bus radial system | 3.230 |
| El-Fergany and Abdelaziz, 2014 | Accelerated Particle Swarm Algorithm | 34 and 118 bus radial systems | 15.5/350.5 |
| El-Fergany and Abdelaziz, 2013 | Artificial Bee Colony | 34 bus radial system | 10.080 |
| Karuppiah et al., | GSA and BFOA algorithms | IEEE 14 and IEEE 30 bus systems | N/A |
| 2018 | | | |
| Shehata et al., 2022 | Autonomous Groups Particle Swarm and Grey Wolf optimizers AGPSO-GWO | IEEE 30 and 118 bus systems | N/A |
| Shokouhandeh et al., 2021 | Artificial Bee Algorithm | IEEE 30-bus system | N/A |
| Shabeen et al., 2019 | Strategies of Differential Evolution (DE) | 30 and 354 bus test systems | N/A |

As it is shown in results of sections 4.2.1, 4.2.2 and 4.2.3, this research’s methodology allows after properly training a neural network to find the optimal location of reactive compensation for any transmission system and this has been tested and demonstrated in three IEEE bus-bars transmission systems. Once the neural network is trained, testing is a process that only takes a single machine cycle of processing having processing times of milliseconds, by far exceeding other methodologies.

5. Conclusions

Training is essential for a neural network's correct performance, for this purpose a large amount of training data is needed. In this investigation, data sets of 196, 900 and 13924 voltages profiles were generated for training in each case of study (IEEE 14, 30 and 118 bus-bars), thus guaranteeing that all possible compensation cases were covered.

By training the neural network with a large number of data and considering all reactive compensation scenarios, neural network was able to correctly classify with 100% accuracy the best scenario for the reactive compensation location. The network's performance is also validated when applying the neural network to bigger transmission systems and obtaining the same accuracy.

Based on this research results, a classification neural network can be used in an electrical power system as an optimization method as long as an objective function is adapted for the output of the network. In this work, the objective function was a modified approach to the standard
deviation (achieving values closer to 1pu), thus improving the whole transmission system voltages’ profiles.

Finally, the methodology used in this research and its results shows that it is a valid alternative to be integrated and used in electrical power systems.

Declarations

Author contribution statement

Manuel Jaramillo: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Luis Tisan; Jorge Muñoz: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

Manuel Jaramillo was supported by Universidad Politécnica Salesiana del Ecuador.

Data availability statement

Data will be made available on request.

Declaration of interest’s statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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