A Particle Swarm Optimization Trained Feedforward Neural Network for Under-Voltage Load Shedding

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ABSTRACT

This paper suggests an under-voltage load shedding (UVLS) approach to avoid voltage collapse in stressed distribution systems. Prior to a blackout, a failing system reaches an emergency state, and UVLS is executed as the final option to prevent voltage collapse. Hence, this article introduces an optimal UVLS method using a feedforward artificial neural network (ANN) model trained with the particle swarm optimization (PSO) algorithm to obtain the optimal load shedding amount for a distribution system. PSO is used to obtain the best topology and optimum initial weights of the ANN model to enhance the precision of the ANN model. Thus, the dispute between the optimum fitting regression of the allocation of ANN nodes and computational time was disclosed, while the MSE of the ANN model was minimized. Moreover, the proposed method uses the stability index (SI) to identify the weak buses in the system following an emergency state. Different overload scenarios are examined on the IEEE 33-bus distribution network to validate the efficacy of the suggested UVLS scheme. A comparative study is performed to further assess the performance of the proposed technique. The comparison indicates that the recommended method is effective in terms of voltage stability and remaining load.

Keywords: Under-Voltage Load Shedding, Artificial Neural Network, Particle Swarm Optimization, Stability Index, Voltage Stability, Voltage Collapse

1. INTRODUCTION

In the last decade, large blackout events have occurred in various countries, causing major blows to residents financial and social progress [1]. One of the most critical causes of blackout incidents is voltage instability, which can lead to voltage collapse [2]. Generally, under-voltage load shedding (UVLS) is used as an emergency control and management technique against voltage instability to prevent blackouts after all other possible mitigation methods for voltage collapse have been exhausted [3]. On the contrary, the under-frequency load shedding (UFLS) approach is used in case of critical faults such as unexpected decline in frequency due to loss of generator or loss of synchronization in interconnected large-scale networks [4], [5].

In the literature, three types of UVLS schemes are presented: conventional, adaptive, and computational. The development of UVLS schemes using computational intelligence techniques (CITs) has attracted numerous researchers around the world. This is because CITs are robust and flexible. Also, CITs allow nonlinear problems to be solved without difficulty. Basically, CITs are metaheuristic optimization algorithms consisting of swarm-based approaches such as artificial bee colonies (ABC) [6], evolutionary methods like the genetic algorithm (GA) [7], physics-based algorithms such as the black hole algorithm (BHA) [8], and machine learning approaches like the artificial neural network (ANN) [9], etc., which have been applied in UVLS approaches.

To further illustrate, a recent study considered a metaheuristic algorithm known as the moth swarm algorithm (MSA) to deal with steady state load shedding, with the objectives of reducing the load shedding amount, minimizing the active power loss, and enhancing the tested system's voltage stability and profile [10]. The authors in [11] utilized a metaheuristic algorithm known as improved moth flame optimization (IMFO). IMFO applied for a load shedding scheme to reduce the amount of load shed, improve the loadability of the system, and avoid voltage collapse.

In [12], the researchers applied particle swarm optimization (PSO) to a load shedding optimization problem in a distribution network to improve the reliability and reduce the amount of load shed. Another application of PSO for an optimal load shedding scheme is proposed in [13] to maximize the public benefit and minimize the amount of load curtailment in competitive electrical energy markets. Likewise, an optimization model using PSO to minimize power loss and load shedding during contingencies is presented in [14].

However, the major shared disadvantages of the existing CITs-based UVLS frameworks are their high computational time, premature convergence problem, and inability to attain voltage stability. These shortcomings can result in a suboptimal amount of load shedding. UVLS schemes, which use CITs such as GA and PSO,

Manuscript received on September 27, 2022; revised on December 22, 2022; accepted on March 9, 2023. This paper was recommended by Associate Editor Yuttana Kumsuwan.

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Digital Object Identifier: 10.37936/ecti-eec.2023212.249825

often suffer from these challenges.

Several hybrid approaches for optimum load curtailment have been suggested to overcome the limitations of CITs. Linear programming was combined with PSO to efficiently minimize the amount of load shedding with fast convergence time [15]. Similarly, PSO was combined with simulated annealing (SA) to effectively handle the load shedding problem for long-term voltage stability [16]. A hybrid method incorporating the GA and PSO to decide the optimum amount of load shedding for overloaded systems is presented in [17]. Besides, the authors in [18] presented the effectiveness of hybridizing the slime mold algorithm (SMA) with sinusoidal chaos for optimal load shedding in radial distribution networks.

Furthermore, the work in [19] suggested a UVLS scheme for voltage stability improvement by integrating the ABC and PSO algorithms taken from a software estimation project to execute load shedding on an overloaded system. Studies show an enhancement in results achieved when two CITs are hybridized, as the benefits of two algorithms enhance their performances. However, these hybrid approaches are unsuitable for real-time implementation of load shedding schemes due to the large computational time taken to obtain the optimal amount of load to shed through optimization.

The study in [20] is the most relevant method in the literature. The authors focused on a hybrid technique by combining ANN with GA to reduce the load to shed and maximize voltage stability. The authors applied GA in two stages: to structure the optimization model and to produce the datasets for the ANN training, while the ANN is used to determine the load-shedding value for the given input eigenvalue. However, this method has the following shortcomings: (1) The time taken for the operation of cross-over of GA is large, causing a slower convergence period, and (2) it does not consider improving the accuracy of the ANN model, resulting in inaccurate prediction and suboptimal load shedding.

Based on the discussion above, there are four major problems with existing methods: First, approaches that use CITs have great precision but suffer from slow convergence times. Second, approaches that use ANNs need a long time for computation to obtain the optimal amount of load shedding. Third, when using ANN as the prediction model, the method of training the ANN model is the main disadvantage. Fourth, hybrid metaheuristic approaches can attain quick convergence but may suffer from suboptimal outputs or not be suitable for real-time application of load shedding operations.

On one hand, ANN is the most robust and adaptable method for solving non-linear regression. On the other hand, ANN can attain adequate outputs for well-known instances but cannot deliver precise outputs for unknown instances. Nonetheless, the major issue with ANN is the time needed for its training as well as the optimal fitting regression of the ANN structure. In this paper, the aforementioned issues are resolved by employing the PSO algorithm to optimize the ANN structure's training approach. This approach is split into two stages: First stage: obtaining the optimal topology. Second, optimizing the initial weights of the feedforward ANN structure In other words, the first stage addresses the dispute between the execution time and the optimal fitting regression of the ANN node allocation, whilst the second stage minimizes the training error of the ANN. Thus, the proposed ANN technique can efficiently determine the optimum load shedding amount under different loading scenarios. The proposed ANN structure's inputs are the active power (P), voltage magnitude (V), stability index (SI), and load priority limit (Plim.) of the distribution systems, while the output is the amount of load shedding (Pshed).

Hence, this paper proposes a new optimal UVLS technique based on a feedforward ANN model enhanced using the PSO algorithm to obtain the optimal load shedding amount in overloaded distribution systems while maximizing the system's remaining load and improving the voltage stability of the system after load shedding.

The contributions of this paper are divided into three main ideas:

- Fast computational time: Meager interest has been given to ANN based UVLS scheme due to its long computational time. To address this issue, the PSO is used to obtain the right topology for the ANN model. By doing so, the measurement errors of the ANN model are minimized, and the optimal fitting regression of the ANN node allocation is addressed. Consequently, effective performance of the proposed ANN model with fast computation is accomplished.
- High accuracy: The proposed UVLS scheme can considerably enhance the voltage stability of the buses in the distribution system while sustaining the maximum possible load after load shedding. This high accuracy is achieved by obtaining the optimal initial weights of the training nodes using the PSO algorithm. Thus, the estimating behavior of the proposed ANN model with minimized mean squared error (MSE) is achieved.
- High efficiency: The proposed UVLS method considers the priority of the loads in the distribution system to allocate importance to several load types (vital, semi-vital, and non-vital) during the load shedding process. This is done to represent real and efficient aspects of the proposed UVLS method design. Consequently, load curtailments in critical infrastructures such as healthcare facilities, etc., during the proposed UVLS method are avoided. Hence, the vital loads in the distribution system are maintained while only non-vital loads are curtailed efficiently during the load shedding process in the distribution network.

The remainder of this article comprises the following sections: Section 2 covers the background of the tools and techniques used for the proposed method. Section 3 describes the implementation of the proposed method. Section 4 presents the results and discussion. Lastly, Section 5 concludes the research article.

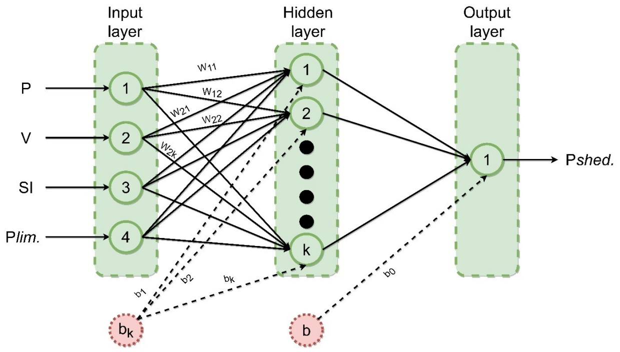


Fig. 1*: Graphical Representation of the ANN Model.*

2. TOOLS AND TECHNIQUES

2.1 Artificial Neural Network (ANN)

ANN is a machine learning method that can be employed as a tool to process data. The performance characteristics of ANN are like the functions of the biological nervous system in the human brain. ANN comprises interconnected neurons to achieve performance similar to that of humans during problem solving [21]. ANN requires correct data to determine the output objects accurately, but during the application network modeling, it does not need a great deal of knowledge. Through training, the knowledge of the network is enhanced. In order to transform the training data, the ANN performs non-linear mapping among the set of input and output nodes.

ANN topology is grouped into two categories, namely feedback and feedforward systems. Due to the low memory consumption in the application phase, the latter is regularly used [22]. Moreover, while working with non-linear structures, for instance, the power system and distribution system, the feedforward ANN has proven to be very effective [23]. Generally, a feedforward ANN with multilayers comprises an input, hidden, and output layer, as presented in Fig. 1.

Furthermore, neurons in every layer are connected using synaptic links known as weights of different neurons, together with bias parameters in the previous layers. Mathematically, this structure is expressed by Eq. (1):

$$y = \sum_{i=1}^{m} w_{ij} s_j + b_j \tag{1}$$

where m represents the number of incoming signals, w_{ij} are weights connected to the nodes of the layer (input and hidden), and s_j denotes input, and b_j is the bias of the nodes of the layer (hidden and output). Normally, to learn the mechanism of a feedforward ANN network, the back propagation (BP) algorithm is utilized. The BP algorithm is a complex gradient algorithm that is used to improve the effectiveness of the ANN. The training error is minimized by adjusting every node's weight and bias until the outcome at the output layer determines outputs as close to real outputs as possible, hence improving the performance of the ANN. Commonly, the mean squared error (MSE) is selected as the fitness function. Thus, the fitness function is written as Eq. (2):

$$MSE = \frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{n} \left[A_j(i) - E_j(i) \right]^2 \tag{2}$$

where m is the total incoming data, n is the total output data, $A_i(i)$ denotes actual outputs, and $E_j(i)$ represents estimated output. When a feedforward ANN is designed, two major problems are encountered: (1) determining the best topology of its architecture, that is, the total hidden layers and total nodes in it, and (2) optimizing the initial weights of the training nodes.

2.2 Hidden Layer Size of ANN

When designing feedforward ANN, determining the optimal number of nodes in each hidden layer with respect to the total number of hidden layers is a critical undertaking. This is because the optimal number of nodes and hidden layers can solve the dilemma between the optimal fitting regression of the ANN structure and its computational time [24]. Overfitting regression of the ANN structure occurs when computational time becomes too large due to too many nodes in the hidden layers of the ANN model. On the contrary, linear fitting regression is achieved when the ANN has very limited nodes in the hidden layers, resulting in a small computation time. Commonly, the trial-and-error method is used in order to obtain the hidden layer size. However, this approach is insufficient as it suffers from a large computational time.

2.3 Initial Training Weights of ANN

The BP technique is utilized based on error surface finding to train the feedforward ANN structure. This method of finding varies with gradient descent considering the escalating variation in the weight ΔW, as stated in Eq. (3):

$$w_{ji}^{l}(t) = w_{ji}^{l}(t-1) + \Delta w_{ji}^{l}(t) \tag{3}$$

where $w_{ji}^{l}(t)$ is the next weight at iteration (t), $w_{ji}^{l}(t-1)$ is the previous weight from its previous state $(t-1)$ and $\Delta w_{ji}^{l}(t)$ is the $(+/-)$ incremental variation in the weight? There are two stages for every iteration in the BP algorithm: the forward stage and the backward stage. The former is for generating an updated solution, and the latter is for calculating and changing the MSE to the latest weights using Eqs. (2) and (3). This process remains while the ideal weights for the training of the ANN are found. Numerous findings reported that this approach is helpless to acquire the optimal training weights as it mainly relies upon the size of ΔW [25]. A bigger ΔW will accelerate the training and result in big oscillating exploration on the error surface, which could produce a never-converging optimal solution. Inversely, a smaller ΔW will cause slower training and result in small oscillations in the error area, triggering the training

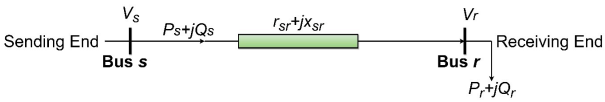


Fig. 2: *Two-Bus System.*

process to stop before the minimum error is obtained. Thus, considering this notion, optimal initial weights are important in constructing an efficient ANN model.

2.4 Particle Swarm Optimization (PSO) Algorithm

Kennedy and Eberhart introduced an evolutionary method known as PSO [26]. The PSO algorithm is an excellent search technique for engineering applications. The primary notion of this technique is that it attempts to determine the optimized space, where every area has a point of probability for a possible solution. A swarm intelligence method driven by the attitudes of birds flocking and fish schooling is named PSO. By imitating the behavior, intelligence, and communication skills of birds and fish, optimization of non-linear problems can be accomplished. The method of the PSO algorithm includes four phases: (1) Within a random particle value, the PSO optimizer begins the exploration. This particle value is chosen by considering the degree of probability of solution spaces, taking into account some changing optimizations. (2) In order to explore the optimized solutions in the same area, it assesses the past and the following best fitness values, $\left(Pbest_i\right)$ and $\left(P_{li}\right)$, respectively. (3) In order to determine the value of global fitness, the positions of the best and the positions of the global best $\left(Gbest_i\right)$ are compared. By using Eqs. (4) and (5), these positions are modified and updated for the subsequent phase mathematically:

$$Z_i^{k+1} = f \times Z_i^k + r_1 \times c_1 \times \left(Pbest_i - D_i^k\right) + r_2 \times c_2 \times \left(Gbest_i - D_i^k\right) \tag{4}$$

$$D_i^{k+1} = D_i^k + Z_i^k \tag{5}$$

where k represents the number of iterations, D_i and Z_i are the current position and current velocity of every i^{th} particle, f denotes the inertia weight of the velocity, c_1 and c_2 are the coefficient for acceleration, r_1 and r_2 are the random speed values of the exploration area between zero and the maximum speed. (4) To enhance particle movement phases in every iteration, the finest particle concerning the fitness assessment is obtained and stored. Those phases will run until the total number of iterations is reached or the stopping condition is attained. The number of iterations and the stopping criteria are set based on the needed accuracy and the time for control processing.

2.5 Voltage Stability Index SI

The voltage stability index, known as SI, is appropriate for the distribution system and applied in the load curtailment approach. The work in [27] introduced SI to effectively assess the stability condition of the buses in a distribution system. The most sensitive bus that might trigger voltage collapse as the loading in the system rises can be detected using SI. In order to demonstrate that SI is efficient in determining the weak buses in a distribution network, the IEEE 33-bus test network is simulated in MATLAB to obtain the SI profile of the test network, which is shown in Section 7.1 of the paper. It can be seen that the SI value for each bus decreases as the voltage magnitude of each bus decreases. Therefore, SI can be utilized to determine the weak buses, which could lead to voltage collapse in an overloaded system, and SI can be applied to optimize load shedding methodologies. Thus, in order to decide the optimal location to curtail load in the distribution network, this work incorporates the SI as an indicator to obtain a more efficient solution. A standard two-bus system configuration is presented in Fig. 2 to understand SI.

Each receiving bus is supplied by only one sending bus in a radial distribution network. The equation of the SI is stated in Eq. (6) [28].

$$SI_r = \left|V_s\right|^4 - \left[4\left(P_r x_{sr} - Q_s r_{sr}\right)^2 - 4\left(P_r r_{sr} - Q_s x_{sr}\right)^2\right]\left|V_s\right|^2 \tag{6}$$

where SI_r is the voltage stability index for the receiving bus, V_s is the sending end bus voltage, P_r is the active load at the receiving bus and Q_s is the reactive load at the sending bus. r_{sr} and x_{sr} represent the resistance and reactance of the line s-r, respectively.

Note that a larger SI value is required for buses in the system to be stable against voltage instability and prevent voltage collapse when the load demand increases [29]. Voltage collapse is expected to occur as the SI value approaches zero. Hence, in order to improve the SI value to a satisfactory value, the system's loading must be reduced. This can be achieved by shedding some loads from certain buses in the system.

This work will determine the voltage of sending and receiving buses, the active and reactive power of receiving buses, and the resistance and reactance values of each line in the distribution system through load flow analysis. The power flow equations are solved using the Newton-Raphson algorithm through MATLAB programming. At the optimal locations identified by the SI, the total amount of load to be curtailed should be determined by applying an appropriate technique. As mentioned earlier, in this work, an optimized feedforward ANN model based on PSO is used as the tool to find the optimal amount of load to be shed.

2.6 Load Priorities

Load priority limit, (Plim.) is considered in this work, where the total allowable load that can be curtailed from each bus in the network is constrained by the load priority percentage. The lowest possible remaining load that should be preserved in each bus of the distribution network after load shedding is denoted by (Plim.). This can be expressed as in Eq. (7).

$$P_{\lim(i)} = P_{(i)} \times Load\,priority\,(\%)_{(i)} \tag{7}$$

where i is the individual bus number in the distribution network and $P_{lim(i)}$ represents the lowest possible load that needs to be maintained on the bus. $P_{(i)}$ signifies total load in the bus prior to load shedding while $Load\,priority\,(\%)_{(i)}$ denotes load priority percentage of the bus. Consequently, the remaining load (Prem.) in every bus must not be lower than the prime (Plim.), as expressed below:

$$P_{\lim(i)} \leq P_{rem(i)} \leq P_{(i)} \tag{8}$$

where $P_{rem(i)}$ represents the total load available in the ith bus after load curtailment.

The loads connected in each bus are categorized as non-vital and vital loads according to the percentage of $Load\,priority\,(\%)_{(i)}$. The vital load (Pvit.) in each bus and the lowest possible amount of load that should be retained (Plim.) in each bus after load curtailment have a relationship as stated in Eq. (9).

$$P_{vit(i)} = P_{\lim(i)} \tag{9}$$

where $P_{vit(i)}$ is the amount of vital load at the ith bus. Hence, the non-vital load (Pnon-vit.) can be calculated by:

$$P_{non-vit(i)} = P_{(i)} - P_{vit(i)} \tag{10}$$

where $P_{non-vit(i)}$ is the amount of non-vital load at the ith bus.

By applying the simple equations of Eqs. (7)-(10), the amount of non-vital load in each bus of the distribution system can be precisely determined with the known amount of load in the bus before load shedding $P_{(i)}$ and the load priority percentage of the bus $Load\,priority\,(\%)_{(i)}$. Thus, the proposed UVLS method is able to curtail the non-vital loads only during the load shedding process. By doing so, curtailment of any vital loads in the system during the demand reduction process is prevented.

The category of loads (non-vital and vital loads) in every bus of the system is based on its economic and technological significance: residential loads, industrial loads, commercial loads, and incessant loads. Health care, navigation, military, and public service loads belong to the incessant load group. Incessant loads are vital loads and should be served without disconnection. For those purposes, the proposed UVLS scheme will shed only the non-vital loads in the system according to the load priority percentage limits instead of disconnecting random loads in each bus. This will ensure the vital loads connected to each bus of the system can operate without interruption. Fig. 3 presents the load priority percentage plot, which shows the minimum percentage of load (vital load percentage) that should be preserved in each bus of the IEEE-33 bus network.

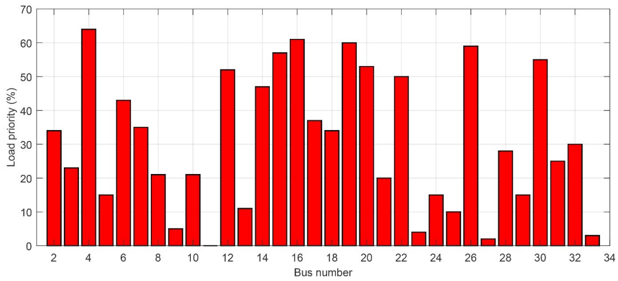


***Fig. 3**: The Load Priority Limit Plot of the IEEE 33-Bus System.*

3. PROPOSED METHOD

In this section, the proposed UVLS algorithm to obtain the optimal load shedding amount for the distribution system in the emergency state is described. The flow chart of the proposed ANN-PSO based UVLS method is presented in Fig. 4.

Using MATLAB software, an optimal UVLS method based on ANN and PSO for distribution networks is proposed. The inputs of the ANN technique are active power (P), voltage magnitude (V), stability index (SI), and the load priority limit (Plim.) of the distribution networks, while the amount of load shedding (P*shed.*) is the output.

As previously mentioned, the accuracy of the load shed amount determined using the ANN method primarily depends on the ANN system's training strategy. This begins by choosing the optimal topology of the ANN model. Next, the initial weights of the ANN model are optimized. Two sets of procedures are introduced in terms of the hybrid ANN-PSO method to optimize the training strategy. The PSO optimizer's parameters are fixed as follows: $f = 0.7$, $k = 500$, $c_1 = 1.5$, $c_2 = 1.5$. Additionally, the MSE of the ANN model is selected as the objective function to be minimized using the PSO algorithm. Fig. 5 illustrates the ANN-PSO algorithm's complete training procedure.

3.1 ANN-PSO Training Method

The five major phases of training the ANN-PSO model are as follows:

1. A substantial number of events comprising various loading points (an input feature of ANN-PSO) are generated at random. A standard load flow program (Newton-Raphson method) is used to obtain the training knowledge data to confirm that only appropriate events are opted for the following phase. In order to generate adequate training datasets for the ANN-PSO model training, this study utilizes 1650 randomly generated data points.
2. The 1650 training data are created by incrementing the total loading level in each bus of the system by 5% up to extreme loading (50% of the total network loading). The increment is divided evenly. Note that in the simulation phase of the industry, this procedure is

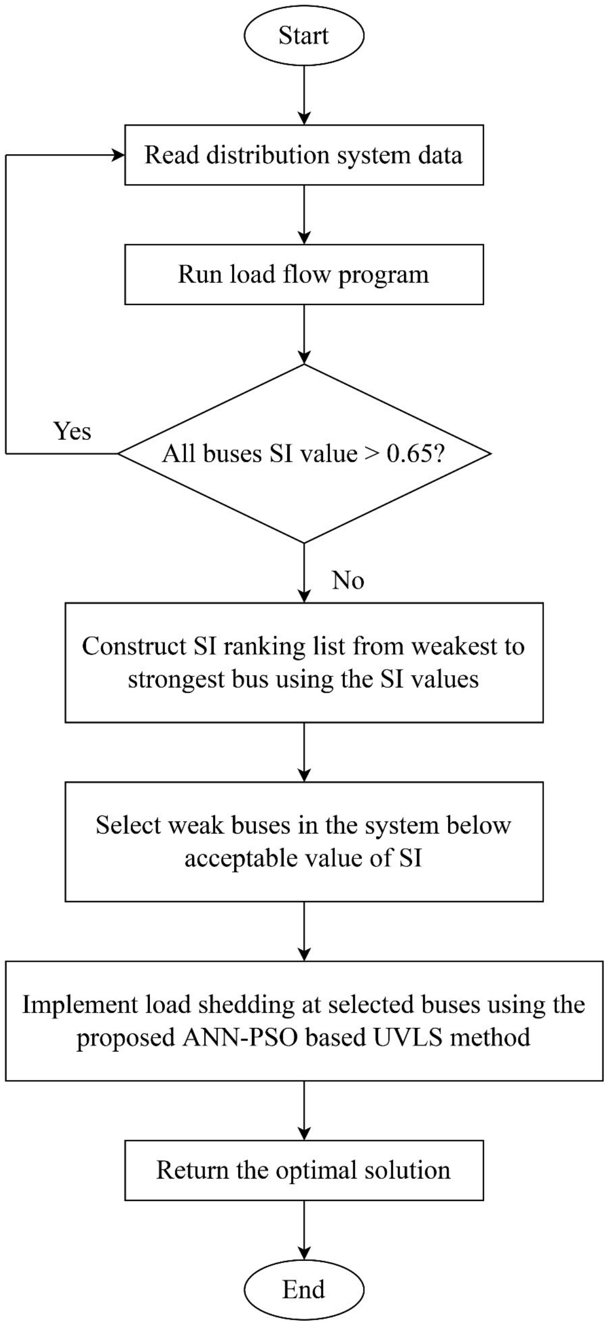


***Fig. 4**: Flowchart of Proposed Method Implementation.*

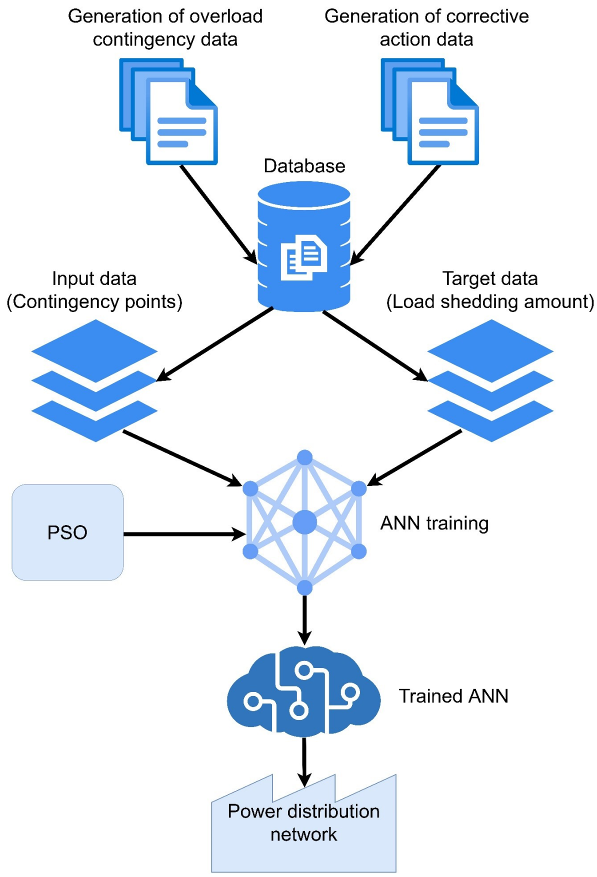


***Fig. 5**: ANN-PSO Training Procedure Diagram.*

employed. For example, the Advance Power Solution Company uses a similar approach [30]. This way, the distribution network loads vary for each bus. Hence, the 5% load increment, beginning from the lowest possible load, can be accomplished.

3. The SI algorithm is applied to compute the voltage stability index values (an input feature of ANN-PSO) of the buses in the network.
4. The load priority percentage of the test system, consisting of the minimum remaining load percentage that should be kept (vital load percentage) in individual buses, is used to calculate the load priority limit values (an input feature of ANN-PSO) of the buses in the system using the process described in Section 2.6 of this paper.
5. The amount of non-vital load in each bus of the network can be calculated using Eq. (7–10) expressed in Section 2.6 of this paper in order to obtain the load shedding amount (output feature of ANN-PSO).
6. The ANN-PSO training algorithm is designed with input and output features obtained from the aforementioned phases.

The trained ANN-PSO model is utilized to determine the load shedding amount for unknown cases during the testing stage.

3.2 Training Data Generation

For the neural network method, the quality of the data should be exceptional. The neural network must have excellent generalization ability. Thus, the training data must be properly created. Hence, it is important to confirm that all created datasets to be included in the database are generated at various loading points. Therefore, many load flow computations with various loading levels should be created randomly to acquire an adequate number of training data for training knowledge data. Then, the solutions from the load flow programs are gathered as datasets.

A popular method is to obtain the network's response to various contingencies and then gather the sample sets

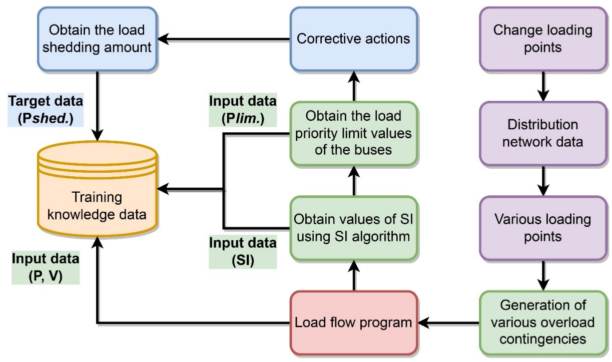


***Fig. 6**: Schematic Diagram of the Training Data Generation Process.*

of pre-contingency features together with the resulting sample sets of output features. For the ANN-PSO training and testing, the datasets are created by generating various overload contingencies for each load bus in the system. The input datasets are created by changing the load level of load buses (by ±5%) in the network within the suitable limits, which, in turn, are based on the power demand, voltage profile, voltage stability index, and load priority limits. On the other hand, the target datasets (load shedding amounts) are obtained for all load buses using the amount of non-vital load in each bus. In order to avoid extreme computational complexity in the online implementation, it is trained offline.

For the 33-bus system, 1650 random training data points are obtained as the input and output features. 1320 data points are taken for training from the 1650 random training data, while the remaining 330 data points are taken for testing the proposed ANN-PSO model. The operating configuration is stored for record after the corrective measure (UVLS process) is executed and is kept in the database. This process is conducted repeatedly until the acceptable voltage level at which the network can operate without any voltage collapse or blackout is achieved. Fig. 6 illustrates the schematic representation of the training data generation method of the ANN-PSO algorithm.

3.3 Data Normalization

Scaling of data, also known as data normalization within a uniform range, for example, between 0 and 1, is vital due to the following reasons:

- Data normalization avoids minor numbers being overridden by big ones.
- Furthermore, data normalization avoids premature saturation of hidden neurons when the input data contains large numbers, which will hinder the learning procedure.

Certainly, there is no single standard process in the data normalization approach to normalizing the inputs and outputs. In this work, the min-max normalization is used to normalize all data to remove the influence of features that have distinct ranges. The process is accomplished by applying the following expression:

$$h_{normalized} = \frac{h - h_{min}}{h_{max} - h_{min}} \tag{11}$$

where $h_{normalized}$ is the normalized dataset, h represents the original dataset, h_{min} denotes the smallest value of the dataset, and h_{max} is the largest value of the dataset. Each input dataset is normalized between 0 and 1. At the beginning of the ANN-PSO algorithm, the normalization process is performed to transform the datasets into a type that the neural network can work optimally.

3.4 Obtaining the Optimum Topology of ANN Model Using ANN-PSO Algorithm

ANN structure is integrated with the PSO algorithm in this first algorithm to achieve optimal topology for the feedforward ANN system. Consequently, a hybrid method is employed for verification, where the total number of neurons is gradually increased in the hidden layer without necessitating manual selection of the total number of neurons in the hidden layer, which may lead to imprecise output. The key procedures for this are presented in the flowchart shown in Fig. 7.

In this algorithm, the lower and upper boundaries of the number of neurons are set to 10 and 20. In this paper, four inputs in the input layer while one output in the output layer with one hidden layer is attained with the lowest training error. The optimal number of neurons in the hidden layer, determined based on the optimization technique, is 17 neurons. The optimum topology will be implemented in the second algorithm to obtain the optimum initial weights of the ANN structure.

3.5 Finding the Initial Weights of the ANN Structure Using ANN-PSO Algorithm

The second hybrid approach using ANN and PSO techniques is developed to obtain the optimal initial weights for the ANN model after the topology of the ANN system has been chosen. As the assumed initial weight improves, the optimal initial weights are obtained to polish the network's output result. Throughout this, the ANN approach is applied with the PSO strategy. The primary stages of the second hybrid algorithm are exhibited in the flowchart shown in Fig. 8.

In this algorithm, the values of the lower and upper boundaries of the weights are fixed at -0.9 and 0.9, respectively. Hence, the optimal initial weight values are acquired after applying this second hybrid algorithm. Fig. 9 shows the exploration history of the ANN-PSO algorithm.

Next, in order to train the ANN structure using the optimized initial weights, the "nntool" command in MATLAB is utilized. Then, in the area of initial weights of the "nntool" box, the optimized training weights are substituted for the original initial weights. As a result, the effectiveness of the ANN structure using the optimal training approach based on the ANN-PSO algorithm

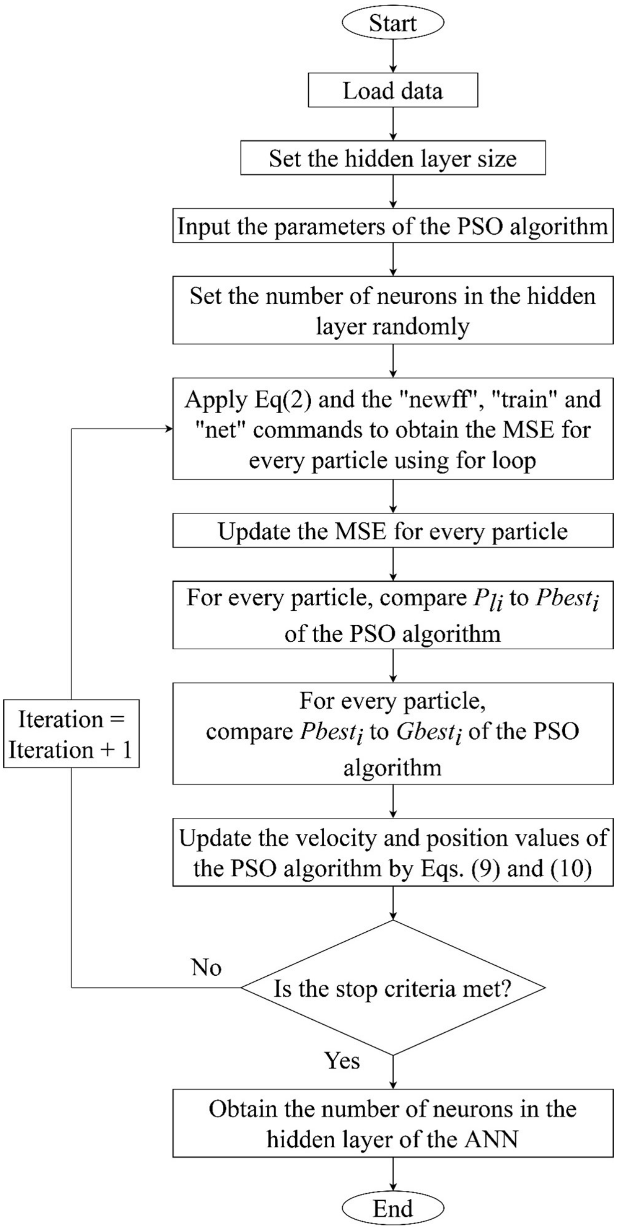


***Fig. 7**: Flowchart of Key Procedures for the First Approach to Determine the Optimum Topology of ANN.*

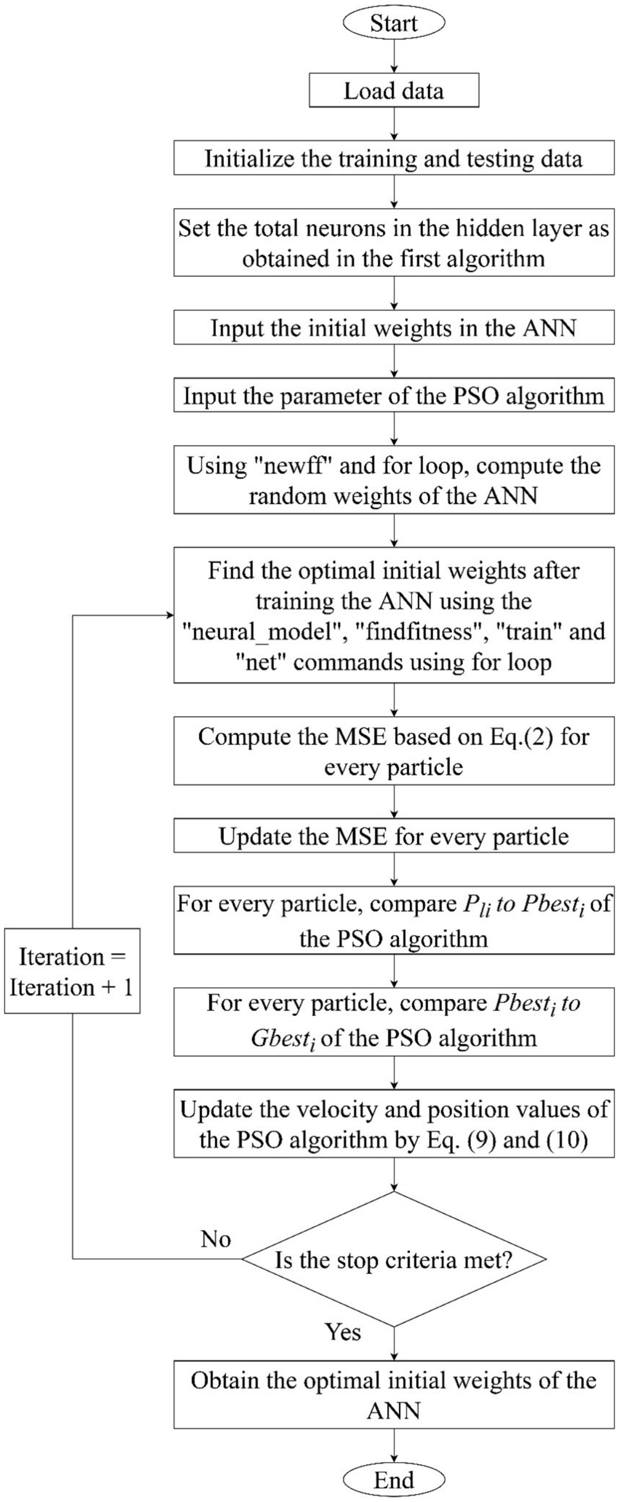


***Fig. 8**: Flowchart of Primary Procedures for the Second Approach to Establish the Optimum Initial Weights.*

achieved superior output compared to the conventional ANN. This is due to the smaller MSE of 5.42×10^{-7} and smaller epochs of 35, whereas the MSE and epochs of the non-optimized ANN are 2.57×10^{-5} and 66, respectively, as presented in Figs. 10.

Table 1 depicts the fundamental statistical analysis of the proposed method. Principally, this strategy does not require any additional elements in the application phase to enhance its correctness, therefore making it simpler to design.

4. RESULTS AND DISCUSSION

In this section, the effectiveness of the proposed ANN-PSO algorithm for optimal load shedding is evaluated by performing simulations in MATLAB. The simulations were demonstrated on the IEEE 33-bus network, and the one-line diagram of the test network is presented in Fig. 11. Baran & Wu [31] established this well-known distribution test system. The 33-bus test network consists of 33 buses, 32 branches, and 33 constant loads. It operates at a rated voltage of 12.66 kV. The bus data

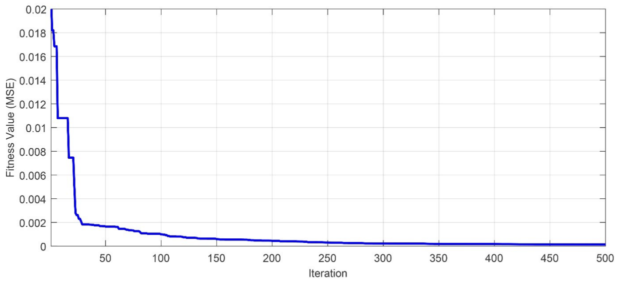
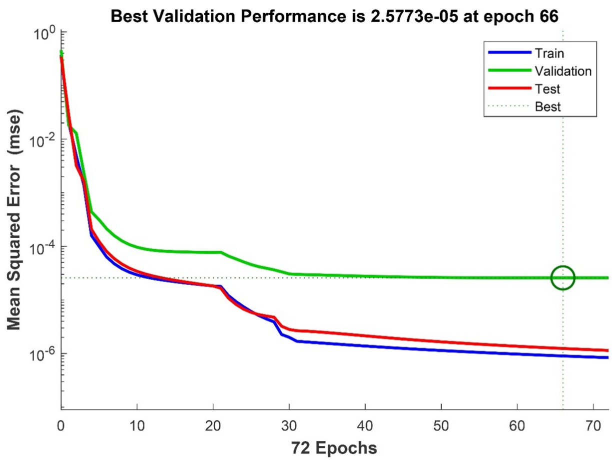
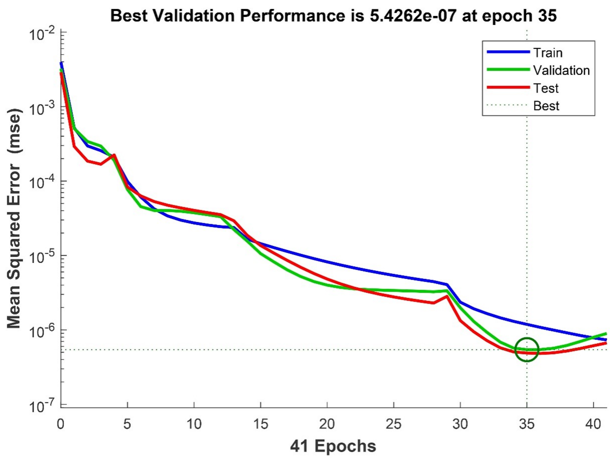


***Fig. 9**: ANN-PSO Algorithm Search History.*



(a)



(b)

***Fig. 10**: Plot of Best Validation Performance of: (a) The Non-Optimized ANN and (b) The Optimized ANN.*

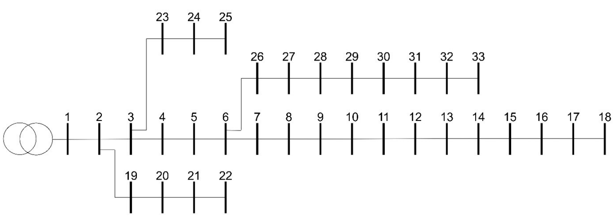


***Fig. 11**: IEEE 33-Bus System.*

***Table 1**: Fundamental Statistical Analysis.*

Training No.	ANN Design	Total Weights and Biases	MSE
1	4\times10\times1	61	2.57\times{10}^{-5}
2	4\times14\times1	85	3.37\times{10}^{-6}
3	4\times20\times1	121	1.49\times{10}^{-6}
4	4\times18\times1	109	1.38\times{10}^{-6}
5	4\times17\times1	103	5.42\times{10}^{-7}

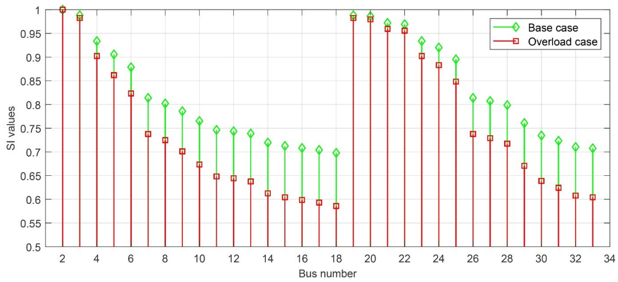


***Fig. 12**: SI Values for 60% Overload.*

***Table 2**: Case Studies.*

Case No.	Description
1	Standard case test network with no load shedding
2	Load shedding using the conventional UVLS
3	Load shedding using optimal UVLS with ANN-PSO approach

and line data of the 33-bus network were obtained from [32]. In the original case, the total power demand of the system was 3.715 MW and 2.3 MVA. The load priority percentages, $Load\,priority\,(\%)_{(i)}$ of each bus in the 33-bus test system are plotted and presented in Section 4.2 of this paper.

Three scenarios: (1) no overload, (2) 25% overload, and (3) 50% overload are simulated to appreciate the significance of the proposed load shedding method. Two popular techniques, namely conventional UVLS and conventional ANN, as well as the proposed ANN-PSO technique, are applied to the abovementioned three scenarios. Accordingly, three case studies are constructed to assess the response of the distribution system for the three cases in the three scenarios. The details of the case studies are given in Table 2.

The aim of this paper is to develop a hybrid ANN-PSO algorithm for optimal load shedding and evaluate it against the conventional ANN technique to validate the advantages of the proposed method. Therefore, a comparative study between the conventional ANN and the proposed method will be performed at the end of this section. The entire simulations are performed in a MATLAB environment on a 64-bit computer with an

***Table 3**: Top Twelve Sensitive Buses with SI Values Below the Threshold Value.*

No.	Bus Number	SI Value	No.	Bus Number	SI Value
1	18	0.5858	7	14	0.6126
2	17	0.5931	8	31	0.6243
3	16	0.5986	9	13	0.6375
4	15	0.6042	10	30	0.6386
5	33	0.6043	11	12	0.6443
6	32	0.6078	12	11	0.6482

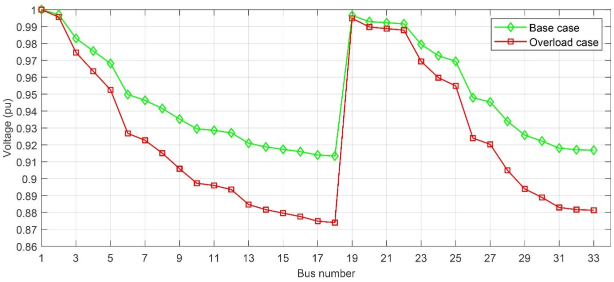


***Fig. 13**: The Trend of Voltage Magnitude for 60% Overload..*

i7-4720 2.60GHz CPU and 8.0GB RAM.

4.1 Optimal Location of UVLS

Fig. 12 reveals the plot of SI values of the 33-bus test network against 60% overload. It can be noted that there are 12 buses with SI values below 0.65 (the threshold value set to detect weak buses in the system), as listed in Table 3 and labeled as sensitive buses.

Furthermore, it is noticed that the voltage magnitude of the weak buses connected to the test network drops below the acceptable value of 0.9 pu as presented in Fig. 13.

This indicates that the voltage profile of the network is affected by the weak buses connected to the system and can result in a voltage collapse of the system. It is worth mentioning that the bus loading factor negatively affects the voltage magnitude of the bus. The resultant plot is presented in Fig. 13, which demonstrates that the voltage magnitude of the twelve weak buses (identified by SI) decreases. Therefore, SI values can be utilized to detect the weak buses in the network.

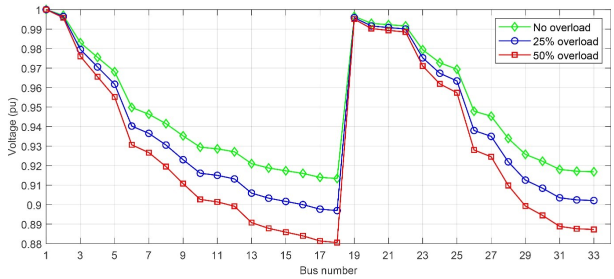
Accordingly, the SI is used to determine the number of weak buses and the best location for load shedding for the three scenarios in this work. This is because the implementation of SI offers more optimal results for the load shedding location, as shown in Table 4.

4.2 Case 1: Test Network with No Load Shedding

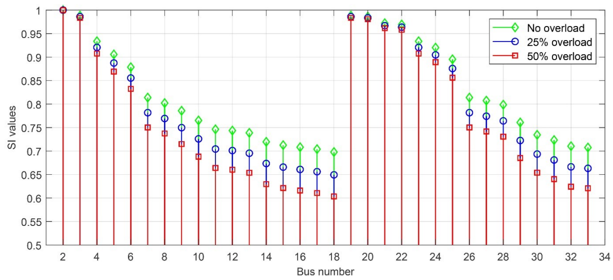
The first of the three scenarios is one without any load shedding. As the system is exposed to major overloads, the voltage profile and the SI values of the buses in the test network decrease, as shown in Fig. 14(a) and (b), respectively. In this state, the voltage profile of the system falls below the allowable limit (0.9 pu) for two scenarios, namely 25% overload and 50% overload. Thus, the test network requires a load-shedding strategy in order to prevent voltage collapse and instability.

***Table 4**: Best Location(s) to Shed Load for Different Overload Scenarios.*

Overload Scenario	Number of Weak Buses	Bus Number to Shed Load
0%	0	None
25%	1	18
50%	8	18, 17, 16, 33, 15, 32, 14, 31



(a)



(b)

***Fig. 14**: Test Network Without UVLS: (a) The Voltage Profile and (b) The SI Values.*

***Table 5**: Specifics of the Conventional UVLS Stages.*

No.	Voltage Threshold (pu)	Load Shedding Value (%)
1	0.9	20
2	0.88	20
3	0.86	10

4.3 Case 2: Conventional UVLS

In this case, the conventional UVLS method was simulated using the voltage levels and the fixed amount of load shedding for every voltage level. This method depends on the UVLS relay settings. A fixed amount of load will be shed, stage by stage, for each voltage level. The pre-defined stages of the conventional UVLS are tabulated in Table 5.

The voltage profile for every overload scenario with

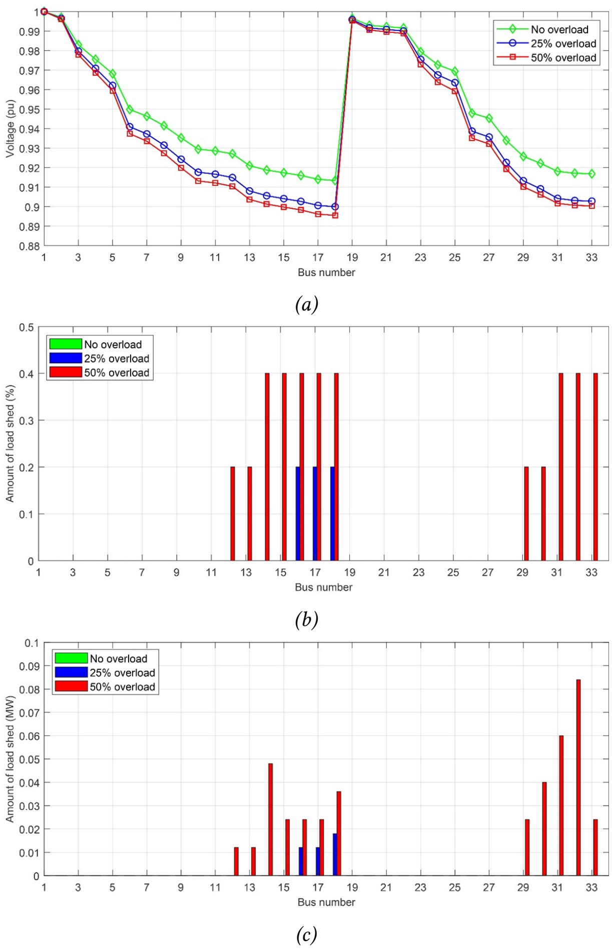


***Fig. 15**: Test Network with Conventional UVLS: (a) The Voltage Profile, (b) The Load Shedding Amount in Percentage, and (c) The Load Shedding Amount in MW.*

***Table 6**: Conventional UVLS Results Summary.*

Overload Scenario	Total Load Shedding Amount (MW)	Minimum Voltage (pu)	
		Before UVLS	After UVLS
0%	0	0.9134	0.9134
25%	0.042	0.8969	0.9000
50%	0.412	0.8805	0.8955

conventional UVLS is shown in Fig. 15(a), while the amount of load shed for every bus in percentage and MW with conventional UVLS are exhibited in Fig. 15(b) and (c), respectively.

Table 6 summarizes the results obtained with the conventional UVLS method. It is evident from Table 6 that the conventional UVLS sheds an insufficient amount of load. This condition can cause system instability and lead to voltage collapse or cascaded blackouts.

As can be seen in Fig. 15 (b) and (c), the loads curtailed with the conventional UVLS are focused only on the buses at the end of the test system due to the radial structure of the distribution system. Following overload scenarios, the voltage magnitude of the buses in the test network falls below the stability level. As shown in Fig. 15(a), the amount of load shed with the conventional UVLS adapts to the significance of the scenarios. However, this method does not take into account the priority of the loads in the buses or the amount of vital loads in the buses. Hence, to address these shortcomings, the implementation of an optimal UVLS method is required. Thus, simulations of the proposed method that offers the optimal amount of load shedding at the optimal locations are discussed in the next part.

***Table 7**: Summarized Results of Optimal UVLS with ANN-PSO Algorithm.*

Overload Scenario	Total Load Shedding Amount (MW)	Minimum Voltage (pu)	
		Before UVLS	After UVLS
0%	0	0.9134	0.9134
25%	0.081	0.8969	0.9033
50%	0.932	0.8805	0.9157

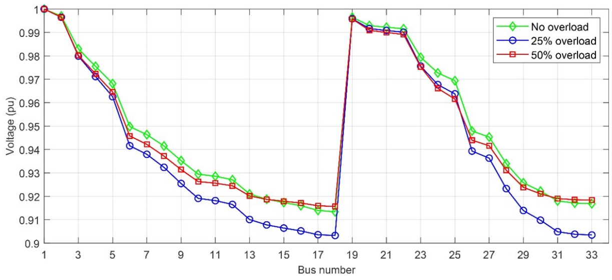
4.4 Case 3: Optimal UVLS

In this case, the simulation and evaluation of the proposed optimal load-shedding method using the ANN-PSO algorithm are presented. The voltage profile of the network and the SI values of each bus in the network for every overload scenario before applying the proposed optimal load shedding approach are as presented in Fig. 14(a) and (b), respectively.

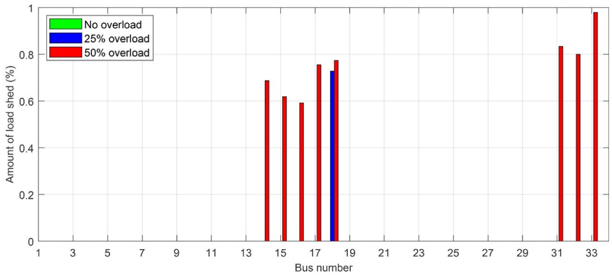
Fig. 16(a) illustrates the voltage profile of the network for every overload scenario after implementing the proposed method (ANN with PSO), while the amount of load shed in each bus after optimization with the ANN-PSO method for 25% overload and 50% overload scenarios is depicted in Fig. 16(b) and (c), respectively. Table 7 presents the proposed method's total amount of load shed and the minimum voltage of buses in the system for each overload scenario.

According to Fig. 16(a) and Table 7, the proposed strategy acts to ensure the test system's stability for every overload scenario where the voltage magnitude of every bus in the network is no less than 0.9 pu. Using SI, buses 14, 15, 16, 17, 18, 31, 32, and 33 are identified as the most sensitive buses in the test system. These buses are chosen as the best locations for load shedding. It can be observed that ANN-PSO sheds an adequate load. Hence, the proposed method can prevent system instability and protect the system from voltage collapse or cascading blackouts. It is also evident that better results are obtained using optimal UVLS with the ANN-PSO algorithm.

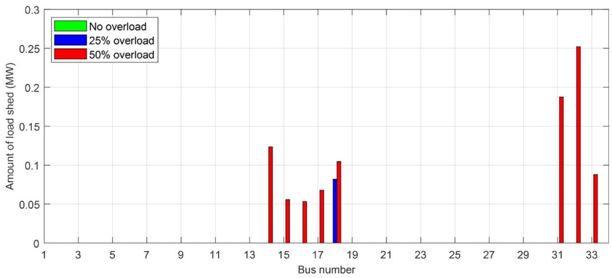
To further confirm the effectiveness of the proposed optimal load shedding approach, the following section reports a comparative study covering the simulations and evaluations of the optimal UVLS method employing the



(a)



(b)



(c)

***Fig. 16**: Test Network with Proposed Method: (a) The Voltage Profile, (b) The Load Shedding Amount in Percentage, and (c) The Load Shedding Amount in MW.*

original ANN against the proposed ANN-PSO technique.

4.5 Comparative Results

In this section, the proposed method and the conventional ANN method (ANN without PSO) are simulated to assess the effectiveness of the individual methods in the overload scenarios.

The following common procedures are considered in each technique in order to achieve a fair comparison: First, the voltage level necessitating load shedding for every methodology is set at 0.9 pu. Second, the load priority percentage, $Load priority\,(\%)_{(i)}$ of every bus in the test network, as demonstrated in Fig. 3 in Section 2.6 of this paper, is employed for every method. Third, the voltage stability index, SI is utilized as the tool to determine the optimal locations of load shedding in the test network for each technique. However, the total amount of load to be shed will be determined using the different techniques mentioned earlier.

This strategy enables curtailment of loads from the weaker buses determined by the SI and delivers the required data to suggest the best locations for shedding loads while considering the load priority limits of the buses in the network. As a result, this evaluation investigates the voltage profile of the test networks, the remaining load, the total amount of load shed, and the minimum voltage of the bus in the network for each method for every overload scenario.

It can be observed that, for every overload scenario, the ANN-PSO based optimal UVLS method performs better than the conventional ANN. More exceptionally, the proposed optimal UVLS using the ANN-PSO algorithm attained the best fitting regression with minimum measurement errors compared to the conventional ANN, indicating that utilizing PSO to optimize the topology and initial weights of the feedforward ANN structure results in a minimized MSE value with fast computational time for load shedding optimization.

Moreover, the UVLS using the ANN-PSO algorithm ensures a greater amount of remaining load in the test network with higher bus voltage values than the UVLS using the original ANN, as tabulated in Table 8.

UVLS using the ANN-PSO algorithm surpasses the conventional ANN by a tiny margin in the 25% overload scenario, while in the 50% overload scenario, the proposed method works substantially better by achieving a higher voltage with a lesser amount of load shed. Thus, it can be noticed that as the severity of the overload condition grows, the number of buses available for load shedding increases, and the ANN-PSO algorithm works much more efficiently.

Additionally, it was observed that the total remaining load in each bus after load shedding with ANN-PSO satisfied the load priority limit requirement. This demonstrates that the proposed UVLS approach based on the ANN-PSO algorithm works efficiently by finding the minimum load to be removed without curtailing additional load from the system, protecting the vital loads in the system.

4.6 Validation of Proposed Method

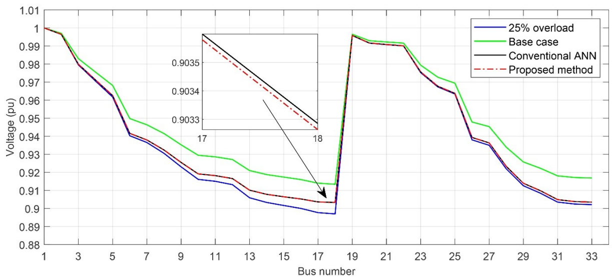
In order to further confirm the success of the proposed UVLS scheme under different overload conditions, the simulation results of the 25% overload scenario and 50% overload scenario, respectively, have been compared in detail with the UVLS method using the conventional ANN.

The voltage profile improvement after load shedding with optimized ANN and original ANN as compared to those overload cases without load shedding and the base case are presented in Figs. 17.

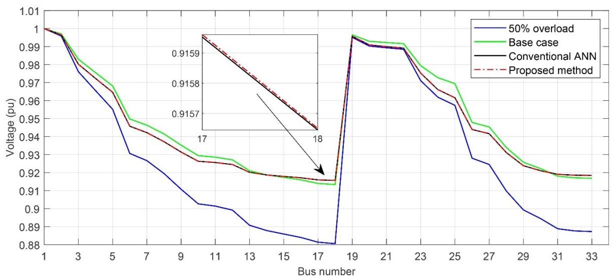
It can be seen that UVLS using the conventional ANN as well as the proposed method result in considerable enhancements in the voltage magnitudes of the different buses in the network for both 25% and 50% overload conditions. However, in the 25% overload scenario, the proposed method obtained slightly lower voltage magnitude at certain buses as compared to UVLS using the conventional ANN, as presented in the zoomed-in part of Fig. 17(a). This is commonly due to the lesser load shed by the proposed method compared to the original

***Table 8**: Comparative Results Summary.*

Method	Parameter	Overload Scenarios	
		25%	50%
Original ANN	Remaining load (MW)	4.561	4.639
	Total load shedding amount (MW)	0.082	0.933
	Minimum voltage (pu)	0.9033	0.9156
ANN with PSO	Remaining load (MW)	4.562	4.640
	Total load shedding amount (MW)	0.081	0.932
	Minimum voltage (pu)	0.9033	0.9157

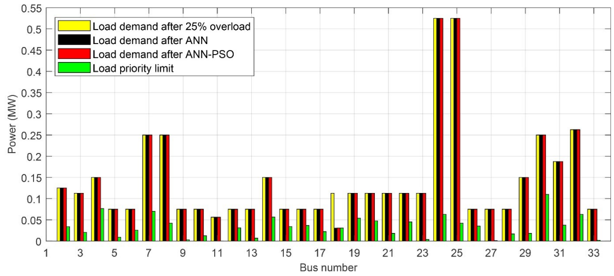


(a)

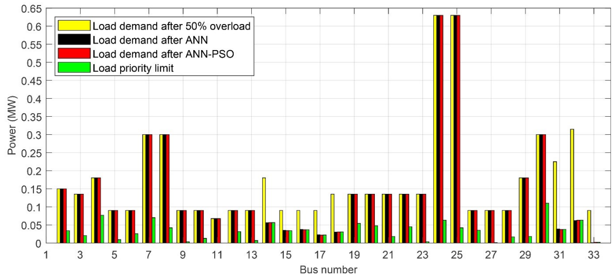


(b)

***Fig. 17**: Voltage Profile Improvement After UVLS with the ANN-PSO Algorithm Versus the Original ANN for: (a) 25% Overload Scenario and (b) 50% Overload Scenario.*



(a)



(b)

***Fig. 18**: Remaining Load After Optimal UVLS with the Proposed Method Versus the Original ANN for: (a) 25% Overload Scenario and (b) 50% Overload Scenario.*

ANN. Consequently, there is a slight variation in the voltage profile improvement due to the load shedding amount predicted by different methods.

On the other hand, the voltage profile improvement in the 50% overload scenario resulted in slightly higher voltage magnitude at certain buses as compared to UVLS using the original ANN, as revealed in the zoomed-in part of Fig. 17(b). In this instance, when comparing the suggested UVLS technique with the conventional ANN based UVLS method, the amount of load shed by the latter method is greater than the former method. However, the former method achieved a better voltage magnitude improvement, as shown in the zoomed-in part of Fig. 17(b). This reveals that as the overload condition becomes more significant, the performance of optimal UVLS becomes superior, benefiting the optimized ANN more than the non-optimized ANN.

After load shedding in a 25% overload scenario, conventional ANN preserves 4.561 MW of remaining load, denoting that 0.082 MW of load is shed after UVLS, while in the instance of UVLS using ANN-PSO, the remaining load is 4.562 MW. It has been observed that the proposed method sheds 1 kW less load than the UVLS using conventional ANN, signifying optimized ANN's excellent achievement in retaining the maximum amount of remaining load after optimal UVLS.

Similar to the 25% overload scenario, the optimal UVLS approach is applied to the 50% overload case. The result in Table 8 implies that UVLS using the ANN-PSO algorithm surpasses the original ANN in terms of attaining the greatest amount of remaining load after optimal UVLS. Furthermore, ANN-PSO has a smaller MSE value and smaller epochs than the conventional ANN. The proposed method maintains 4.640 MW of remaining load, shedding 0.932 MW of load from the network, while load shedding using the conventional ANN sheds 1 kW more than the proposed technique, as shown in Table 8. Like the 25% overload case, UVLS using the ANN-PSO algorithm surpasses the original ANN in obtaining the highest remaining load while enhancing voltage stability, as the principal objective of this work is to increase the amount of load maintained.

Fig. 18 presents the comparison of the results obtained for UVLS using ANN-PSO and conventional ANN, implying the load demand after overload (yellow bar), amount of remaining load after conventional ANN (black bar), amount of remaining load after ANN-PSO (red bar), and amount of load priority limit for every bus (green bar). Particularly, Fig. 18(a) illustrates the amount of remaining load for the 25% overload scenario, whereas Fig. 18(b) shows the load remaining for the 50% overload scenario after optimal UVLS in MW at each bus using ANN-PSO and conventional ANN, corresponding to the load priority limits considered.

From these figures, it can be observed that both UVLS approaches satisfy the minimum load priority limits set, curtailing only the non-vital loads in the system. An interesting conclusion can be drawn after examining each overload scenario: the ANN-PSO algorithm is more advantageous than the conventional ANN in terms of competence and effectiveness as the proportion of overload in the system increases.

5. CONCLUSION

This paper proposes a new UVLS method using an optimized feedforward ANN approach based on the PSO algorithm to prevent voltage collapse following overload conditions in distribution networks while considering the remaining load. This optimization was split into two sections, namely choosing the optimal topology and optimizing the feedforward ANN structure's initial weights. In the first optimization, the dispute between the optimum fitting regression of the ANN node allocation and computational time was resolved, whereas in the second section, the ANN structure's MSE was minimized. Accordingly, the prediction of load shedding by the ANN-PSO has been enhanced under different overload scenarios compared to the original ANN. Furthermore, the proposed algorithm performs accurately in different overload conditions due to the implementation of a proper database of contingencies for training the neural network. In addition, the acquired findings using the ANN-PSO algorithm have been evaluated against the original ANN in terms of the voltage profile, total remaining load, amount of load shed, and the minimum voltage of the bus in the system for every overload scenario. It was noticed that UVLS using the ANN-PSO algorithm outperforms the conventional ANN by significantly enhancing the voltage profile of the network in an emergency state and preventing voltage collapse or blackout while ensuring more remaining load. The proposed UVLS method retained 0.22% and 0.18% of the extra remaining load for 25% and 50% overload scenarios, respectively. Also, the proposed UVLS method achieved 0.7% and 3.9% voltage profile improvements for 25% and 50% overload scenarios, respectively. Moreover, as the system is severely overloaded and more buses are available for load shedding, ANN-PSO works noticeably better than the original ANN. The benefit of the ANN-PSO method is that its application is straightforward, with barely any mathematical intricacy, and it offers a more optimal result. Additionally, application of the proposed UVLS method for real-time applications as a flexible and robust approach to recovering a network in an emergency state would be valuable for potential extension of this work.

ACKNOWLEDGMENTS

This research was supported by Universiti Tun Hussein Onn Malaysia (UTHM) through GPPS (vote H626).

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