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Research article

An effective Load shedding technique for micro-grids using artificial neural network and adaptive neuro-fuzzy inference system

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Abstract: In recent years, the use of renewable energy sources in micro-grids has become an effective means of power decentralization especially in remote areas where the extension of the main power grid is an impediment. Despite the huge deposit of natural resources in Africa, the continent still remains in energy poverty. Majority of the African countries could not meet the electricity demand of their people. Therefore, the power system is prone to frequent black out as a result of either excess load to the system or generation failure. The imbalance of power generation and load demand has been a major factor in maintaining the stability of the power systems and is usually responsible for the under frequency and under voltage in power systems. Currently, load shedding is the most widely used method to balance between load and demand in order to prevent the system from collapsing. But the conventional method of under frequency or under voltage load shedding faces many challenges and may not perform as expected. This may lead to over shedding or under shedding, causing system blackout or equipment damage. To prevent system cascade or equipment damage, appropriate amount of load must be intentionally and automatically curtailed during instability. In this paper, an effective load shedding technique for micro-grids using artificial neural network and adaptive neuro-fuzzy inference system is proposed. The combined techniques take into account the actual system state and the exact amount of load needs to be curtailed at a faster rate as compared to the conventional method. Also, this method is able to carry out optimal load shedding for any input range other than the trained data. Simulation results obtained from this work, corroborate the merit of this algorithm.

Keywords: micro-grids; energy management; distributed generation; back propagation artificial neural network; stochastic gradient descent; adaptive neuro-fuzzy inference system

1. Introduction

In an electricity grid, electricity consumption and production must balance at all times, any insignificant imbalance could cause grid instability or severe voltage fluctuations, and causes failures within the grid. Total generation capacity is therefore sized to correspond to the total peak demand with some margin of error and allowance for contingencies (such as plants being off-line during peak demand).

However, electrical generation and transmission system may not always meet peak demand requirements- the greatest amount of electricity required by all utility customers within a given region. In this situation, overall demand must be lowered, either by turning off services of some devices or cutting back the supply voltage (brownouts) in order to prevent uncontrolled service disruption such as power outages (widespread blackouts) or equipment damage. Utilities may imposed load shedding on service areas via rolling blackouts or by agreements with specific high-use industrial customers to turn off their equipment at times of system wide peak demand.

Rolling blackouts are the result of load shedding. Load shedding could be defined as the way that the electrical grid is design to 'shed' some of the electrical load if the demand becomes too great by shutting off power to particular geographical areas. In doing so, only certain parts of the grid are shut off as needed, in order to prevent damage to the entire electrical system.

During an emergency situation, system operators are required to carry out load shedding decisions based on system security concerns, such as voltage, current, power and frequency constraints and maintain system stability. Since the distribution system is the final link of the interconnection between power systems and consumers, when ever it's necessity to reduce the load in order to guarantee the safety of the system, usually the curtailment occurs in the distribution system.

Capacity deficiency is as a result of generation failure or transmission failure, and under frequency is as a result of sudden increase of unexpected load. These scenarios could lead to a cascade of the power system. Different types of load shedding techniques for controlling and monitoring of frequency and voltage in power systems are available as illustrated in Figure 1. However, it is some how difficult to determine the amount of load shedding with some of these techniques in order to improve frequency stability in micro-grids MGs considering the uncertainty of renewable sources. Researchers nowadays focus more on the development of computational intelligence under under frequency load shedding scheme because of is capabilities to evaluate optimal load shedding and solve the non-linear and multi-target issues in the power system that is incapable to be solved by traditional under frequency load shedding or even adaptive under frequency load shedding schemes [1]. Various applications of some computational intelligence techniques for load shedding in power systems are presented in [2].

A number of successful researches have been carried out on load shedding. A novel multi-objective under frequency load shedding in micro-grid using genetic algorithm is presented in [3]. A robust under voltage load shedding scheme against voltage stability [4]. Optimal design of adaptive under frequency load shedding using artificial neural networks in isolated power system [5]. Optimization techniques for planning automatic under frequency load shedding in new Zealand's power system [6]. Suwanasri [7] proposed a load shedding control strategy in an electric distribution system. Moazzami [8] proposed a new optimal unified power flow controller placement and load shedding coordination approach using the hybrid imperialist competitive algorithm-pattern search method for voltage collapse prevention in power system. Aponte [9] proposed time optimal load shedding for distributed power system, his objectives were to yield optimal load shedding as well as the load shedding amount. However, most of these techniques could solve the load shedding problem but with some drawbacks associated with them. Some under frequency load shedding technique do not take into account the presence of high renewables which may account to either over shedding or under shedding. Also, although adaptive and genetic algorithm (GA) techniques enhance the reliability of convectional load shedding, these techniques also suffer from un-optimum load shedding due to variations in df/dt behaviour, and large computational time and slower response especially with GA. [10] talked about improved load shedding scheme considering distributed generation. He compared different under frequency load shedding schemes considering the amount of distributed generators (DGs) connected to feeders in real-time. An optimal load shedding approach for distribution network with DGs considering capacity deficiency modelling of bulked power supply [11,12] proposed an adaptive load shedding scheme for frequency stability enhancement in micro-grids. Optimal scheduling of electrical power in energy-deficient scenarios using artificial neural network and bootstrap aggregating is proposed in [13]. The author implements the bagging algorithm to reduce error in load shedding. [14] proposed enhancement of power system stability by optimal adaptive under frequency load shedding using artificial neural network. A new load shedding approach for micro-grids in the presence of wind turbines is proposed in [15,16] presents a coordinated control of smart micro-grid during and after islanding operation to prevent load shedding using energy storage system. A new under frequency load shedding technique based on combination of fixed and random priority of loads for smart grid applications is presented in [17]. However, the above techniques could find it difficult when the data change other than the known data.

Therefore, this paper is proposing an effective load shedding technique for micro-grids, using a combination of two algorithms, artificial neural network and adaptive neuro-fuzzy inference system ($ANFIS$). Adaptive neuro-fuzzy inference system is a combination of artificial neural network and fuzzy logic system that has the ability of coping with changed data other than the known data. Simulations were carried out for both artificial network and adaptive neuro-fuzzy inference system. Results obtained proved the effectiveness of the proposed technique. Stochastic gradient descent (SGD), an efficient model which makes neural network more practical is implemented in this work.

The rest of this paper is structured in the following manner. The proposed algorithm is analysed in section 2. Section 3 describes the processes of the artificial neural network and adaptive neuro-fuzzy inference system algorithms. Section analyses the convectional load shedding method. Simulation results are explained in section 5. Finally, section 6 presents the conclusion.

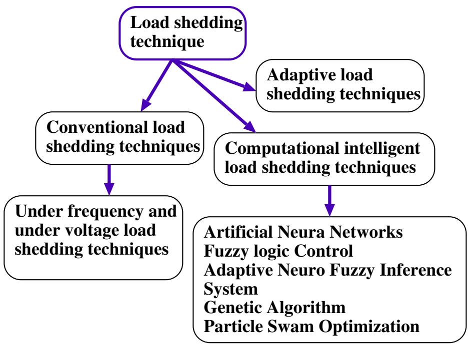

Figure 1. Types of load shedding.

2. Proposed Algorithm for the Micro-Grid

The increase in electricity demand, and the continually growing penetration of renewable energy resources, such as wind and solar photovoltaic, is revealing a number of drawbacks in the existing power system operational procedures that may limit the integration of these resources. As modern, small scaled counterparts of the bulk power grids, micro-grids are promising to achieve the goals of improving efficiency, sustainability, security, and reliability of future electricity networks. A micro-grid is a discrete energy system consisting of distributed energy sources(including demand management, storage and generation) and loads capable of operating in parallel with, or independently from, the main power grid. The inspiration behind micro-grids is to bring power generation closer to the point where it is consumed. In this way, distributed energy resources ($DERs$) and industrial, commercial, or residential electricity end-users are deployed across a limited geographic area, thereby incurring fewer thermal losses while bypassing other limitations imposed by the congested transmission networks.

The Micro-grid (MG) in question comprises of Wind turbine, Photovoltaic cells, Diesel engine, and Battery for energy storage system. The micro-grid operates in three modes i.e grid-following (grid-connected), grid-forming (autonomous mode), and transition between the two modes (resynchronization). In autonomous mode, if the demand is less than generated power, generation from the distributed energy sources will be decreased to maintain power balance and or used by the energy storage system (ESS) to store the excess energy. If demand exceeds generation, the stored energy is used to supplement for the deficit. In a situation where in the generated power including the stored energy from the battery could not meet demand, load shedding must be applied to prevent a system cascade.

The micro-grid consists of energy management unit (EMU), which is a local controller and it receives information from the various generation agents. The energy management unit liaise with the energy management central controller ($EMCC$), which determines the set point of the micro-grid. The energy management unit lessen the high computational and information handling by the energy management central controller, and also, in the event of any breakdown by the energy management central controller, it will not halt the operation of the micro-grid. There are three types of customers that are connected to the micro-grid, which include domestic, commercial and industrial customers. It also consists of three types of loads such as vital, semi-vital, and non-vital. In grid-connected mode, any power mismatch between load demand and generation is compensated by the main grid. In a situation where in the power mismatch cannot be compensated by the main grid, load shedding is implemented by the protection relays of the main power system. During autonomous operation, the isolation of the distribution system from the main grid causes sudden power imbalance between total generation and load demands [18]. A large excess of load over local generation in the islanded system could result in a rapid frequency drop [19]. For such a large imbalance, a speed controller (governor) of the synchronous generator would not be able to stabilize the response. The only way to stabilize the frequency and voltage response to its nominal value is to reject several loads through load shedding. Therefore, our main concern is during autonomous operation, through which the frequency could go beyond its allowable operating limit if the power mismatch is not adequately replenished. If the micro-grid is forced to separate from the main grid, it should employ its own load shedding scheme to maintain the stability of the frequency in isolated mode. The proposed micro-grid of this work as in

[16] is illustrated in Figure 2.

Back propagation artificial neural network($BPANN$) is used in this work. Artificial neural network is a biological inspirational structure that is loosely modelled after the neuronal structure of the mammalian cerebral cortex but on much smaller scales. A large neural network or commonly called Artificial Neural Network (ANN) might have hundreds or thousands of processor units, whereas a mammalian brain has billions of neurons with a corresponding increase in magnitude of their overall interaction and emergent behaviour. Although artificial neural networks are generally not complex as biological neural networks, some researchers have accurately simulated the function of the retina and modelled the eye rather well. The information processing of artificial neural networks resembled to that of biological neural systems.

Artificial neural network is an interconnected system which is able to solve highly non-linear functions in a short time. Artificial neural network is typically organized in layers. These layers are made up of a number of interconnected nodes which contain an activation function. Patterns are presented to the network via the input layer which communicates to one or more hidden layers where the actual processing is done via a system of weighted connections. The hidden layers then link to an output layer where the answer is output. The structure of the neural network is depicted in Figure 3.

Suitable data are required to extract enough information between the input and output to train an Artificial neural network. The weights of inputs ($x_1, x_2....x_n$) are determined by $w_{1j}, w_{2j}...w_{nj}$ which determine their strength. The inputs and their respective weights are fed into the transfer function. An activation function added to the transfer function will decide whether the signal is generated or not, by comparing to some threshold value. The transfer function determines the threshold value, and the error is represented as the difference between the artificial neural network output and the target. The error is propagated backward to adjust the weights of input so that desired output matches the neural networks' output. Figure 4. shows the data propagation from input layer to output layer.

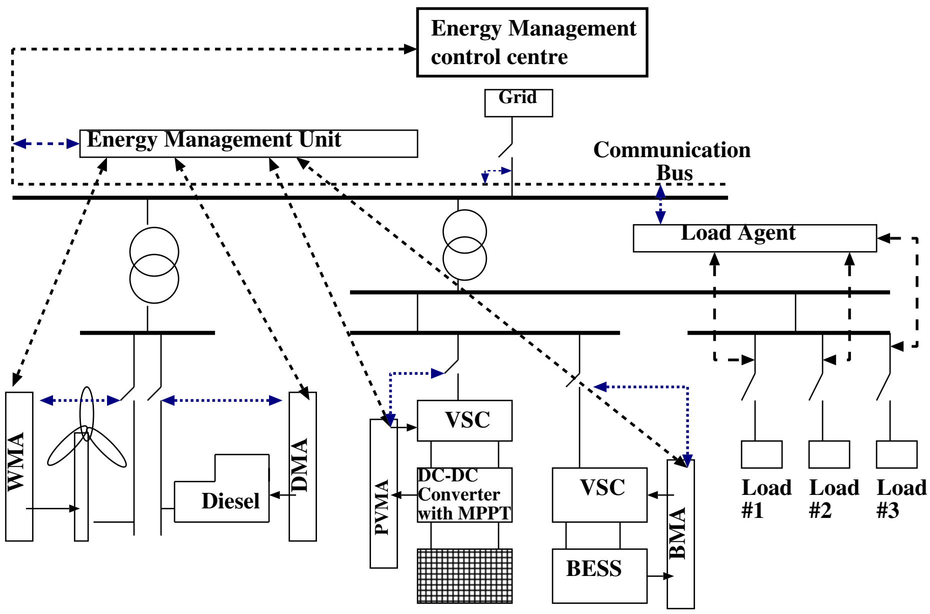

Figure 2. Proposed micro-grid structure.

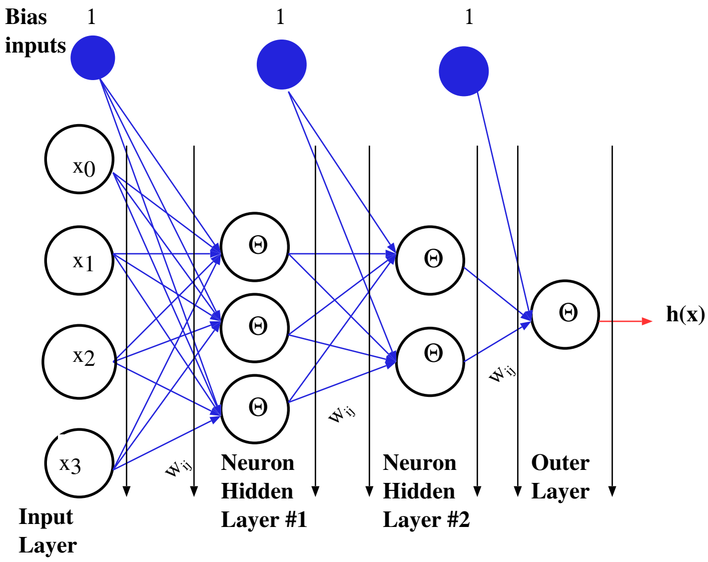

Figure 3. Structure of the neural network.

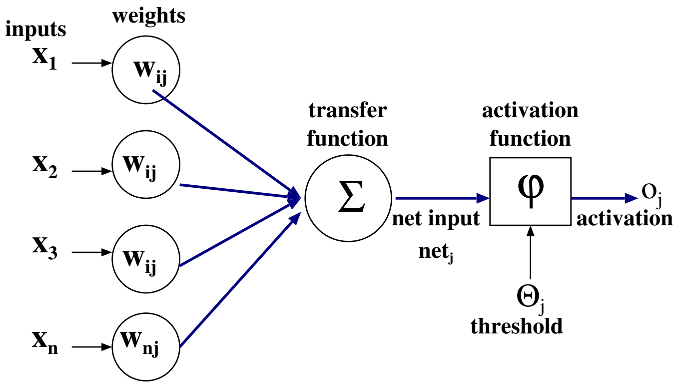

Figure 4. Data propagation in neural network.

3. Stochastic Gradient Descent in Back Propagation Artificial Neural Network

The efficient model that goes with Neural Network, which makes it more practical is the stochastic gradient descent (SGD). The process of stochastic gradient descent is to minimize the error function, *ie* the neural network requires to compute the error derivative of the weight $E(W)$. In stochastic gradient descent, the weights determine the hypothesis which is the output of the network, and in order to compute the error, we need to evaluate the hypothesis at every point in our sample. Here we minimize the error $e(w)$ as illustrated below.

Although there are many different kinds of learning rules used by neural networks, the delta rule is often utilized by the most common class of artificial neural network such as the back propagation neural network ($BPNN$). Back propagation is an abbreviation for the backwards propagation of error. With delta rule, learning is a supervised process that occurs with each circle or epoch (*i.e* each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weights adjustments. More simply, when a neural network is initially presented with a pattern, it makes a random guess as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights. The process of delta rule back propagation neural network is illustrated in Figure 5. The error $e(w)$ is minimized as illustrated below.

$$e(h(x_n), y_n) = e(w). \tag{1}$$

where y_n is the target value and $(h(x_n)$ is the value of the output. To minimize the error we need the gradient $\nabla e(w)$. Therefore we used the partial derivative of the error and the weight.

$$\nabla\ e(w) : \frac{\partial e(w)}{\partial w^l_{ij}} fori, j, l \tag{2}$$

Computing (2), we can evaluate it one by one. That is, every single weight in the network can evaluate it error. But for efficient computation, we apply chain rule. Therefore,

$$\frac{\partial e(w)}{\partial w^l_{ij}} = \frac{\partial e(w)}{\partial S^l j} * \frac{\partial S^l j}{\partial w^l ij} \tag{3}$$

$$\frac{\partial S^l_j}{\partial w^l ij} = x^l_i \tag{4}$$

This is the output. For $i = 1$ and $l = L$, the output becomes

$$x^L_1 = \Theta\left(S^L_1\right) \tag{5}$$

where S^L_1 is the signal which is passed through a soft threshold value Θ to get the output. Differentiating with respect to Θ

$$\Theta'\left(S^L_1\right) = 1 - \Theta^2\left(S^L_1\right) \tag{6}$$

Since we do not have the second term, we represent it to be delta.

$$\frac{\partial e(w)}{\partial S^l_j} = \delta^l_j \tag{7}$$

This is delta for the final layer which we need for the computation. The reason for finding delta for the final layer is that, if we know delta later, we would be able to find delta earlier. This means we are propagating backwards hence the name back propagation. Therefore, we have

$$\delta^L_1 = \frac{\partial e(w)}{\partial S^L_1} \tag{8}$$

$$e(w) = e\left(x^L_1, y_n\right) \tag{9}$$

where y_n is the target value. Now propagating δ^l_i to get the otherδ^{l-1}_i

$$\delta^{l-1}_i = \frac{\partial e(w)}{\partial S^{l-1}_i} = \sum_{j=1}^{d^l} \frac{\partial e(w)}{\partial S^l_i} \times \frac{\partial S^l_i}{\partial x^{l-1}_i} \times \frac{\partial x^{l-1}_i}{\partial S^{l-1}_i} = \sum_{j=1}^{d^l} \delta^l_j \times w^l_{ij} \times \Theta'\left(S^{l-1}_i\right) \tag{10}$$

$$\delta_i^{l-1} = \left(1 - \left(x^{l-1}\right)^2 \sum_{j=1}^{d^l} w_{ij}^l \delta_j^l\right) \tag{11}$$

This method is used because the convergence rate is faster for feed forward networks. The stochastic gradient descent is used to reduce the mean square error (MSE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e(w)^2 = \frac{1}{n}\sum_{i=1}^{n}\left(x_1^L - y_n\right)^2 \tag{12}$$

where n is the number of examples, x_1^L is the value of the output and y_n is the value of the target.

3.1. Algorithm of the backward propagation

1. Initialize all weights w_{ij} at random
2. For $t = 0, 1, 2, ...do$
3. Pick $n\epsilon 1, 2, ...N$
4. Forward compute all x_j^l
5. Backward compute all δ_j^l
6. Update the weights: $w_{ij}^l \leftarrow w_{ij}^l - \eta x_i^{l-1}\delta_j^l$
7. Iterate to the next step until it is time to stop
8. Return the final weight w_{ij}^l

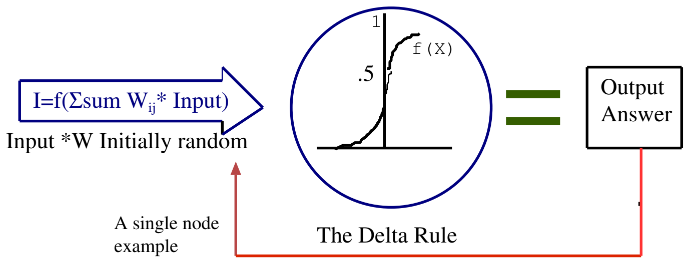

Figure 5. Structure of the delta formation.

3.2. Data set generation

The data involved in the neural network consist of load demand, frequency variation, percentage load shedding, wind speed and solar irradiation. The electricity power system in Sierra Leone consists of two sections.

1. The Electricity generation and Transmission Company (*EGTC*)-which sole responsibility is for the generation and transmission of electricity throughout the country.
2. The Electricity Distribution and Supply Authority (*EDSA*)- this is responsible for the supply, distribution, and retail sale of electricity for the entire country except in areas which the electricity commission has issued a distribution licence to another appropriately qualify entity. Electricity distribution and supply authority purchases electricity from electricity generation and transmission company under a power purchase agreement approved by the commission.

In industrial micro-grids, various operating conditions may lead to severe frequency fluctuations [20]. These conditions may include power plant failure, transmission line failure, transformer failure, and/or sudden increase in load by closing a feeder after the generation sources are almost operating at their maximum peak. If no other particular remedy is thought, these fluctuations may jeopardize the system stability against which load shedding is recognized as an effective countermeasures. In Sierra Leone, the convectional method of load shedding is still being used when ever the frequency or voltage is observed to be moving away from its nominal value. System operators have to open up some feeders in order to restore the system frequency or voltage to its acceptable value. This system is not effective as it mostly result to either over shedding or under shedding, which can cause system instability. However, an efficient power system is expected to have sufficient reserve power capacity, which is actually the opposite for Sierra Leone due to less power production as compare to the demand.

The artificial neural network is designed with four inputs and one output. The inputs include the load demand, frequency change, wind speed, and solar irradiation. The percentage of load shed during each frequency change is the output. The training of the Neural network commences once the input and output are selected, and the weights and bias have been initialized. The Levenberg-Marquardt back propagation neural network algorithm is used in the training of the neural network because of it least error and fast convergence.

The data are divided into three places; 70% is used for training, 15% is used for validation- this will reduce the over fitting, and 15% used for testing- to predict the final output. Sometimes the output of the network may differ from the target after training, especially when data set changes. The stochastic gradient descent is applied in back propagation to minimize the error so that the network output will be very close or equal to the target. Table 1 shows the frequency and percentage load shedding of the proposed network, table 2 illustrate the voltage before and after load shedding, and table 3 shows the load demand and renewable sources data.

3.3. Adaptive neuro-fuzzy inference system

The adaptive neural fuzzy inference system($ANFIS$) is a kind of artificial neural network that is based on Takagi-Sugeno fuzzy inference system in which the parameters associated with specific membership functions are computed using either a back-propagation gradient descent algorithm alone or in combination with a least squares method [21]. The technique was developed in the early $1990s$. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy $IF - THEN$ rules that have learning capability to approximate non-linear functions. Hence, adaptive neuro-fuzzy inference system is considered to be a universal estimator.

Adaptive neuro- fuzzy inference system is used to predict the optimal amount of load shed for any input range other than the trained data set. Fuzzy logic determines the output based on the membership function and the fuzzy rule set. The training and check data set will be used to train the fuzzy system by adjusting the membership function parameters. Thus because of fuzzy system, the use of other sensors is not important [22]. Fuzzy gives the exact amount of load to be shed and the error percentage is very low. The Adaptive neuro-fuzzy inference system architecture with two inputs and one output is illustrated in Figure 6. The output of the *ith* node in layer 1 is denoted as $O_{i,j}(i)$:

Table 1. Frequency and percentage load shedding.

Stage	Frequency(H_Z)	% load shedding
1	49.3	5
2	49.0	10
3	48.8	10
4	48.4	10
5	48.2	10
6	48.0	5
7	47.98	10
8	47.86	10
9	47.74	10
10	47.62	10
11	47.5	10

In layer 1, every node i in this layer is an adaptive node with a node function:

$$O_{1,i} = \mu A_{\text{¢}i}(x), fori = 1, 2 \tag{13}$$

$$O_{1,i} = \mu B_{i-2}(y), fori = 3, 4 \tag{14}$$

Table 2. Voltage before and after load shedding.

Voltage before ($perunit(pu)$)	Voltage after(pu)	Load shed(%)
0.95	0.9587	5
0.943	0.9531	10
0.939	0.9549	15
0.933	0.9558	20
0.927	0.9574	25
0.921	0.9597	30
0.914	0.9622	35
0.903	0.9644	40
0.899	0.96688	45
0.894	0.9730	50
0.883	0.9766	55
0.873	0.9804	60
0.861	0.9833	65
0.850	0.9858	70

Where $xory$ is the input node i and A_i (orB_{1-2} is a linguistic label associated with this node. Therefore $O_{1,i}$ is the membership grade of a fuzzy set (A_1, A_2, B_1, B_2). The membership function for A

can be any appropriate parametrized membership function. Typical membership function is,

$$\mu A(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \tag{15}$$

where a_i, b_i, c_i is the parameter set. Parameter in this layer are referred to as premise parameters.

Table 3. Data for load demand and renewable sources.

Time	Load demand (kW)	Wind speed($knot$)	Solar irradiation(w/m^2)
00:00	4,200	8.09	0
01:00	2,250	7.54	0
02:00	2,050	7.02	0
03:00	1,700	5.93	0
04:00	1,700	5.38	0
05:00	1,700	4.86	0
06:00	2,550	4.32	0
07:00	4,200	4.32	78
08:00	4,625	4.32	130
09:00	4,500	4.32	156
10:00	4,200	4.41	169
11:00	4,200	6.47	208
12:00	4,500	7.02	252
13:00	4,200	7.02	240
14:00	4,200	7.02	195
15:00	4,625	7.02	169
16:00	4,650	7.54	143
17:00	5,900	8.96	104
18:00	6,800	8.96	52
19:00	7,500	8.96	0
20:00	8,400	8.96	0
21:00	8,400	8.96	0
22:00	8,400	8.96	0
23:00	6,800	8.96	0

In layer two, every node in this layer is a fixed node labelled Π, whose output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu A_i(x) * \mu B_i(y), i = 1, 2 \tag{16}$$

Each node represents the fire strength of the rule. Any other $T - norm$ operator that performs fuzzy can be used as the node function in this layer.

In layer three, every node in this layer is a fixed node labelled N. The *ith* node calculates the ratio of the *ith* rulet's firing strength to the sum of all rulet's firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1, 2 \tag{17}$$

The outputs of this layer are called normalized firing strengths.

In layer four, every node i in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w_i} * f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{18}$$

where $\overline{w_i}$ is the normalized firing strength from layer three and p_i, q_i, r_i is the parameter set of this node. These are referred to as consequent parameters.

In layer five, the single node in this layer is a fixed node label sum. This computes the overall output as the summation of all incoming signals.

$$overalloutput = O_{5,1} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{19}$$

Thus, an adaptive network that is functionally equivalent to a Sugeno-fuzzy model has been constructed.

The proposed structure of the adaptive neuro-fuzzy inference system structure in this work is illustrated in Figure 7.

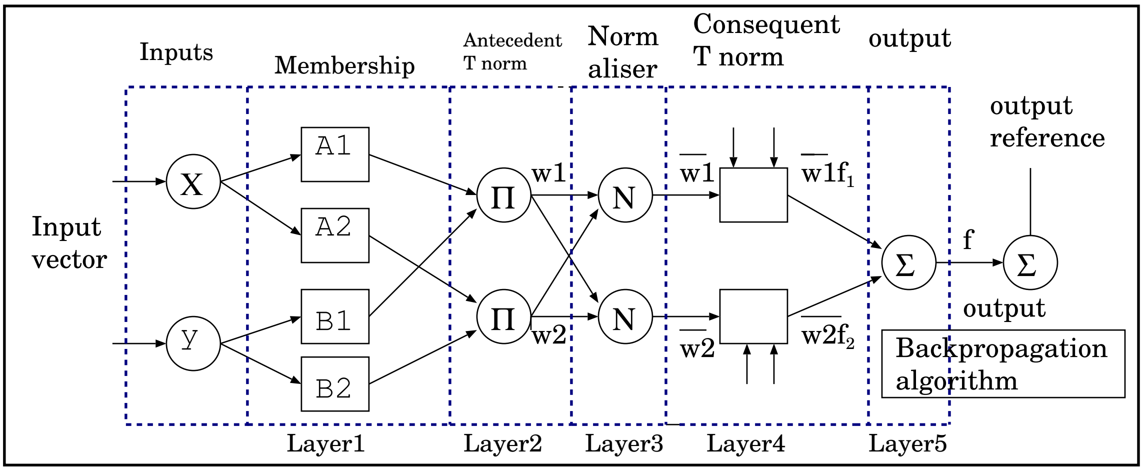

Figure 6. ANFIS Architecture.

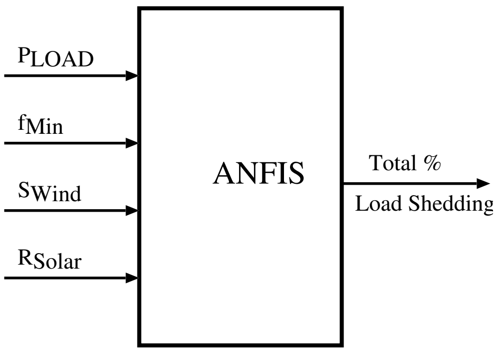

Figure 7. Proposed ANFIS structure.

4. Conventional Load Shedding Method

Conventional load shedding is the simplest and cheapest method in load shedding [23]. But it has a number of drawbacks [22].

1. There is only one stage of load shedding
2. More load is shed than required
3. Modification to the system is costly
4. Slow response time

4.1. Under frequency load shedding (UFLS)

Under frequency load shedding is a common technique that is designed to rebalance load and generation within an electrical island once the unbalanced system is created [24]. Under frequency load shedding must be performed quickly to prevent frequency decline by decreasing power system load to match available generating capacity. Certain frequency threshold values are set to begin the under frequency load shedding. The under frequency load shedding relay is triggered to commence load shedding hence the frequency reaches at that value.

4.2. Under voltage load shedding

Under voltage load shedding is implemented to protect the power system from voltage collapse. Any power system must be operated with an acceptable margin of voltage stability in both normal and contingent situations [4]. Therefore, power system operators need to know not only the weakness of the system but also the mechanisms that cause voltage instability [25]. Voltage instability generally occurred as a result of forced outage of power generator, power line fault or overloading of the power system. This causes a variation in the demand of reactive power in the transmission lines. Under voltage load shedding is therefore carried out to restore the system voltage to its nominal value.

4.3. Programmable logic controller-based load shedding

With a programmable logic controller (PLC) scheme, load shedding is based on the total load and/or detection of under frequency conditions [26]. Each substation programmable logic controller is programmed to initiate a trip signal to the appropriate feeder breaker to shed a pre-set sequence of loads. This static sequence is continued until the frequency returns to a normal, stable level. A $PLC - based$ load shedding scheme offers many advantages such as the use of a distributed network via the power management system as well as an automated means of load relief.

The convectional load shedding method has number of inherent drawbacks. It simply follows a pre-set rule, where in a fixed amount of load is shed when ever frequency deviates from its nominal value. And it also has slow response time. Another drawback especially with programmable logic controller is that, in such applications, monitoring of the power system is limited to a portion of the network with acquisition of scattered data. This drawback is further compounded by the implementation of pre-defined load priority tables at the PLC level that are executed sequentially to curtail blocks of load regardless of the dynamic changes in the system loading, generation, or operating configuration. The system-wide operating condition is often missing from the decision making resulting in insufficient or excessive load shedding.

5. Simulation Results

In the proposed method, the load shedding is solved by using back-propagation artificial neural network ($BPANN$) and adaptive neuro-fuzzy inference system ($ANFIS$). The data used in the training of the neural network are forecast data for a district in northern part of Sierra Leone. The data was first used in back-propagation artificial neural network, and later into the adaptive neuro-fuzzy inference system. Load shedding errors from the two methods were obtained, and results showed that, adaptive neuro-fuzzy inference system method is more robust as compared to the back-propagation artificial neural network method. The proposed work focuses on Capacity deficiency and Under-Frequency. For more robust system, voltage stability was also taken into consideration, as it has been one of the courses for power blackout in many countries. Therefore, voltage stability was also considered in this work, although it was not fully dealt with. The proposed micro-grid structure shown in Figure 2 was used to test the stability of the voltage. Two scenarios are considered during the testing. The first scenario is when there is a sudden increase in load by closing one of the breakers after the generation sources are almost operating within their maximum limit. And the second scenario is when there is power line fault or one of the generation sources ceased from operation.

There are three generators which are rated at 2000kW each with maximum power dispatch of 1800kW each. The total renewable power output is 2500kW. The base and peak loads of the system are 5000kW and 7900kW respectively. A scenario where in a breaker is intentionally closed during peak hours, leading to an increase in load which exceeds the maximum capacity of the generation sources(diesel and renewable generation) is considered. An increase of 500kW is suddenly experienced, leading to a decline in frequency. The conventional power (diesel generators) and renewable sources can only produce a maximum of 7900kW. After the closing of the breaker, the total load increases to 8400kW, which exceeds the maximum capacity of the generation sources. To ensure the stability of the system, the excess load need to be shed. The micro-grid management unit is then initiated and the proposed strategy is adopted to determine the power imbalance (ie. 500kW). Load shedding commences as soon as the frequency reaches 49.3 Hertz (H_Z), and/or the voltage reaches to a minimum value of 0.95 per unit (pu). Figure 8 shows the load demand when there is a sudden increase in load. It can be seen that, at peak time, between 20:00 and 21:00 hours, the load increases from 7900kW to 8400kW. Before the increase in load, the peak load demand was 7900kW. There is a fall in frequency because, the load has exceeded the maximum generation capacity of the micro-grid. Figure 9 illustrate the load demand before the closing of the breaker. And in Figures 10 and 11 represent the solar and wind power generation respectively. During the increase in load, the frequency falls to about 49.3Hz. The micro-grid management unit is initiated and the proposed strategy adopted, which carried out load shedding to restore the frequency back to it nominal value. The frequency behaviour during increase in load is illustrated in Figure 12.

To show the effectiveness of the proposed system, the load shedding was carried out using the conventional, back-propagation artificial neural network, and the adaptive neuro-fuzzy inference system methods. The conventional method has a fixed load shedding amount at each step, which in most cases result to either over shedding or under shedding. The percentage error during load shedding for the convectional method is shown in Figure 13. Applying back-propagation artificial neural network algorithm, the desire output (target) and the artificial neural network output is shown in Figure 14. It can be seen that, the target and the network output almost match together with less error as shown in Figure 15. Figure 16 shows the network training state. A minimum value of gradient coefficient is better for the network training state, and it can be seen from the diagram that, a minimum value of 0.091364 at epoch 62 is obtained.

Figure 17 represents the regression plot. This shows the relation between the desired output and the network output. A regression plot of $R = 1$ indicates that, there is an exact linear relationship between output and targets. If $R = 0.99$, it shows that ,there is a close relationship with the target and artificial neural network output. But if R is close to zero, then there is no linear relationship between output and target. Figure 18 shows the network training performance, which indicate the iteration at which the validation performance reached a minimum. In this figure, the training continues for about 8 more iterations before the training stopped.

Further training of the data into the adaptive neuro-fuzzy inference system algorithm, increases the accuracy of the system to carry out optimal load shedding with minimal error. The membership functions are shown in Figure 19. They are curves that define how each point in the input space is mapped to a membership value(or degree of membership) between 0 and 1, and they represent the degree of truth as an extension of valuation. Figure 20 shows the target and the network output, and the percentage error during load shedding is illustrated in Figure 21. From the diagram, it can be seen that, there is a significant reduction in percentage error compared to artificial neural network. Simulation results clearly corroborate the effectiveness of the proposed method.

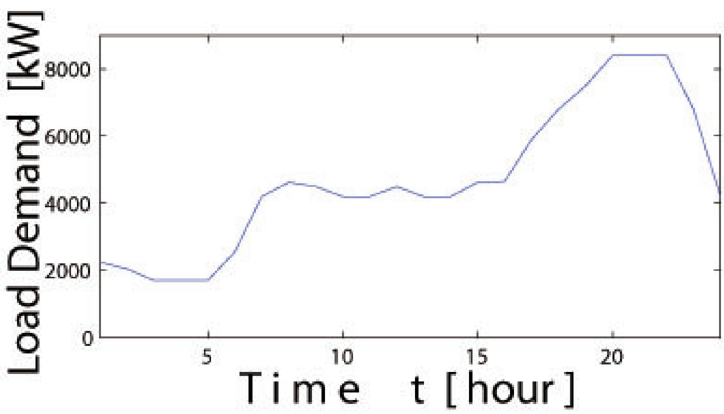

Figure 8. Load demand after increase in load.

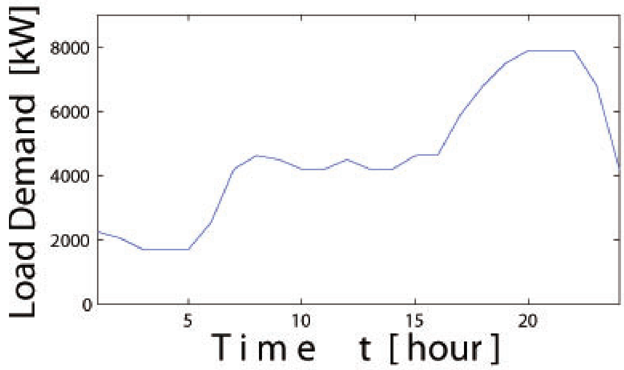

Figure 9. Load demand before increase in load.

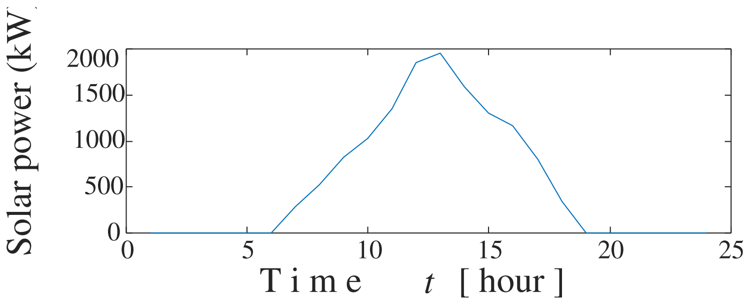

Figure 10. solar power generation.

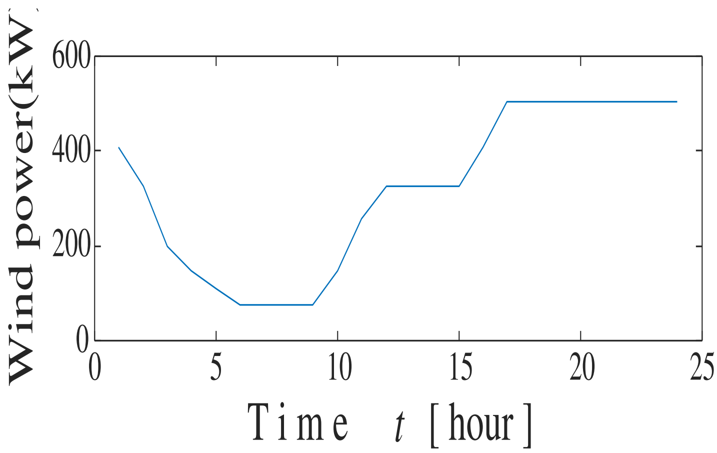

Figure 11. Wind power generation.

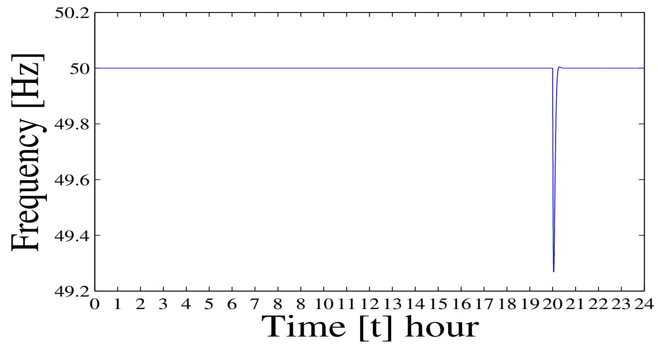

Figure 12. Frequency deviation during increased in load at peak time.

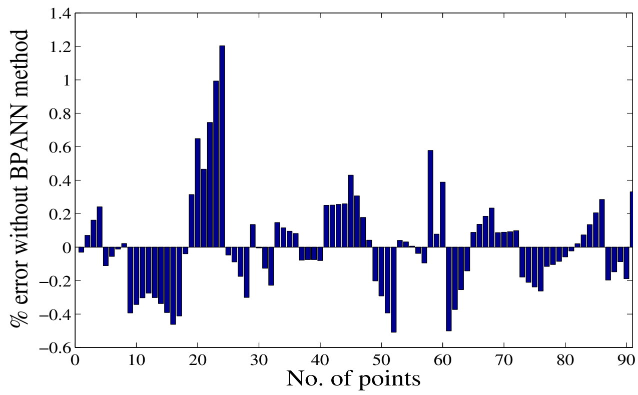

Figure 13. Error validation without BPANN method.

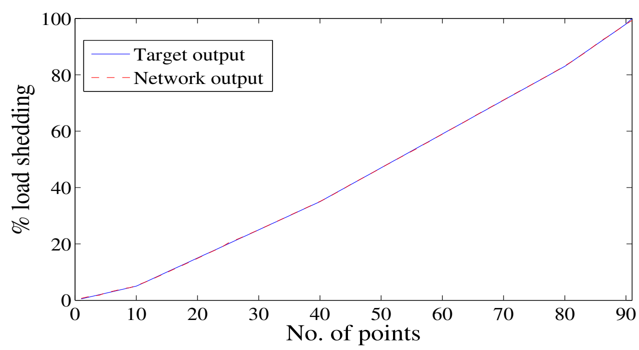

Figure 14. Target and network output.

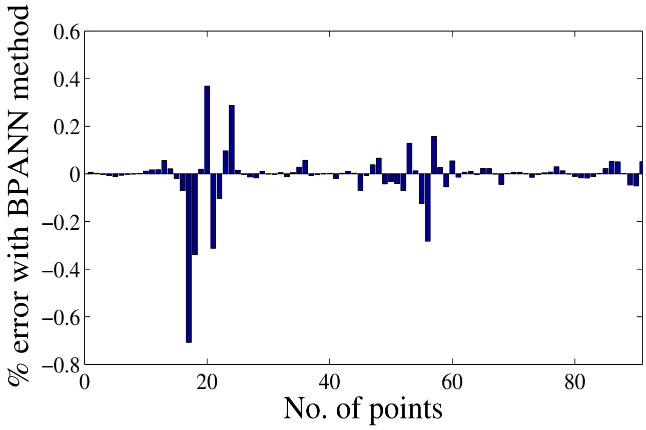

Figure 15. Error validation with BPANN method.

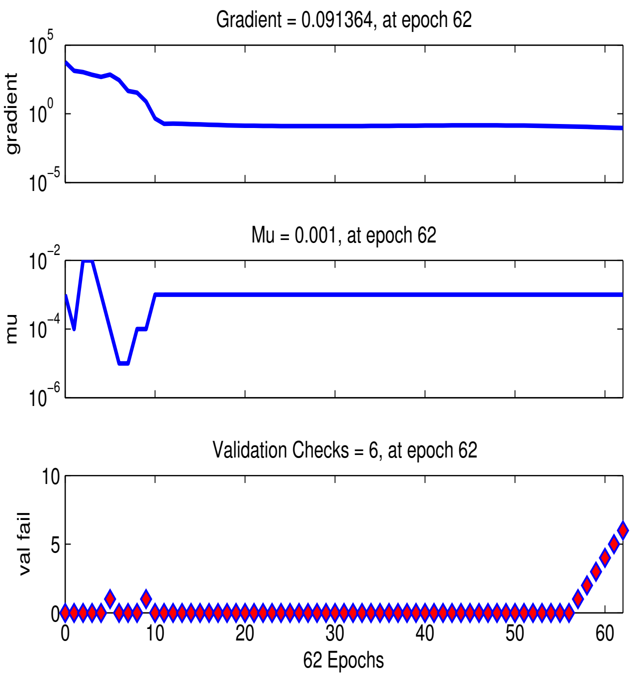

Figure 16. Neural network training state.

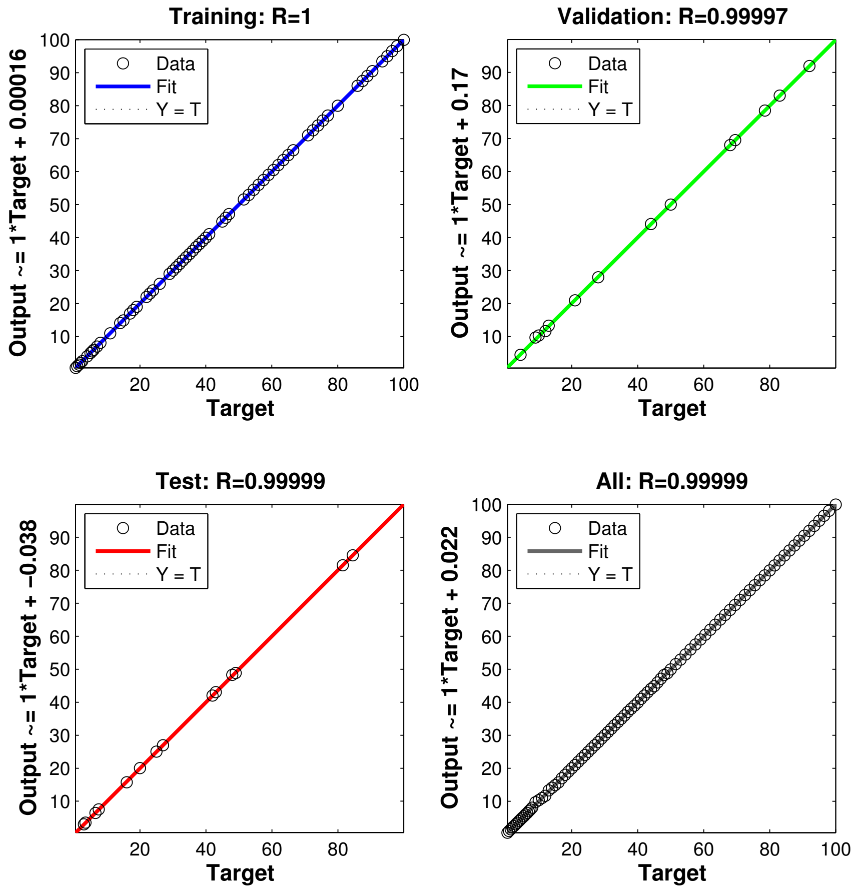

Figure 17. regression plot.

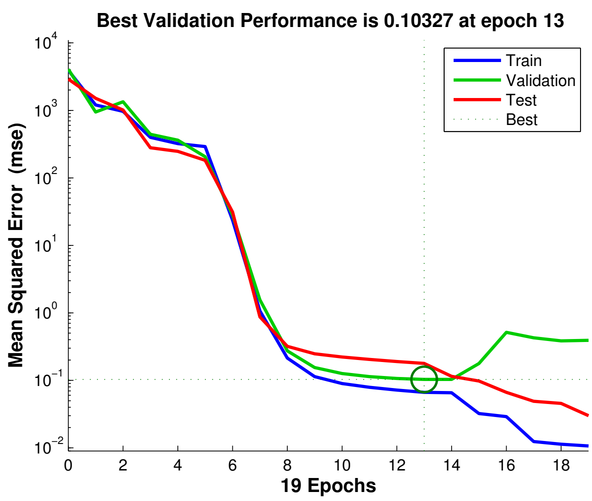

Figure 18. Neural network training performance.

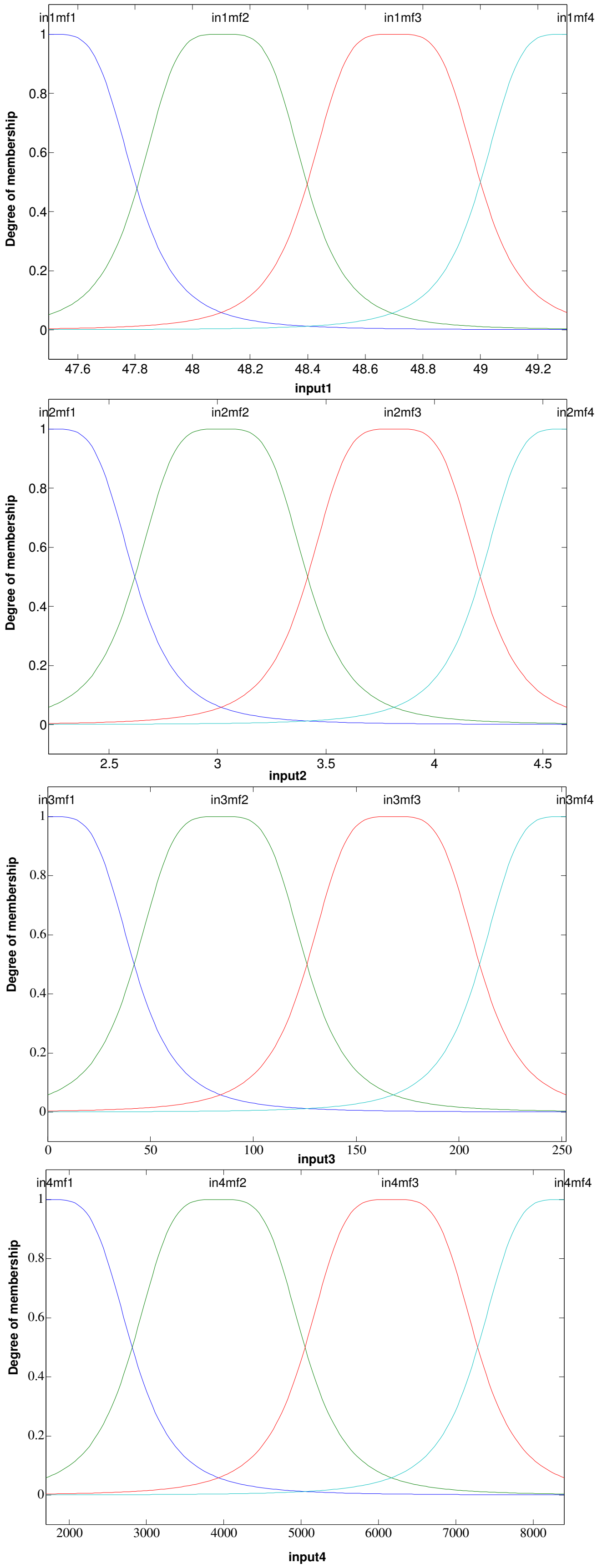

Figure 19. Membership functions of the fuzzy system.

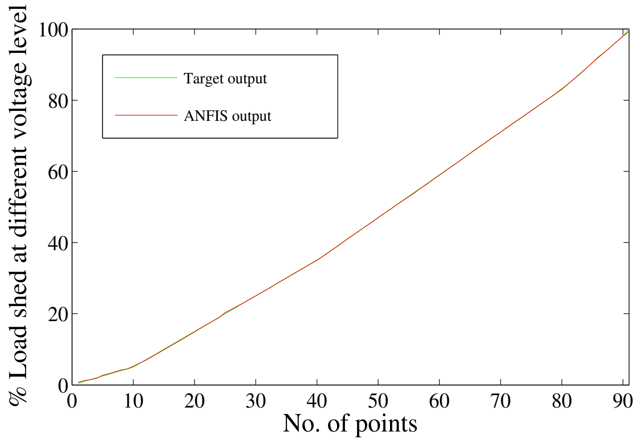

Figure 20. Target and network output for ANFIS load shedding.

Figure 21. Percentage error during load shedding for ANFIS method.

6. Conclusion

The main emphasis of this paper has been on developing optimal load shedding technique that is capable of shedding the required amount of load. The paper utilises the back propagation artificial neural network. This method can determine the exact amount of load to be shed, and at a faster rate compared to the traditional method. To further optimize the capability of load shedding for any range of input data, both neural network and fuzzy logic is combined to form adaptive neuro-fuzzy inference system. This technique can predict the optimal load shedding values for any input other than the trained data with minimum error. The effectiveness and robustness of the scheme have been investigated based on two scenarios. First scenario is when a breaker is closed after the generation sources are almost operating at their maximum limit.The second scenario is when there is a sudden decrease in power as a result of plant failure or power line failure. It is observed that, the developed method manages to immediately perform the load shedding at a faster rate with the required amount to be shed. Simulation results show that with the proposed method, intended quantity of load can be shed at a faster rate, thereby enhancing the stability of the system. Simulations are carried out using artificial neural network and adaptive neuro-fuzzy inference system tool box of MATLAB.

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Conflict of Interest

All authors declared that, there is no conflict of interest in this paper.

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