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Comparison of Multilayer Perceptron Neural Network Architecture in Photovoltaic Plants Fault Classification

Comparação de Arquitetura de Redes Neurais Perceptron de Multicamadas para Classificação de Faltas em Plantas Fotovoltaicas

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ABSTRACT

The goal of this study is to assess the application of Multilayer Perceptron Artificial Neural Networks in fault classification within photovoltaic panels, focusing on key characteristics such as the number of neurons and layers, activation functions, training techniques, and the resulting accuracy. The study employs a comparative analysis approach, examining various characteristics and hyperparameters applied to Multilayer Perceptron Artificial Neural Networks for fault classification in photovoltaic panels. The research methodology involves reviewing publications from the past decade to gather data on these characteristics and their impact on fault analysis in photovoltaic generation systems. This study contributes to the originality of the field by providing a comprehensive comparison of various parameters and techniques used in Multilayer Perceptron Artificial Neural Networks for fault classification in photovoltaic panels. The findings offer valuable insights for researchers and practitioners in the renewable energy sector, aiding in the development of more efficient and reliable fault diagnosis systems for photovoltaic generation.

Keywords: Multilayer Perceptron; Artificial Neural Network; Photovoltaic; Fault Classification.

RESUMO

O objetivo deste estudo é avaliar a aplicação de Redes Neurais Artificiais Multicamadas Perceptron na classificação de falhas em painéis fotovoltaicos, com foco em características-chave, como o número de neurônios e camadas, funções de ativação, técnicas de treinamento e a precisão resultante. O estudo emprega uma abordagem de análise comparativa, examinando várias características e hiperparâmetros aplicados a Redes Neurais Artificiais Multicamadas Perceptron para a classificação de falhas em painéis fotovoltaicos. A metodologia de pesquisa envolve a revisão de publicações da última década para reunir dados sobre essas características e seu impacto na análise de falhas em sistemas de geração fotovoltaica. Este estudo contribui para a originalidade do campo, fornecendo uma comparação abrangente de vários parâmetros e técnicas usadas em Redes Neurais Artificiais Multicamadas Perceptron para a classificação de falhas em painéis fotovoltaicos. Os resultados oferecem insights valiosos para pesquisadores e profissionais no setor de energia renovável, auxiliando no desenvolvimento de sistemas de diagnóstico de falhas mais eficientes e confiáveis para a geração fotovoltaica.

Palavras-chave: Perceptron de Multicamadas; Rede Neural Artificial; Fotovoltaica; Classificação de Faltas.

INTRODUCTION

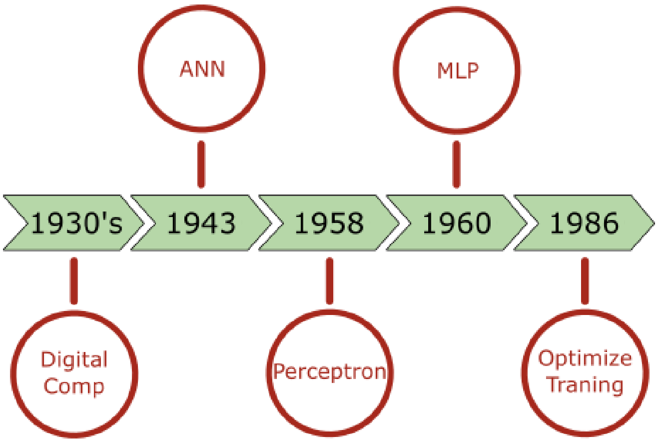
The use of computational modeling plays a highly significant role in the development, optimization, and enhancement of renewable energy systems at various generation scales (FILHO at al, 2022; NASCIMENTO FILHO at al, 2018; MURARI at al, 2020; SILVA at al, 2021). The process of capturing energy from solar radiation has evolved significantly through the application of various optimization techniques, which can enhance the efficiency and reliability of solar energy installations, thereby contributing to a more sustainable future (NASCIMENTO FILHO at al, 2017; NASCIMENTO FILHO at al, 2021; NASCIMENTO FILHO at al, 2022; DE OLIVEIRA at al, 2023). Furthermore, with the increasing proliferation of artificial intelligence techniques, it is anticipated that the optimization process will be further maximized.

In the late 1930s, the first digital computers emerged. and during earlier 1940s, Artificial Neural Networks (ANNs) were being conceived. The first recognized work in the field of Artificial Intelligence was “A Logical Calculus of the Ideas Immanent in Nervous Activity”, produced by Warren McCulloch and Walter Pitts in 1943. This work drew inspiration from the neural system to perform calculations with the implementation of logical expressions (MCCULLOCH, PITTS, 1943).

In the following decade, the principles of the Perceptron were defined at the Cornell Aeronautical Laboratory by Frank Rosenblatt in the article titled “The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain”. The Perceptron is a simple architecture of an Artificial Neural Network, representing an artificial neuron that not only operates with digital logic but also computes input and output data in real numbers (ROSENBLATT, 1958).

To address certain application problems of the Perceptron networks, such as non-linear classification and exclusive or (XOR) logic problems, the Multilayer Perceptron (MLP) neural network was proposed in the 1960s. The MLP gained popularity in the 1980s with the increase in computer processing power and the introduction of the backpropagation algorithm (RUMELHART, HINTON, WILLIAMS, 1985). The training technique for MLP, known as backpropagation, was popularized through the book “Parallel Distributed Processing”, published in 1986 by Rumelhart and McClelland. In Fig 1 is there is the important milestones in MLP timeline.

Fig 1 - Important milestones in MLP timeline



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The MLP has been applied in various fields using machine learning techniques, including in the domain of electrical systems for the analysis and diagnosis of faults in photovoltaic generation systems (BASNET; CHUN; BANG, 2020; BHARATH; HAQUE; KHAN, 2018; CHINE et al., 2016; CHOUAY; OUASSAID, 2017; DA COSTA et al., 2019; DJALAB et al., 2020; LAZZARETTI et al., 2020; RAO; SPANIAS; TEPEDELENLIOGLU, 2019; SABRI; TLEMÇANI; CHOUDER, 2019; VIEIRA, 2021).

Photovoltaic generation has proven to be a significant technology within the realm of renewable energy generation, attracting an estimated global value of $298 billion, representing 60% of the total global investment in renewable energy (IRENA, 2023). In the year 2021 alone, there was an addition of 138 gigawatts (GW) of installed capacity (IRENA, 2023). For comparison, the installed capacity in the entire National Interconnected System in Brazil in the year 2022 is 176 gigawatts (GW) (ONS, 2022). It can be observed in 2021, the added wind generation capacity worldwide was equivalent to 78% of the total installed capacity of the Brazilian power generation system in 2022. In Brazil, photovoltaic generation has also been gaining importance, currently accounting for 12.8% of the total installed capacity, with a perspective to reach 15.2% by 2026 (ONS, 2022).

The increasing presence of renewable energy generation in electrical systems has posed a challenge not only to the stability and systemic operation of electrical grids but also to conventional protection systems. Protections using traditional measured-based protection like overcurrent protection and current differential protection can result in protection maloperations (CAO et al., 2023). This challenge arises from the extensive use of power electronics in this type of generation, leading to atypical characteristics and behavior during faults. These atypical characteristics include low short-circuit current contribution, which affects the sensitivity of conventional protections, unusual voltage response behavior, and the presence of negative sequence component sources.

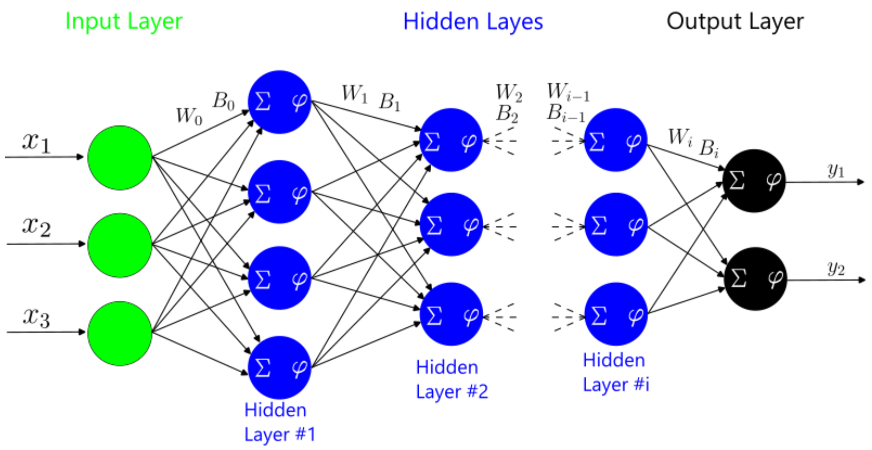
Instead of relying on traditional protection systems, researchers have explored neural network techniques, such as Multilayer Perceptrons, to detect faults in photovoltaic panels. Numerous books and articles have documented the findings of these studies, offering alternative approaches for improving fault detection in this context. This type of protection has the capability to detect faults in photovoltaic panels before the triggering of traditional protection, enabling the anticipation of necessary corrections before the panel presents more severe damage.

In this article, we compare the characteristics applied to Multilayer Perceptron Artificial Neural Networks for fault identification in photovoltaic panels. This include defining the number of neurons and layers, activation functions, training techniques, and the achieved accuracy. These comparisons were be based on documented research published over the 2014 to 2021.

CHARACTERISTICS EMPLOYED IN THE MODELS

An example of a Multilayer Perceptron Artificial Neural Network is represented in Fig 2. In this network, we have the variable matrix X, in this case formed by x_1, x_2, and x_3, connected to the input layer. The output variables y_1 and y_2 form the matrix Y, which is calculated by the output layer. There can be as many input and output variables as necessary. The input and output layers will have the same number of neurons as the number of input and output variables, respectively. The hidden layers are situated between the input and output layers and can have as many neurons as defined by the application. Weight matrices W and Bias vector B are used, calculated during the training phase, along with the activation function φ to compute values to be passed from the previous layer to the next one. The matrix W and the vector B constitute the parameters of the neural network.

Fig 2 - MLP Example



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There is no fixed rule for determining the number of hidden layers to be applied or the number of neurons in each layer. As an illustrative example, in the figure, it is considered a first hidden layer with four neurons and a second hidden layer with three neurons were represented.

This study considers articles published between 2014 and 2021, which employed MLP for the diagnosis of short-circuits in photovoltaic panels based on values such as instantaneous current and voltage in direct current, temperature, irradiance, and power. Tab 1 records, for each article, the number of hidden layers, the number of neurons per hidden layer, activation function, training technique and achieved accuracy.

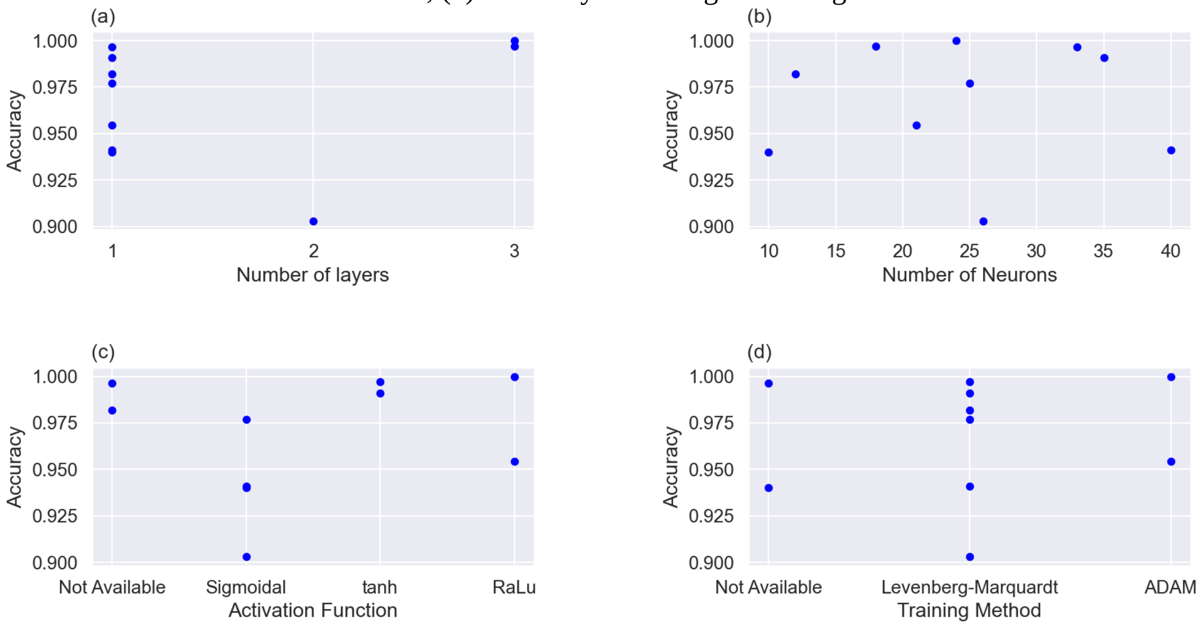
Tab 1 - Comparison of MLP characteristics

Article	Hidden layers/ Neurons Quantity	Activation Function	Técnica de Treinamento	Accuracy
(CHINE et al., 2016)	(13,13)	Sigmoidal	Levenberg-Marquardt	90.3%
(CHOUAY; OUASSAID, 2017)	(40)	Sigmoidal	Levenberg-Marquardt	94.1%
(BHARATH; HAQUE; KHAN, 2018)	(12)	NA	Levenberg-Marquardt	
(SABRI; TLEMÇANI; CHOUDER, 2019)	(25)	Sigmoidal	Levenberg-Marquardt	97.7%
(RAO; SPANIAS; TEPEDELENLIOGLU, 2019)	(6,6,6)	Tanh	Levenberg-Marquardt	99.7%
(DA COSTA et al., 2019)	(33)	NA	NA	99.65%
(LAZZARETTI et al., 2020)	(21)	ReLU	ADAM	95,44%
(BASNET; CHUN; BANG, 2020)	(8,8,8)	ReLU	ADAM	100%
(DJALAB et al., 2020)	(10)	Sigmoidal	NA	94.0%
(VIEIRA, 2021)	(35)	tanh	Levenberg-Marquardt	99.1%

Source: Own Authorship

The considered articles mentioned which characteristics were used but don’t explicitly state the reasons behind the chosen configurations for the models. Some articles did not even mention certain characteristics adopted in the model, which is recorded in Table 1 with cells marked as “NA” (Not available in the article).

Fig 3 – Relation between Accuracy and Network Characteristics. (a) Accuracy according to Number of layers, (b) Accuracy according to Number of Neurons, (c) Accuracy according to activation functions, (d) Accuracy according to training method.



Source: Own Authorship

To facilitate the analysis of the model characteristics, scatterplots were constructed in Fig 3 based on the data from Table 1. These plots depict the relationship between the accuracy achieved by the models, on a scale from 0 to 1, and the main characteristics of the MLP. These graphs support an initial analysis and observations regarding the relationship between accuracy and network characteristics. The next session discusses the relation between accuracy and artificial neural network hyper-parameters number of layers, number of neurons, activation function and training methods.

MODELS CHARACTERISTICS RESULTS AND DISCUSSION

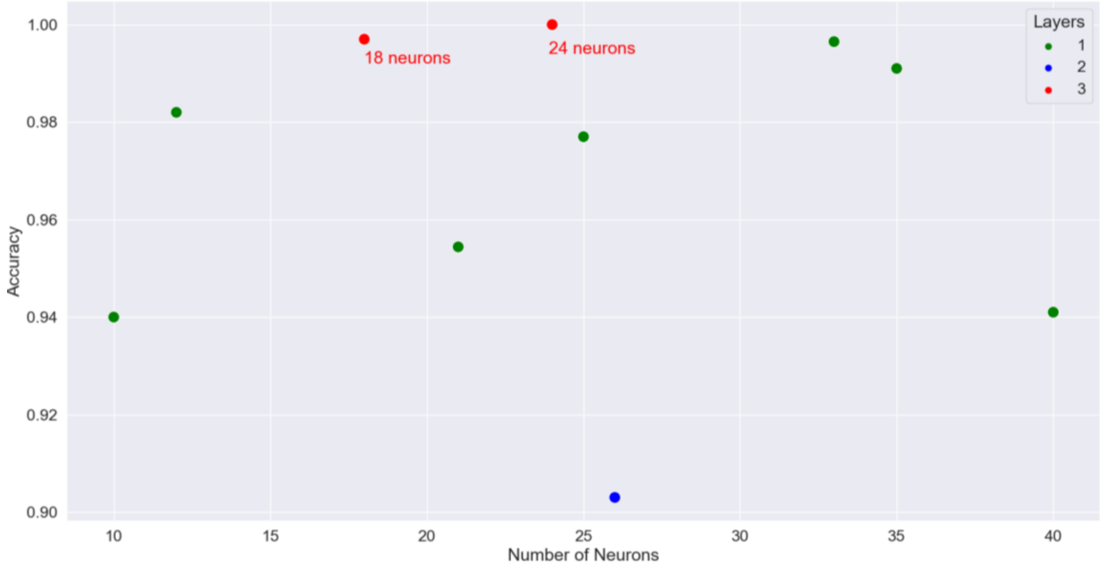
Some articles employed an iterative technique to determine the number of neurons in the model with the aim of achieving the highest accuracy. In (BHARATH; HAQUE; KHAN, 2018) , networks were trained starting from 4 neurons up to 40 neurons in intervals of 4, and the network with 12 neurons was selected. In (DA COSTA et al., 2019), the iteration began with 10 neurons up to 100 neurons, and the network with 33 neurons was chosen. An iterative technique was also employed to define the number of neurons in (LAZZARETTI et al., 2020), adopting a range from 5 to 30 neurons, with 21 neurons being selected.

In all the mentioned iterative cases, only one hidden layer was employed. The majority of the considered articles utilized a single hidden layer, following the stance of certain sources like (DE VILLIERS; BARNARD, 1993), which conducts a comparison between neural networks with one and two hidden layers and concludes that there is no reason to use two hidden layers, and preference should be given to neural networks with just one hidden layer.

On the other hand, it can be observed that the models studied with two or three hidden layers consistently use the same number of neurons per layer, which may not be the optimal solution for multilayer models. In (MAIOROV; PINKUS, 1999), it is suggested that for a two-layer neural network model with hidden functions, one should consider using $2d + 1$ neurons in the first layer and $4d + 3$ neurons in the second layer, where d represents the number of input variables.

As seen in the graph “Number of Neurons x Accuracy” in Fig 3, there is no clear direct relationship between the number of neurons used in the model and the achieved accuracy. However, in the graph “Number of Layers x Accuracy” in the same figure, it can be observed that models with three layers achieved higher accuracy than models with one or two layers. This assertion is visually confirmed in Fig 4, where the models with the highest accuracy, marked in red, consist of three layers but with nearly half the number of neurons compared to the model with more neurons.

Fig 4 - Accuracy according to Number of Neurons and Number of Layers

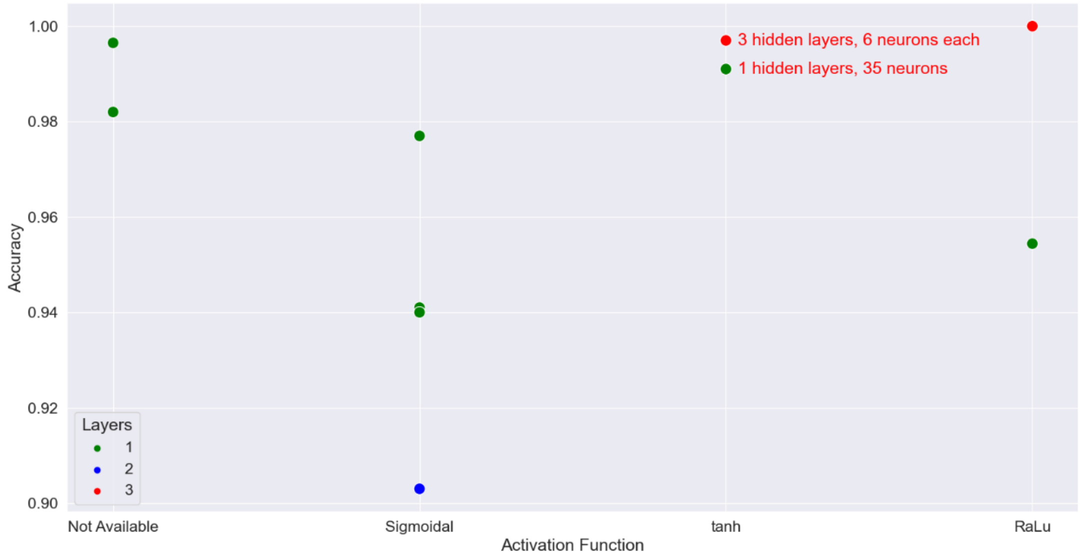


Source: Own Authorship

Considering the training techniques, it is not possible to clearly define, based on the “Training Method x Accuracy” graph in Fig 3, a technique with superior performance for the study's application. Sources like (HAYKIN, 2009) and (GÉRON, 2019) discuss training techniques, or optimization techniques, focusing on performance related to training and model classification times, without conventional correlation to the accuracy achieved by the model.

Regarding the activation function, models that employed the hyperbolic tangent function showed better accuracy, despite having different numbers of neurons and layers, as can be seen in Fig 5.

Fig 5 - Accuracy according to Activation Function



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CONCLUSION

In the use of MLP for fault detection in photovoltaic panels, it is common to employ between one and three hidden layers with up to 40 neurons each. Despite the relatively low number of layers and neurons utilized, impressive results have been achieved with accuracies consistently exceeding 90%.

Directly correlating the number of neurons with accuracy proved challenging. However, the influence of the number of layers used can be observed. While most models have a single hidden layer, the three-layer models consistently achieved higher accuracy compared to models with one or two layers.

The selection of hyperparameters in neural networks has proven to be an empirical area, with no consolidated rule for defining these hyperparameters. Neural networks with lower complexity can become underfitting, while overly complex networks can lead to overfitting. The study demonstrates practical boundaries of hyperparameters that articles applying MLP have addressed for fault classification in photovoltaic panels with the aim of avoiding underfitting and overfitting.

To make the process of finding the best settings for hyperparameters in a Multilayer Perceptron (MLP) neural network more efficient, it's important to set certain boundaries or limits for these hyperparameters. By doing this, you can make use of optimization techniques like Grid Search, Random Search, and Bayesian Optimization. These techniques help you explore different combinations of hyperparameters to find the best configuration for your MLP network.

Setting boundaries for hyperparameters is beneficial because it prevents you from having to search over an excessively wide range for each hyperparameter. This saves both time and computational resources, as you're focusing your search within a defined range that is more likely to contain optimal hyperparameter values. In essence, you're narrowing down the search space to areas where the best configurations are more likely to be found, making the optimization process more efficient and effective.

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