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ELMAN-RECURRENT NEURAL NETWORK FOR LOAD SHEDDING OPTIMIZATION

Widi Aribowo
Department of Electrical Engineering, Faculty of Engineering, Universitas Negeri Surabaya
Jl. Unesa Kampus Ketintang, Surabaya 60231
Email: widiaribowo@unesa.ac.id

Abstract -- *Load shedding plays a key part in the avoidance of the power system outage. The frequency and voltage fluidity leads to the spread of a power system into sub-systems and leads to the outage as well as the severe breakdown of the system utility. In recent years, Neural networks have been very victorious in several signal processing and control applications. Recurrent Neural networks are capable of handling complex and non-linear problems. This paper provides an algorithm for load shedding using ELMAN Recurrent Neural Networks (RNN). Elman has proposed a partially RNN, where the feedforward connections are modifiable and the recurrent connections are fixed. The research is implemented in MATLAB and the performance is tested with a 6 bus system. The results are compared with the Genetic Algorithm (GA), Combining Genetic Algorithm with Feed Forward Neural Network (hybrid) and RNN. The proposed method is capable of assigning load releases needed and more efficient than other methods.*

Keywords: *Load shedding; Power stability; Genetic Algorithm; Recurrent neural networks; Elman network*

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INTRODUCTION

Power systems are complex multi-component dynamic systems in which the system characteristics fluctuate with varying loads and varying generation schedules [1]. Large disorders can cause system and voltage instability. Frequency instability is like a decrease in drastic frequency can cause the system to experience total blackouts. One of the strategies to anticipate possibilities of the drastic decrease in frequency is released some of the burden borne by the system. After some loads are released, loads are borne by plants that are still operating will decreases, and frequency will be able to return to normal condition immediately after a balance occurs between generation and loading. Release the load must be carried out immediately at the time of frequency the system began to decline dramatically. If there is a disturbance in the system cause the available power cannot serving loads, for example, caused by existence generating unit that trips, so to prevent collapse occurs, the system needs to do load Shedding

Maintaining the power system frequency within the permissible limits is an important control task, which in normal conditions is carried out using load frequency control [2]. However, when a sudden power deficit occurs as a result of outage of large generating units or islanding of some parts of power system, even if the existing generating units have enough spinning reserve to supply the demand, their response is not rapid enough to stop the frequency excursion and prevent the operation of generating units' protective relays. The condition may lead to an outage of some of the generating units. Consequently, the outage of a generating unit can worsen the situation and decrease the frequency to a lower level; therefore, the relays of other generating units might trip and lead to power system blackout [3][4].

The process of releasing several loads with a degrade priority is to maintain the stability and reliability of the existing system. Load shedding schemes are needed to maintain power system stability. It is a common habit for electric companies to run loads shedding procedure with adjusting under-frequency relays to decide the predestinated load in various shedding tread when the frequency crashes fall from setting values. The transient stability explores all the probability the problem of the external equipment power system has to be carried out to obtain an expeditious load shedding procedure

Some of the latest methods have been applied to the issue of load release with the hope of obtaining efficient load release. The situation is to maintain a steady state of the power system. A computationally easy algorithm has been progressed. Arya et al. have a novel method based on the sensitivities of the minimum eigenvalue of load flow Jacobian [5]. Arya et al. have differential evolution (DE methods for load shedding stress stability considerations [6]. Yan Xu et al. have a reserved approach using Parallel-Differential Evolution (P-DE) to optimal load shedding for avoiding voltage collapse [7]. Hamid and Musirin have a fuzzy logic method as a mastermind that is recommended an algorithm to uncover the suitable load buses for the goal of load shedding reckoning multi-contingencies [8]. Hong et al. have Load Shedding considering a fuzzy load [9]. Rao et al. have proposed a Genetic algorithm method based on Time priority for optimizing load shedding [10]. Tang et al. have method Adaptive load shedding based on combined frequency and voltage stability [11].

The recurrent neural network method has been applied to various problems in recent years. The technique can be split into two primary categories: full and partially one. Recurrent neural networks were humbly identified in the late 1980s to learn character sequences. Various studies have developed this method.

This study presents a recurrent neural network called an Elman network. The Elman network is called a simple recurrent network (SRN) because it is similar to a fully connected network, but the number and complexity of interconnections are lower than in an RNN [12] [13]. The advantage of RNN is a Neural Network with a feedback facility to its neurons and other neurons. The information flow from input has direction plural (multidirectional). The RNN output does not only depend on the current input but also depends on the input conditions for the past. This condition is intended to accommodate past events included in the computational process and is important for a quite complicated problem and the response of the NN output is related to time variation (time-varying). RNN has a sensitivity to time with memory conditions past

This research will present optimization load shedding using the Recurrent Neural Network (RNN). The results compared with GA and Hybrid methods from previous studies by [14]. The hybrid method by [14] is a combined Genetic Algorithm (GA) and Neural Network (NN). The neural network by [14] was used Feed Forward Neural Network (FFNN).

METHOD

An Elman RNN is a network with an initial configuration based on a regular feedforward neural network. As is well-known, in an FFNN, the information moves in only one direction, forward, from the input nodes, through the hidden nodes, and to the output nodes without cycles or loops. The main difference between the FFNN and the Elman network, because the latter has a layer called the context layer. The neurons in the context layer, called context neurons, hold a copy of the outputs that are given by the neurons of the hidden layer to the output layer. It means that in the following computing step, information that was given as an output by the hidden layer is used as new input information for this layer.

The condition is intended to accommodate past events included in the computing process. This is important for fairly complex problems, and NN output responses are related to time-varying so that NN has a time sensitivity with past conditions memory. The Structure of Recurrent Neural Network shown in Figure 1. The j and k signs present from j and k neurons, each neuron from the input corresponds to weight W_{ji}. The Layers 1 output matches the W_{ji}. Whereas O_j is related to W_{kj}.

Layer 1

$$P_j(t) = \sum_{i=1}^{j} I_j \cdot W_{ji} + b_i + \sum_{i=1}^{j} O_i \cdot W_{ji} \tag{1}$$

$$O_j(t) = O_j(t-1) \tag{2}$$

$$O_j(t) = f(P_j(t)) = \frac{e^{P_j(t)} - e^{-P_j(t)}}{e^{P_j(t)} + e^{-P_j(t)}} \tag{3}$$

Layer 2

$$P_k(t) = \sum_{i=1}^{k} O_j(t) \cdot W_{kj} + b_i \tag{4}$$

$$O_k(t) = P_k(t) \tag{5}$$

The error function is defined:

$$E(t) = \frac{1}{2} \sum_{k=1}^{n} (x_k(t) - O_k(t))^2 \tag{6}$$

Which $x_k(t)$ is output system and n is output neuron. Weight W_{ji} and weight W_{kj} can be adjusted by using the steepest descent algorithm.

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji}(t) = W_{ji}(t) - \eta_1 \frac{\partial E(t)}{\partial W_{ji}(t)} \tag{7}$$

$$W_{kj}(t+1) = W_{kj}(t) + \Delta W_{kj}(t) = W_{kj}(t) - \eta_1 \frac{\partial E(t)}{\partial W_{kj}(t)} \tag{8}$$

$\acute{\eta}_1$is learning rate from RNN. Gradient error E (t) of weight W_{ji} and weight W_{kj} are:

$$\frac{\partial E(t)}{\partial W_{ji}(t)} = -(x_k(t) - O_k(t)) \cdot O_k(t) \tag{9}$$

$$\frac{\partial E(t)}{\partial W_{ji}(t)} = -\sum [x_k(t) - O_k(t) \cdot W_{kj}(t) \cdot (1 - O_j(t)^2) \cdot O_j(t-1)] \tag{10}$$

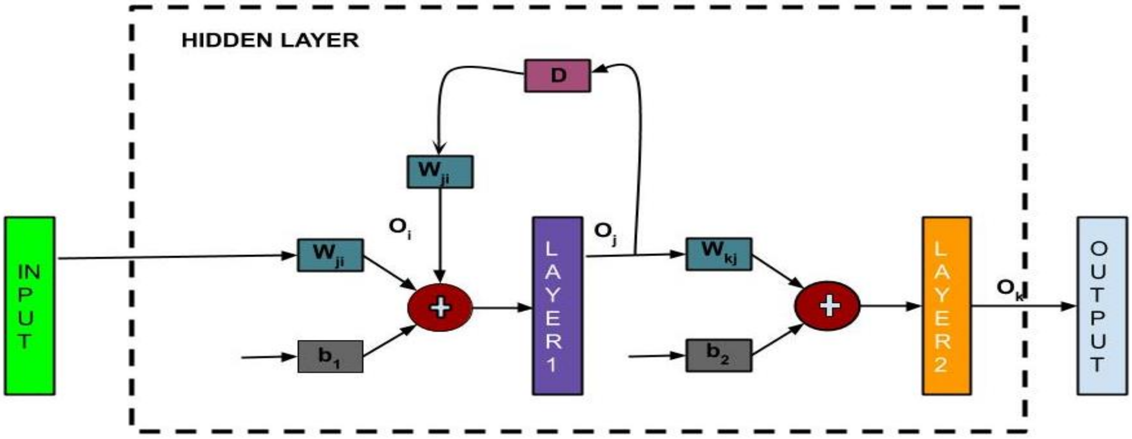

Figure 1. Schematic Representation of The Recurrent Neural Network [15]

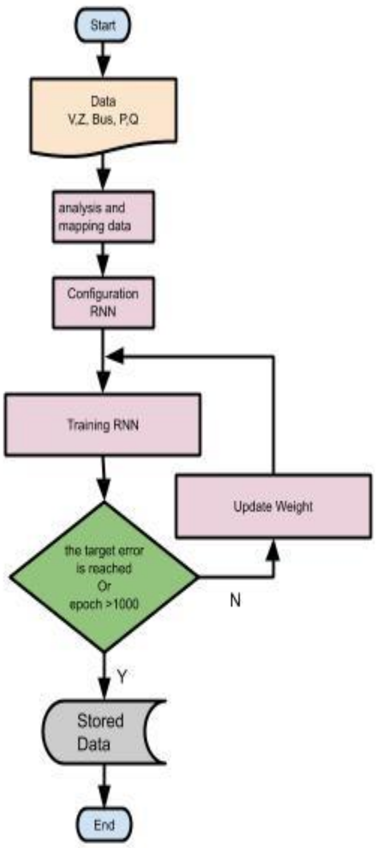

Figure 2. Flowchart of RNN for the proposed approach.

This study adjusted quantitative methods with historical data to estimate control values. Processing and analyzing data are taken from time to time. Data is taken and analyzed in sequence. The step of this research is explained in Figure 2.

Related Work

A previous study conducted by [13], the load shedding tested with 6 bus systems was obtained using a GA and Hybrid method. The result can be seen in Table 1, Table 2 and Table 3.

The performance of the proposed hybrid method is compared with the base case and GA results. The performance comparison of six bus systems, the minimum eigenvalue and the sensitivity of eigenvalues are compared.

Table 1. Comparison Methods in Minimum Eigenvalue and sensitivity of minimum eigenvalue of the six-bus system [14]

Bus number	The minimum eigenvalue for load bus at normal load	Sensitivity eigenvalue calculated by GA	Sensitivity eigenvalue calculated by Hybrid
3	0.1849	0.2221	0.2138
4	0.0041	0.0075	0.0069
5	0.1441	0.1698	0.0946
6	0.0741	0.0145	0.0723

Table 2. Comparison Methods in Bus voltage of 6-bus system before and after load shed [14]

Bus number	Normal bus	Voltage after generation change (pu)	Voltage after load shed by GA (pu)	Voltage after load shed by a hybrid method (pu)
1	1.087	1.0870	1.0870	1.0870
2	1.608	1.6600	1.6600	1.6600
3	0.812	0.9331	0.9659	0.9936
4	0.835	0.9585	0.9933	1.0241
5	0.805	1.1169	1.1100	1.1422
6	0.799	0.9400	0.9658	0.9970

Table 3. Comparison Methods in Real power of load before and after load shed for IEEE 6 bus system [14]

Bus number	Normal load (pu)	Load shed by GA (pu)	Load shed by hybrid method (pu)
3	0.897	0.8291	0.8321
4	0	0	0
5	0.555	0.5334	0.5398
6	0.793	0.6336	0.6473

RESULTS AND DISCUSSION

The bus and line data of 6 bus systems are referred to in [9]. The system consists of 2 generator buses and four load buses. The buses 3, 4, 5 and 6 are load buses. Data research was used to conduct NN training. Table 4 is the parameter used using RNN. Figure 3 is RNN training using data six bus system

Table 4. Parameter proposed Recurrent Neural Network

Syntax	Parameter
Number of Hidden Layer	5
Transfer Function for Hidden Layer	Hyperbolic Tangent Sigmoid Transfer Function (tansig)
Transfer Function for Output Layer	Linear Transfer Function (purelin)
Weight /Bias Function	Gradient Descent with Momentum (learngdm)
Epoch	1000
Learning Rate	0.1
Momentum	0.2

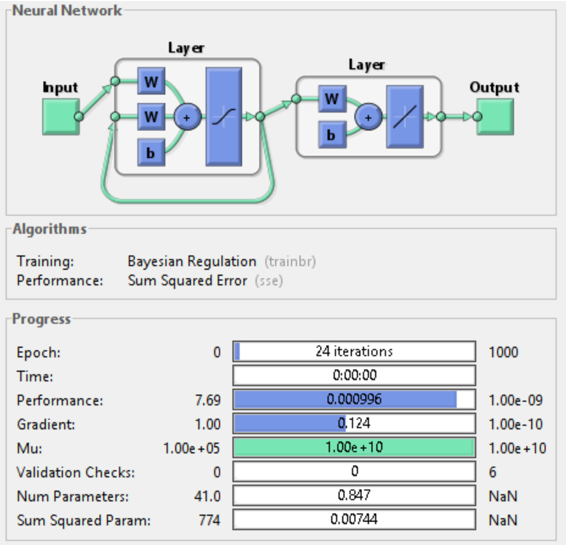

Figure 3. Plot Training of RNN

The neural network training has five hidden layers, and the Hyperbolic Tangent Sigmoid function transfer. The learning rate is used 0.1 with 0.2 momentum. Figure 3 shows the results that completed in 24 iterations of the 1000 epoch limit. The training performance results are 0.000996 with a 0.124 gradient.

The proposed RNN algorithm has stable voltage stability and a minimum load shedding value. Table 5 shows the eigenvalue sensitivity ratio of each method. The Sensitivity eigenvalue can be seen in Figure 4. Next, the results are measured using Mean absolute percentage error (MAPE). The MAPE is a measure of how accurate a forecast system. Table 6 shows a comparison of calculations from MAPE and is illustrated in Figure 5.

Table 5. Sensitivity eigenvalue calculated for IEEE 6 bus system.

Bus number	The minimum eigenvalue for load bus at normal load	Sensitivity eigenvalue calculated by GA	Sensitivity eigenvalue calculated by Hybrid	Sensitivity eigenvalue calculated by RNN
3	0.1849	0.2221	0.2138	0.1831
4	0.0041	0.0075	0.0069	0.0041
5	0.1441	0.1698	0.0946	0.0829
6	0.0741	0.0145	0.0723	0.0267

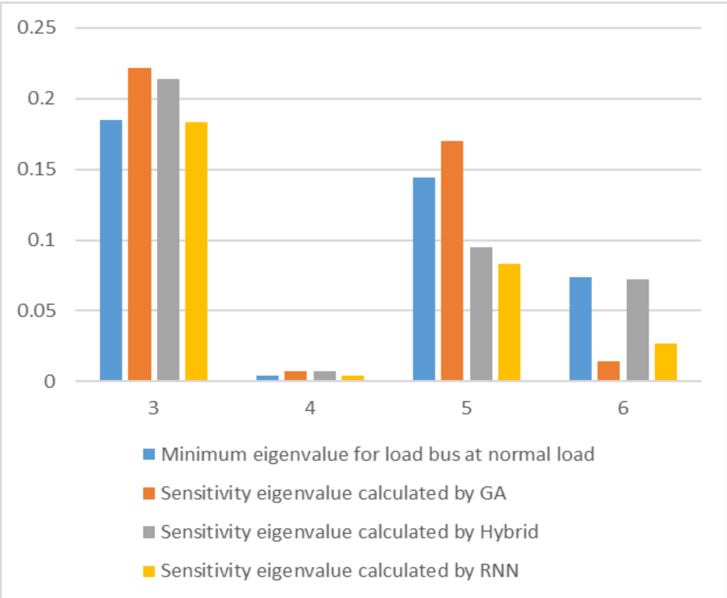

Figure 4. Data of Sensitivity eigenvalue

Table 6. MAPE Of Sensitivity eigenvalue calculated for the IEEE 6 bus system.

Bus number	MAPE Hybrid	MAPE GA	MAPE RNN
3	15.63007031	20.11898323	0.973499189
4	68.29268293	82.92682927	0
5	34.35114504	17.83483692	42.47050659
6	2.429149798	80.43184885	63.96761134

Table 7. Data of Load Shed for the IEEE 6 bus system.

Bus number	Normal load (pu)	Load shed by GA (pu)	Load shed by a hybrid method (pu)	Load shed by RNN method (pu)
3	0.897	0.8291	0.8321	0.897
4	0	0	0	0.0037
5	0.555	0.5334	0.5398	0.5695
6	0.793	0.6336	0.6473	0.8003

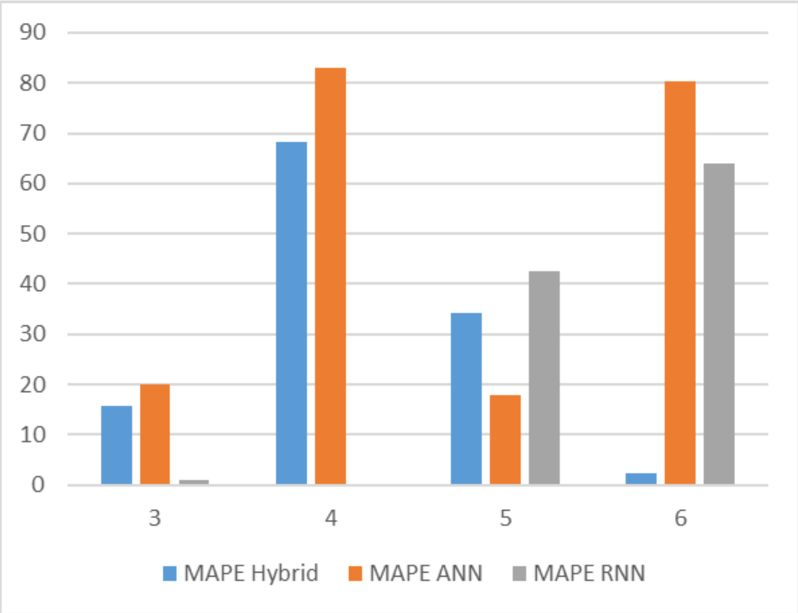

Figure 5. Graph MAPE Of Sensitivity eigenvalue calculated for the IEEE 6 bus system

Table 8. Data of Voltage after generation change for IEEE 6 bus system

Bus number	Normal bus	Voltage after generation change (pu)	Voltage after load shed by GA (pu)	Voltage after load shed by a hybrid method (pu)	Voltage after load shed by RNN method (pu)
1	1.087	1.087	1.087	1.087	1.087
2	1.68	1.66	1.66	1.66	1.6659
3	0.812	0.9331	0.9659	0.9936	0.9252
4	0.835	0.9585	0.9933	1.0241	0.9519
5	0.805	1.1169	1.11	1.1422	1.1183
6	0.799	0.94	0.9658	0.997	0.9324

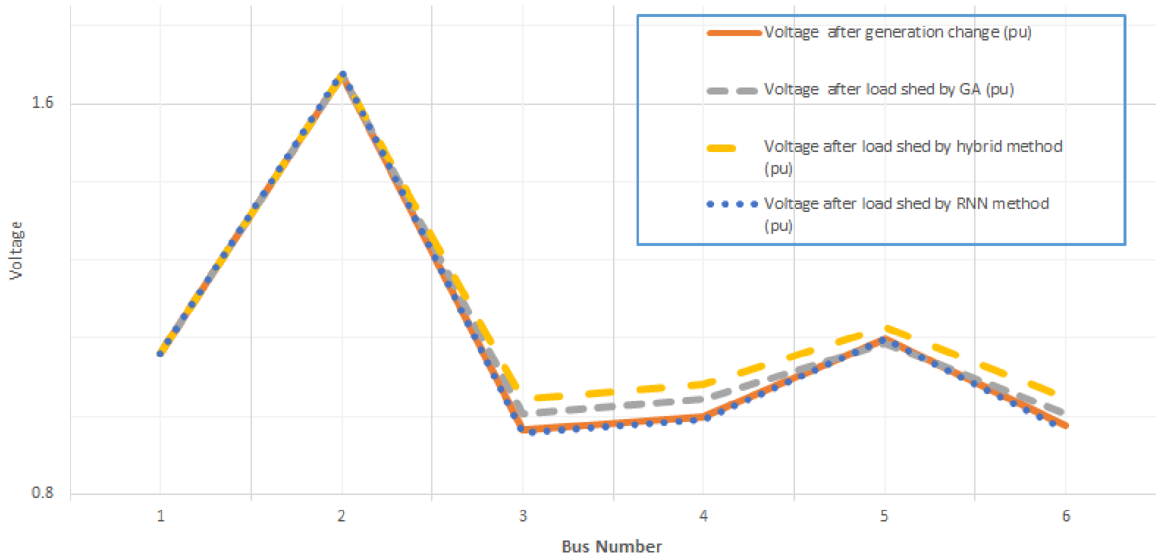

Figure 6. Graph Comparison of Data of Voltage after generation change for IEEE 6 bus system

Table 7 shows calculations of bus voltage, real power, and load values. The results on the 6 bus system show that the RNN algorithm is superior to voltage stability and the lowest load shedding value. Figure 6 shows a comparison before and after load shedding. Generally, the proposed method has a better average than other methods.

CONCLUSION

The performance of the proposed method is measured and applied using 6 bus systems. The proposed RNN method is compared to GA and the Hybrid Method that has been done before that is used as a combination of backpropagations neural network and GA. Data obtained the average error value of load shedding using the RNN method is 1.76%. The result is better than other methods. There is 10.55% using the hybrid method and 11.99% using the GA method.

The average error value of the voltage obtained using the RNN method is 0.47%. This result is better than other methods. There are 3,609% using the hybrid method and 1,751% using the GA method. A comparison in this study shows that the proposed RNN has superiority at minimum voltage deviations and load shedding.

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