A Fletcher-Reeves conjugate gradient algorithm-based neuromodel for smart grid stability analysis

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ABSTRACT

Interest in smart grid systems is growing around the globe as they are getting increasingly popular for their efficiency and cost reduction at both ends of the energy spectrum. This study, therefore, proposes a neuro model designed and optimized with the Fletcher-Reeves conjugate gradient algorithm for analyzing the stability of smart grids. The performance results achieved with this algorithm was compared with those obtained when the same network was trained with other algorithms. Our results show that the proposed model outperforms existing techniques in terms of accuracy, efficiency, and speed. This study contributes to the development of intelligent solutions for smart grid stability analysis, which can enhance the reliability and sustainability of power systems.

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1. INTRODUCTION

Recently, the world's energy system has been undergoing significant transitions. The transitions are primarily driven by the need to update the evolving electrical infrastructure, integrate low-carbon energy sources and satisfy the excess power consumption with new types of demands such as smart homes, electric transportation, while maintaining supply protection [1]. The world in general is being forced to switch from using fossil fuel power plants to using renewable energy sources because of the ongoing climate change, which is in line with the sustainable development goal (SDG) 7 which entails transitioning from the use of fossil fuels into using clean and affordable energy. Although, integrating various sources has its advantages such as improved energy efficiency and also its sustainability, it also introduces new difficulties during the analysis of the stability of the power system.

Therefore, it has become crucial that some kind of intelligent information processing technique be introduced into energy management process as well as overall power system stability prediction and analysis. There is a growing list of algorithms that are being developed suitable for this purpose. This is an improvement over the more conventional technique of simulations combining fixed values for a particular subset and fixed distribution of values for the other subset variables [2], [3], or the even more laborious measurement-based techniques [4], [5]. Therefore, in this paper a Fletcher-Reeves algorithm combined with the conjugate gradient algorithm is being used in analyzing the stability of a smart grid. The operation of this hybrid algorithm is based on the ratio of the norm squared of the recent gradient to the norm squared of the previous gradient. The algorithm, used with the widely known backpropagation algorithm, can therefore train any network provided its weight, net input and transfer functions have derivative functions. The conjugate gradient algorithm also has other versions which includes work in in similar ways with the aim of reducing generalization errors in neural network based applications [6]. These algorithms, or their variants, have been applied for solving problems in a variety of fields and applications [4], [7]–[12]. But the aim of this paper is to use the Fletcher-Reeves conjugate gradient algorithm in training machine learning based models leading to the development of a neuromodel for analyzing smart grid stability.

The integration of renewable energy sources into existing power grids come with its own challenges owing to the unpredictable nature of some of these renewable energy sources. For instance, solar electricity generation is linked to the amount of exposure to sunlight. And quite often, availability and intensity of this solar energy is too unpredictable and cannot be used directly in the quest for taking informed decisions in power generation due to unpredictable cloud characteristics, leading to optical instability in the solar irradiance.

Several statistical methods, such as autoregressive moving average, Kalman filter, and Markov chain model have been researched in an attempt to address smart grid's unreliability. Other early statistical techniques have few limitations which are also significant in smart grid stability, these techniques due to their limitations reduce the precision of the prediction model [13]. These models, typically constructed using non-complex statistical building blocks, perform unsatisfactorily under severe uncertainty. Additionally, these conventional methods for stability forecasting such as the Markov model are only applicable within certain operating ranges [14]. The Fletcher-Reeves conjugate gradient algorithm proposed in this article, however, is a very important constituent of the neuromodel because it combines the advantages of neural networks and optimization algorithms, allowing for fast and accurate convergence to a solution. Additionally, the use of neural networks is also suitable for stability analysis because it can, to a satisfactory degree, capture the nonlinearities and uncertainties in the smart grid system [15]. Using this algorithm-based neural model for smart grid stability can empower system operators helping them make well-informed decisions during or before maintenance and systems operations. It can also help in the development and design process of smart grid control systems that will ensure the reliability and stability of the power system [16].

2. METHOD

2.1. Fletcher-Reeves conjugate gradient algorithm

This research utilizes a Fletcher-Reeves version of the conjugate gradient algorithm to analyze smart grid systems' stability. Fletcher-Reeves conjugate gradient algorithm's operation is based on the ratio of the norm squared of the recent gradient to the norm squared of the previous gradient. Mathematically, the Fletcher-Reeves conjugate gradient algorithm can be represented in (1).

$$x_{k+1} = x_k + \alpha_k d_k, \quad k = 0,1,\ldots \tag{1}$$

Let x_k represent the current solution, with α_k as the step size. The step length α_k is obtained through a line search process aimed at minimizing performance along the chosen search direction, d_k. This direction guides the search toward a minimum point. Initially, the search direction is set as the negative gradient of performance. In later iterations, it is recalculated using both the updated gradient and the previous search direction, as shown in (2).

$$d_{k+1} = -g_k + (d_k \times z) \tag{2}$$

Where g_k is the gradient of the objective function and the entity 'z' may be evaluated through a few methods. For this algorithm under discussion, it is evaluated through the use of (3).

$$z = \frac{normnew\_sqr}{norm\_sqr} \tag{3}$$

Where "$norm\_sqr$" is the normal square of the previous gradient, and "$ormnew\_sqr$" is the norm square of the current gradient [6]. A new update of the Fletcher-Reeves conjugate gradient algorithm [17], suggests another formula for calculating the new gradient of the previous search direction, d_k which is given by (4).

$$d_{k+1} = \begin{cases} -g_{k+1}, & if\ k = 0 \\ -g_{k+1} + \beta_k d_k, & if\ k > 0 \end{cases} \tag{4}$$

Where β_k is a scalar quantity and g_{k+1} is the new gradient of the objective function.

2.2. Neural network architecture

The neural network architecture used in this study consists of three (3) layers which includes the input layer, the hidden layer, and the output layer. The input layer had 12 neurons corresponding to the 12 features in the dataset and an output layer. The hidden layer had 47 neurons and used the hyperbolic tangent (tanh) activation function. The output layer had one neuron, which predicted the target variable using the sigmoid activation function.

The tanh activation function was chosen for the hidden layer because of its ability to model complex non-linear relationships between the input and output variables. The sigmoid activation function was used in the output layer because it is suitable for binary classification problems. For this architecture, a training dataset of 70% (42,000 samples) is fed into the network during training, and the network is trained and adjusted according to its observed error surface. A validation dataset of 15% (9,000 samples) was then employed to evaluate the ability of the network to handle new data that were not part of the training, and to stop the training as soon as this ability becomes reduces below a treshold. Finally, a testing dataset of 15% (9000 samples) was used, which provides an individual measure of network performance during and after training. This network structure was selected based on previous research on similar datasets and problems, and was refined through experimentation with different configurations of the neural network. The ultimate goal was to achieve high accuracy in predicting the target variable while avoiding overfitting the training data.

Figure 1 shows the structure of the artificial neural network (ANN) employed in testing/training the dataset. It includes the different layers of the network. The input layer consists of 12 different inputs which includes the energy producer, the consumers, the reaction time amidst other input variables. The output layer represents the percentage stability.

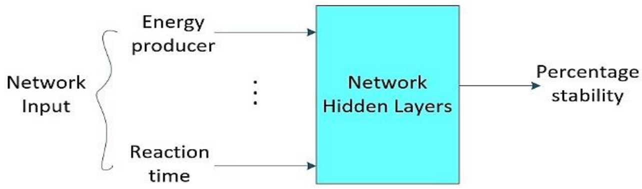

Figure 1. Neural network architecture

3. RESULTS AND DISCUSSION

After training the neural network, the observed regression from the neural network described above was plotted. It was observed, as shown in Figure 2, that the neural network achieved an overall regression R squared value of 0.98155. Other parameters were also evaluated, and they include the validation (0.98227 regression), the testing (0.98146 regression). Overall, our results suggest that, in response to the training provided, the ANN successfully learn the hidden inter-relationships between the variables make accurate predictions on new, separate data, highlighting the potential of neural networks as a powerful tool for modelling and prediction in various fields.

The plots shown in Figures 3 and 4 represent the 3D display of the relationship between selected inputs and the target. The plot was able to capture the patterns in the data, and render the relationship between the variables in a visually easy-to-appreciate format. The essence of these plots is that, apart from the pattern learned by the ANN, it now becomes easier and intelligible for experts to visually estimate the relevance of each variable at different values of other variables.

The choice of the tanh (hyperbolic tangent) transfer function for the hidden layer is a common activation function in neural networks. The tanh function, as listed in Table 1, maps the input values to the range (-1, 1), introducing non-linearity to the model. This non-linearity enables the network to learn complex patterns and relationships in the data, improving the model's ability to capture more intricate features of the input. However, it is essential to consider that the tanh function can suffer from the vanishing gradient problem, especially during the early stages of training. The sigmoid transfer function is used in the output layer. It maps the input values to the range (0, 1), which is suitable for binary classification tasks as in the case of this article. The output values represent probabilities, with values closer to 0 indicating one class and values closer to 1 representing the other class. The sigmoid function is commonly used in binary classification problems because it allows for a probabilistic interpretation of the model's output, which is often useful in decision-making scenarios.

The total number of neurons in the network indicates the size of the hidden layer. In this case, the hidden layer contains 40 neurons. The number of neurons in the hidden layer is often a hyperparameter that needs to be tuned during the network's design. Too few neurons may result in the network being unable to learn complex patterns, while too many neurons can result in a situation where the network simply learns the exact interrelations between the variables only for the provided data, while grossly underperforming for other data. The selection of 40 neurons indicates that the model's architecture is likely designed to strike a balance between complexity and generalization. The total number of weight elements represents the number of parameters that need to be learned.

In this network, there are 60 weight elements. Each connection between neurons in the network has an associated weight that is adjusted during training to minimize the error. The number of weight elements is directly related to the complexity of the network and the total number of trainable parameters. In larger networks, the number of weight elements can become substantial, leading to longer training times and the risk of overfitting if not properly regularized.

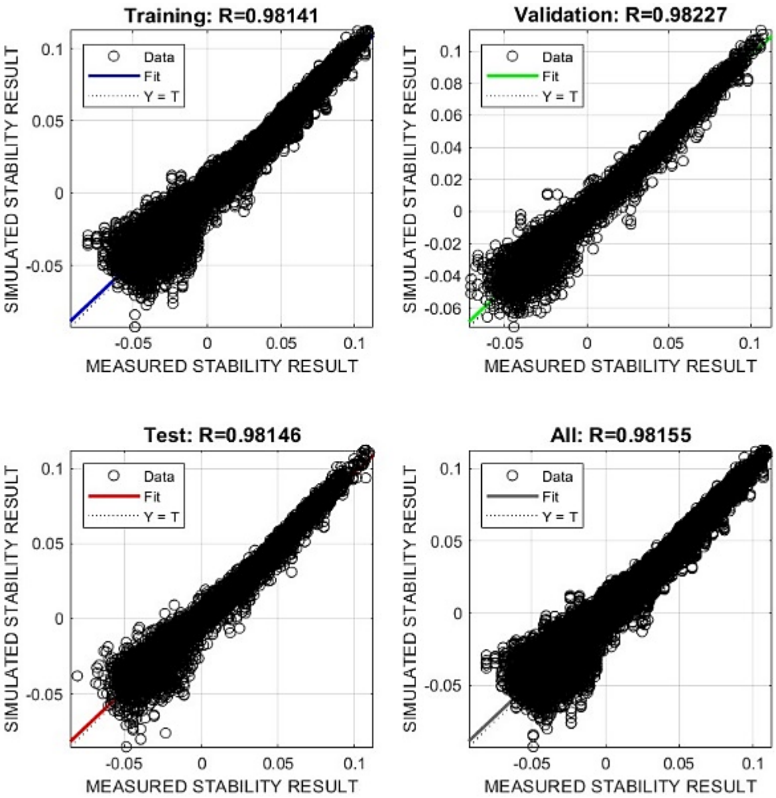

Figure 2. Performance of the neuromodel for stability assessment

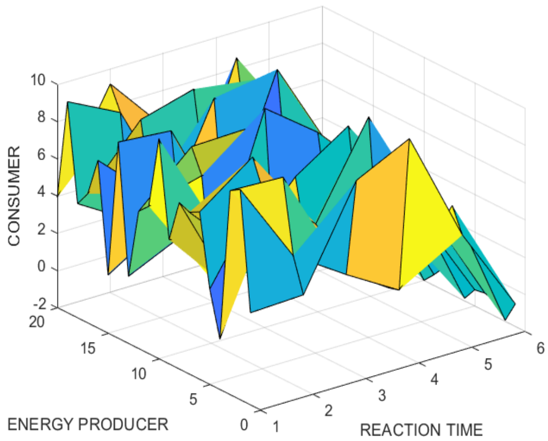

Figure 3. Stability analysis 1

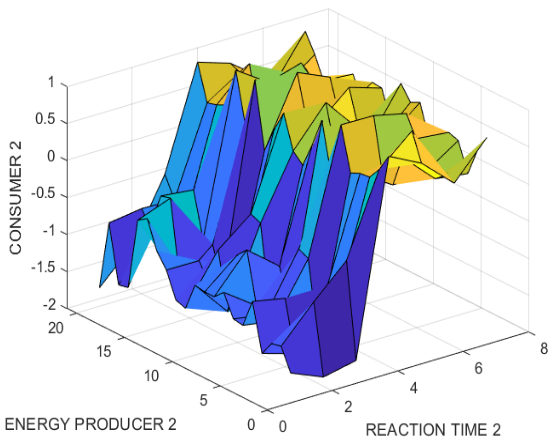

Figure 4. Stability analysis 2

Table 1. Neural network specifications

ANN parameters	Description/Value
Type of transfer function (hidden layer)	tanh
Type of transfer function (output layer)	Sigmoid
Weight update mechanism	A Fletcher-Reeves conjugate gradient algorithm
Total number of neurons	40
Total number of weight elements	60
Maximum epochs	600

The maximum number of epochs sets an upper limit on the number of times the total training data is fed to the network during the training phase. Training the network for a fixed number of epochs helps control the duration of the training process and avoids overfitting. If the training performance plateaus before reaching the maximum epochs, early stopping techniques can be employed to halt training prematurely, thereby preventing unnecessary iterations and saving computational resources. Overall, the chosen ANN parameters reveal a well-configured neural network for a binary classification task. However, it's important to note that achieving optimal performance often involves experimenting with different architectures, hyperparameters, and evaluation metrics specific to the dataset and problem at hand. The provided ANN parameters serve as a starting point for training a model and can be further refined and optimized through iterative experimentation and fine-tuning.

In Table 2, a comparison is made between the performance of the Fletcher-Reeves conjugate gradient algorithm and other types of neural network algorithms in training the network under similar conditions. These include the gradient descent algorithm, the Levenberg-Marquardt algorithm, and the layer sensitivity-based ANN for the training, validation and testing. The satisfactory performance of the algorithms deployed for training the neural network in this work shows the applicability of neural network in evaluating and predicting the stability of smart grid systems. This is in agreement with the growing list of applications of other softcomputing techniques as reported in [18]–[27].

Table 2. Outlook of the network performances

Network	Training		Testing		
	Training VAF	Validation VAF	CMD	VAF	RMSE
FRCG_ANN	98.77	97.83	0.9866	96.26	3.57
GDA_ANN	94.89	95.44	0.9652	95.12	7.03
LM_ANN	96.55	96.62	0.9839	93.57	4.10
LSB_ANN	97.07	97.87	0.9822	95.46	4.97

4. CONCLUSION

The Fletcher-Reeves conjugate gradient algorithm-based neuromodel is a promising approach for smart grid stability analysis. The study presented in this paper has shown that this algorithm can be successfully applied to power system stability analysis with high accuracy and efficiency. The use of ANN in analysing power stability, provides a flexible and versatile platform for the analysis and control of power systems, and the Fletcher-Reeves conjugate gradient algorithm is a powerful optimization tool that can be used to improve the training process of these networks. The observations from this work indicate that the proposed neuro model can accurately predict the stability of power systems, based on the input features that were used in the model. This provides a valuable tool for power system operators and planners, who need to make critical decisions about system stability and reliability. Overall, the Fletcher-Reeves conjugate gradient algorithm-based neuromodel posses the capability to reduce error in power system stability assessment, and its application in this field should be further explored and developed.

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