

# Reduction of Load Shedding to Enhance Voltage and Frequency Distribution Network Using PSO-ANN

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## Abstract

*The distribution network suffers from low voltage problems, low frequency, and rising power losses greater than transmission systems. Load shedding is one solution to these challenges and is widely regarded as the last choice for avoiding voltage collapse and outages caused by significant disturbances. The conventional approach to load shedding reduces loads without regard for their significance until the voltage of the network is enhanced. Shedding loads without taking priority into account will cause power interruptions in critical facilities. In this paper, PSO-ANN algorithm-based load shedding to improve the voltage and frequency of distribution networks. Furthermore, a multi-objective function is developed that takes into account the linear static voltage stability margin (VSM) and the amount of load reduction. The aim of the work is to obtain the optimal level of voltage stability and remaining load when implementing load shedding while maintaining the load priority of each bus in the distribution network. Using MATLAB software requirements, the proposed technique has been implemented for two scenarios (overload, line disconnection) of the IEEE 33 bus system. The results showed that the proposed technique is the most distinctive compared to the results of the voltage sensitivity method and the conventional approach.*

## Keywords

PSO-ANN, Load Shedding, Stability, Sensitivity.

## I. INTRODUCTION

During recent decades, overloads and voltage stability have become the most important issues leading to power outages in different regions of the world. Therefore, the application of under-voltage load shedding (UVLS) must be highly efficient, because overloads in the electrical network cause voltage instability and thus power outages [1,2].

Recent research illustrates the evolution of load-shedding approaches based on computational intelligence techniques (CITs). Nonlinear problems are easily solved using these techniques. As a result, numerous researchers have used CITs to optimize the load-shedding method by decreasing voltage drop while meeting all restrictions [3]. CITs are essentially metaheuristic algorithms that are utilized in UVLS methods. These include evolutionary techniques such as the genetic

algorithm (GA) [4], swarm-based techniques like artificial bee colonies (ABC) [5], physics-based techniques like the black hole algorithm (BHA) [6], and machine learning techniques such as the artificial neural network (ANN) [7], and others.

Another technique, improved moth flame optimization (MFO), was used to reduce load shedding, increase network load ability, and avoid voltage collapse [8]. Also, particle swarm optimization (PSO) is recommended as an ideal load-shedding strategy in order to maximize the benefits by reducing load-shedding in competitive power markets [9]. Genetic algorithm (GA) and the PSO were used as a hybrid approach to evaluate the optimal load-shedding in smart grid systems. The Fast Voltage Stability Index (FVSI) is used to find the weak buses and then calculate the optimal amount of load to be shed. The findings indicate improved reduced load



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shedding and enhanced voltage profile [10].

Moreover, the UVLS scheme, which incorporates the ABC and PSO algorithms, is suggested to enhance voltage stability by implementing load shedding on an overloaded system. Research indicates that the combination of two CITs improves performance since the advantages of both algorithms work better together [11]. However, hybrid methods take a long computational time to obtain the optimal amount of load to be eliminated, which makes them unsuitable for load shedding schemes. In summary, excessive computational time and premature convergence were the main drawbacks of the above CIT-based load shedding frameworks, which can lead to suboptimal load shedding. Without taking load priority into account, load shedding optimization has been used to increase distribution system reliability [12–14]. However, when load shedding is used, load priority is considered, but distribution system overload issues are disregarded [15, 16]. Therefore, the performance of the UVLS algorithms stated above could not be sufficient or satisfactory.

ANN is the most reliable and flexible technique available for handling non-linear regression. Conversely, ANN is able to produce satisfactory results for known occurrences but is unable to provide accurate results for unknown instances. Additionally, the main problem with ANNs is the amount of time they require to train and the regression that best fits the ANN structure [17]. In this article, the ANN structure's training strategy is optimized by using the PSO approach to address the aforementioned problems. The proposed algorithm determines the ideal load shedding amount in overloaded distribution networks while optimizing the system's remaining load and enhancing the voltage stability of the network following load shedding.

The next sections make up the rest of this article: A description of the tools and approaches utilized in the proposed method is provided in Section II. . The proposed method's construction is explained in Section III. . Section IV. illustrates the methods used for comparison. The findings and discussion are presented in Section V. . Finally, the article is concluded in Section VI. .

## II. TECHNIQUES AND TOOLS USED IN THE PROPOSED METHOD

This section provides an overview of each of the tools and techniques that were employed in the design of the proposed load-shedding method for the distribution power system.

### A. Particle Swarm Optimization Algorithm

Kennedy, Eberhart, and Shi first proposed the particle swarm algorithm in their 1995 article "Particle Swarm Optimization" [18]. Its functioning is modeled after the behavior of swarms of fish and birds, where each individual's movement is the

consequence of a combination of the unique decisions made by all the individuals in the swarm. A sequence of steps is taken to create the algorithm [19]:

1. Determine how many individuals are in the swarm. Every individual needs to be informed of their position, value, speed, destination, and the best situation they have existed in.
2. Assess every particle using the goal function.
3. Update each particle's position and speed. By using (1) and (2), the positions of the best ( $Pbest_i$ ) and the positions of the global best ( $Gbest_i$ ) are modified and updated for the subsequent phase:

$$Z_i^{K+1} = f \times Z_i^K + r_1 \times c_1 \times (Pbest_i - D_i^K) + r_2 \times c_2 \times (Gbest_i - D_i^K) \quad (1)$$

$$D_i^{K+1} = D_i^K + Z_i^K \quad (2)$$

Where;  $K$ : Number of iteration,  $D_i, Z_i$ : Current position and current velocity of each particle,  $f$ : Inertia weight,  $c_1, c_2$ : The coefficient for acceleration,  $r_1, r_2$ : The random speed values.

4. If the outcomes don't meet the optimization standards specified in the goal function and its limitations, go back to step 2 again until convergence is attained.

### B. Artificial Neural Network

An artificial neural network (ANN) starts calculations to mimic how the human brain learns [20]. ANN represents one of the CITs that can be used to find the optimal outcome, and it is the most capable algorithm for reducing optimal loads [21]. While proper data determination of the output objects is necessary for ANN, it does not require extensive understanding during application network modeling.

Moreover, the feedforward ANN has been shown to be extremely effective when operating with non-linear structures, such as distribution and power systems [22]. The three composition layers needed to model a feedforward neural network with error backpropagation learning are the input, hidden, and output layers. Every layer's neurons are connected by means of synaptic linkages, or the weights of various neurons, in conjunction with the bias parameters from the layers before them. This structure can be mathematically described by (3):

$$y = \sum_{i=1}^m w_{ij} s_j + b_j \quad (3)$$

Where;  $m$ : Number of incoming signals,  $w_{ij}$ : Weights connected to the nodes of the layer,  $s_j$ : Denotes input,  $b_j$ : The bias of the nodes.

Back-Propagation (BP) is the algorithm typically used to learn the mechanism of a feedforward artificial neural network. Utilized to increase the ANN's efficacy is the BP algorithm, a complex gradient technique. The performance of the ANN is increased by minimizing the training error through the adjustment of each node's weight and bias until the output layer produces outputs that are as nearly identical to real outputs as possible. Usually, the fitness function chosen is the mean squared error (MSE), which is therefore expressed as (4):

$$MSE = \frac{1}{m} \sum_{i=1}^m \sum_{j=1}^n [A_j(i) - E_j(i)]^2 \quad (4)$$

Where;  $m$ : Total incoming data,  $n$ : Total outputs data,  $A_j(i)$ : Actual outputs,  $E_j(i)$ : Estimated output.

### C. Voltage Stability Margin (VSM)

The voltage stability margin (VSM) is a method of determining how close a system is to a voltage breakdown. VSM can be utilized as an index for optimal load shedding in a system. Assuming that buses  $m$  and  $n$  have a branch called  $i$  (Fig. 1). This branch's loading index is determined using (5):

$$L_i = 2 \frac{V_n}{V_m} \cos \delta_{mn} - 1 \quad (5)$$

Where;  $V_n, V_m$ : Voltage magnitudes of buses  $n$  and  $m$ ,  $\delta_{mn}$ : Voltage angle difference between the two buses. The range of the loading index is 0 to 1. Under the no-load mode, it equals 1, while under the voltage collapse state, it equals 0. To find the VSM for a desired feeder made up of several branches with different loading indices, utilize (6):

$$VSM_{feeder} = \prod_{i \in B} L_i \quad (6)$$

Where  $VSM_{feeder}$  is the voltage stability margin for the intended feeder in a radial system and  $B$  is set of branches feeder [23]. The restriction regarding VSM is seen as:

$$0 < VSM < 1 \quad (7)$$

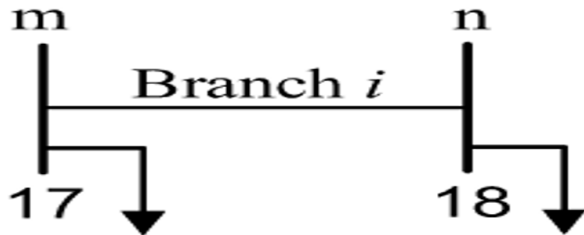


Fig. 1. Radial feeder of a distribution system

In practice, in order to keep the voltage profile at standard values, the restriction of the VSM system is considered at:

$$0.67 < VSM < 1 \quad (8)$$

### D. Load Priorities

The load priority list sets a minimum allowable load that must be retained following the load shedding operation. Consequently, an inequality function can be used to define the load limit, as shown [23]:

$$S_i^{prior} < S_i^{remain load} < S_i \quad (9)$$

Where;  $S_i^{prior}$ : Load priority limit,  $S_i^{remain load}$ : Remaining load on the bus,  $S_i$ : Load at normal condition. Table I shows the percentage load priority limits for IEEE 33-BUS.

TABLE I.  
PERCENTAGE LOAD PRIORITY LIMITS FOR THE IEEE 33-BUS

Number of bus	Percentage (%)	Number of bus	Percentage (%)
1	0	18	34
2	34	19	60
3	23	20	53
4	64	21	20
5	15	22	50
6	43	23	4
7	35	24	15
8	21	25	10
9	5	26	59
10	21	27	2
11	0	28	28
12	52	29	15
13	11	30	55
14	47	31	25
15	57	32	30
16	61	33	3
17	37		

### III. THE PROPOSED METHOD

In MATLAB software, an efficient UVLS technique for distribution networks based on PSO and ANN is suggested to determine the optimum load shedding amount for the distribution system in an emergency situation to improve the voltage profile and to avoid losing vital loads via the UVLS procedure.

The PSO technique is used to optimize the training strategy of the ANN structure. A multi-objective function is developed that takes into account the linear static voltage stability margin (VSM) and the amount of load reduction. The suggested approach is intended to keep critical loads in the system operating during the load-shedding procedure.

The aim of the objective function is to assess the optimal load shedding based on some indicators in the system, and it is formulated as:

$$f = \max(VSM + P_{\text{Remaining load}}) \quad (10)$$

Where;  $f$ : The objective function,  $VSM$ : Voltage stability margin,  $P_{\text{Remaining load}}$ : Total remaining load.

The maximum  $f$  is chosen as the best fitness value, and the optimization steps are repeated multiple times. Where it generates the optimal amount of remaining load, the load-shedding scheme that corresponds to the maximum  $f$  is chosen.

The flowchart of the proposed PSO-ANN algorithm-based load shedding is presented in Fig. 2. The ensuing subsections provide a description of the specific tools employed in this work.

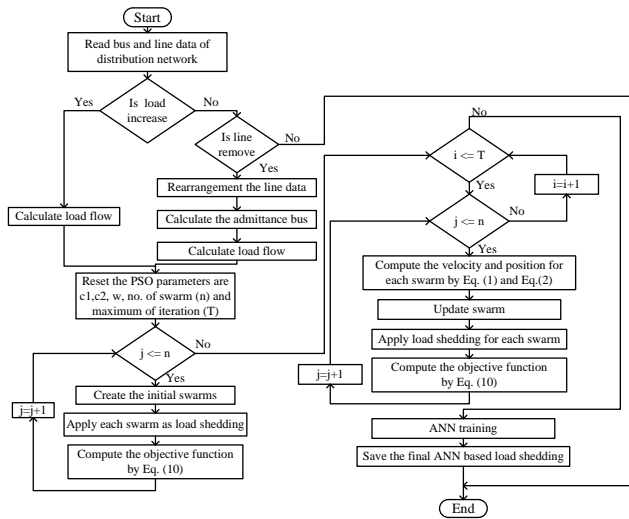


Fig. 2. Flowchart of the proposed algorithm.

### IV. METHODS USED FOR COMPARISON

There are two methods used to compare with the proposed method: the sensitivity method and the conventional method.

#### A. Sensitivity Method (SM)

For comparison with the proposed algorithm, a load-shedding approach based on voltage and frequency sensitivity was described. The overall amount of load shedding is calculated using the rate of change of frequency, and the amount of load shedding on each bus is calculated using the voltage sensitivity of each bus. The calculation was carried out with load priority in consideration.

This calculation will determine the quantity of load that will be reduced. To compute the contrast between loaded and generated power, use the equation below:

$$\frac{2H_i}{f^\circ} \frac{df}{dt} = P_m - P_e = P_{diff} \quad (11)$$

Where;  $f^\circ$ : rated frequency,  $H$ : Inertia Constant,  $\frac{df}{dt}$ : rate of frequency change,  $P_m$ : power of each machine in the system on an individual basis,  $P_e$ : electrical power required by each piece of equipment in the system,  $P_{diff}$ : power differential between generated and loaded.

The amount of disturbance can be calculated by estimating the relationship between frequency and power incompatibility using (11). By employing a QV analysis, the voltage sensitivity of each bus is assessed to determine the quantity of load that will be disconnected.

$$P_i = \sum_{j=1}^n V_i V_j Y_{ij} \cos(\delta_{ij} - \theta_{ij}) \quad (12)$$

$$Q_i = \sum_{j=1}^n V_i V_j Y_{ij} \sin(\delta_{ij} - \theta_{ij}) \quad (13)$$

Consequently, the voltage sensitivity at each bus is:

$$\frac{dQ_i}{dV_i} = \sum_{j=1}^n V_i V_j Y_{ij} \sin(\delta_{ij} - \theta_{ij}) \quad (14)$$

A minor fraction of the overall load that needs to be removed to maintain system equilibrium will be shed from each bus [24].

$$S_i = \frac{(dV_i/dQ_i)}{(\sum_{j=1}^n dV_i/dQ_i)} * P_{diff} \quad (15)$$

Where;  $\frac{dQ_i}{dV_i}$ : voltage sensitivity,  $\frac{dV_i}{dQ_i}$ : voltage sensitivity is reciprocal,  $Y$ : admittance,  $S_i$ : complex power.

#### B. Conventional Method (CM)

The voltage levels and the quantity of load to be shed for each voltage level, as shown in Table II, were used in this method to mimic the conventional UVLS approach [25].

TABLE II.  
STAGES OF CONVENTIONAL LOAD SHEDDING

stage	Threshold Voltage (pu)	Load Shedding Percentage (%)
1	0.9	20
2	0.88	20
3	0.86	10

V. RESULT AND DISCUSSION

This section uses MATLAB simulations to assess the efficacy of the proposed PSO-ANN algorithm for optimal load shedding. The IEEE 33 bus, which is seen in Fig. 3 was used to showcase the simulations. The system consists of 32 branches and 33 buses. The load demands have a 2300 kVAR reactive power and a total active power of 3715 kW. It is driven by a synchronous generator that has a voltage of 12.66 kV at 60 Hz and a base capacity of 100 MVA [26]. Table I, shows the load priority restrictions based on the percentage of vital loads in each bus.

A. Training Result

Using the Back-Propagation (BP) algorithm based on the error correction rule, the weights and bias of each node are updated. The process involves two passes through the entire network: a direct pass, where the weights and bias are fixed, and an indirect pass, where the weights and bias are adjusted through an “error correction rule.” Adjustment continues until the actual outputs become close to the desired outputs.

The structure of ANN used in the proposed algorithm is show in Fig. 4. The mean square error (MSE) value was  $1.11 \times 10^{-5}$  after 250 epochs and the regression rate was  $R = 0.99878$  of (PSO-ANN) method as showed in Fig. 5 and Fig. 6, correspondingly.

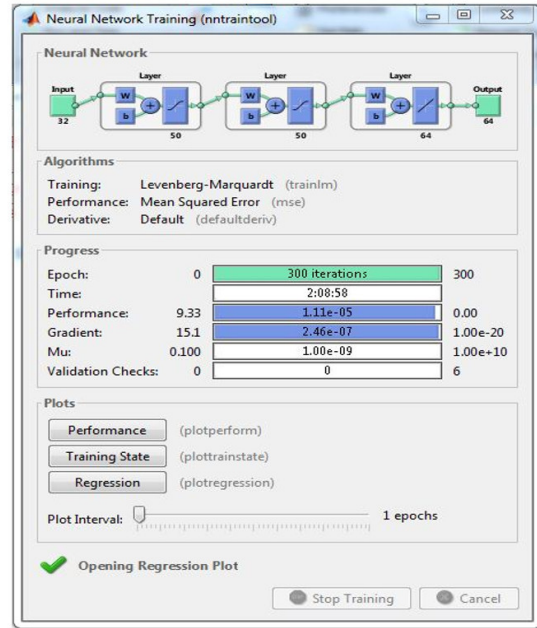


Fig. 4. The structure of ANN.

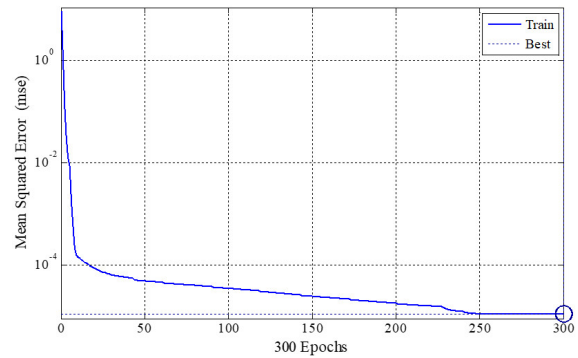


Fig. 5. Convergence of PSO-NN.

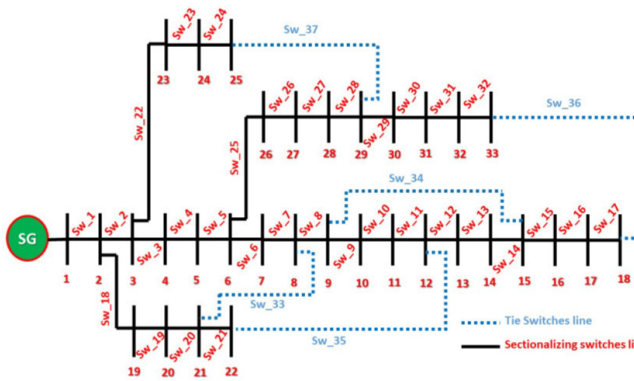


Fig. 3. Test system (IEEE 33-bus).

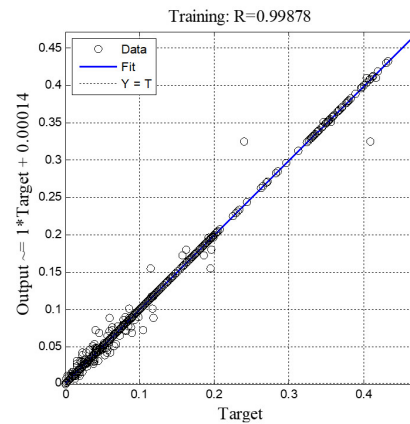


Fig. 6. Regression for the PSO-NN.

## VI. RESULT OF SCENARIOS

Two scenarios (overload and line loss) are simulated to estimate the importance of the proposed load-shedding method. The first scenario has three cases as shown below:

### 1) No Overload

In this case, there is no increase in loads. Table ?? and Fig. 7 show the voltage profile and Table III shows the comparison of the proposed technique with other methods for this case. Fig. 8 also shows the remaining load in the absence of overload.

### 2) Overload 30%

In this case, the proposed method and other methods are applied after increasing the load by 30%. Table IV and Fig. 9 show the voltage profile and Table 6 shows the comparison of the proposed technique with other methods for this case. Fig. 10 also shows the remaining load at this load increase.

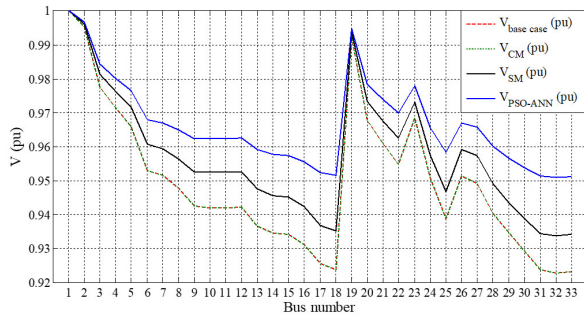


Fig. 7. Voltage profile at no overload.

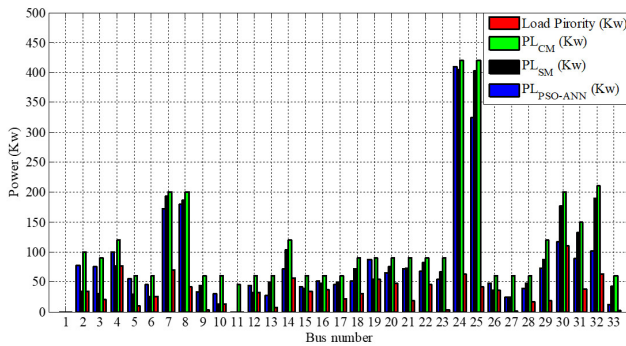


Fig. 8. Power remaining at no overload.

Bus number	$V_{PSO-ANN}$	$V_{(SM)}$	$V_{(CM)}$	$V_{Base\ case}$
2	0.99665	0.99608	0.99521	0.99521
3	0.98432	0.98129	0.97755	0.97755
4	0.98024	0.97645	0.97161	0.97161
5	0.97652	0.97186	0.96605	0.96605
6	0.96802	0.96072	0.95305	0.95305
7	0.96693	0.95931	0.95154	0.95154
8	0.96496	0.95647	0.94783	0.94783
9	0.96233	0.95255	0.94262	0.94262
10	0.96236	0.95254	0.94201	0.94201
11	0.96242	0.95257	0.94203	0.94203
12	0.96253	0.95264	0.94228	0.94228
13	0.95918	0.94757	0.93672	0.93672
14	0.95789	0.94572	0.93475	0.93475
15	0.95743	0.94515	0.93419	0.93419
16	0.95566	0.94244	0.93131	0.93131
17	0.95248	0.93694	0.92569	0.92569
18	0.95162	0.93518	0.92397	0.92397
19	0.99464	0.99367	0.99227	0.99227
20	0.97840	0.97338	0.96785	0.96785
21	0.97389	0.96766	0.96101	0.96101
22	0.97005	0.96257	0.95484	0.95484
23	0.97801	0.97326	0.96852	0.96852
24	0.96559	0.95739	0.95088	0.95088
25	0.95845	0.94686	0.93877	0.93877
26	0.96697	0.95928	0.95137	0.95137
27	0.96568	0.95738	0.94923	0.94923
28	0.96026	0.94917	0.94053	0.94053
29	0.95658	0.94350	0.93462	0.93462
30	0.95377	0.93882	0.92927	0.92927
31	0.95134	0.93455	0.92394	0.92394
32	0.95100	0.93385	0.92298	0.92298
33	0.95130	0.93434	0.92329	0.92329

TABLE III.  
RESULT OF COMPARISON AT NO OVERLOAD

Items	PSO-ANN	SM	CM	Base case
$P_{Loss}$ (Kw)	92.60952	151.07537	207.93496	207.93496
$Q_{Loss}$ (Kvar)	65.40070	108.50756	149.11539	149.11539
VSM	0.647825	0.53567	0.484364	0.484364
$V_{min}$ (pu)	0.95100	0.93385	0.92298	0.92298
Frequency (Hz)	59.53695	59.24462	58.96032	58.96032
Power load (Kw)	2680.63637	2918.38546	3715	3715
Load shedding (%)	27.84289	21.44319	0	—
$P_{Loss}$ reduction	55.5 %	27.3 %	0	—
$V_{min}$ improvement	3 %	1.2 %	0	—

TABLE IV.  
VOLTAGE PROFILE AT OVERLOAD 30%

Bus number	$V_{PSO-ANN}$	$V_{(SM)}$	$V_{(CM)}$	$V_{Base\ case}$
2	0.99663	0.99515	0.99384	0.99365
3	0.98392	0.97672	0.97115	0.97023
4	0.98014	0.97076	0.96351	0.96235
5	0.97662	0.96505	0.95638	0.95497
6	0.96833	0.95098	0.93971	0.93768
7	0.96723	0.94914	0.93773	0.93567
8	0.96650	0.94557	0.93299	0.93074
9	0.96367	0.94075	0.92644	0.92379
10	0.96344	0.94080	0.92563	0.92299
11	0.96341	0.94083	0.92565	0.92301
12	0.96352	0.94092	0.92599	0.92335
13	0.95990	0.93450	0.91905	0.91594
14	0.95887	0.93213	0.91663	0.91331
15	0.95851	0.93140	0.91605	0.91255
16	0.95683	0.92792	0.91273	0.90870
17	0.95402	0.92077	0.90630	0.90118
18	0.95315	0.91845	0.90450	0.89888
19	0.99472	0.99216	0.99006	0.98976
20	0.97904	0.96682	0.95865	0.95734
21	0.97469	0.95964	0.94987	0.94826
22	0.97097	0.95326	0.94197	0.94006
23	0.97705	0.96649	0.95955	0.95823
24	0.96694	0.94620	0.93694	0.93479
25	0.96187	0.93286	0.92161	0.91865
26	0.96746	0.94918	0.93758	0.93544
27	0.96635	0.94678	0.93488	0.93260
28	0.96167	0.93610	0.92394	0.92100
29	0.95911	0.92869	0.91654	0.91312
30	0.95644	0.92274	0.91005	0.90597
31	0.95367	0.91744	0.90440	0.89884
32	0.95326	0.91661	0.90340	0.89757
33	0.95309	0.91731	0.90377	0.89797

TABLE V.  
COMPARISON AT OVERLOAD 30%

Items	PSO-ANN	SM	CM	Base case
$P_{Loss}(Kw)$	86.48142	239.62352	338.59735	366.97212
$Q_{Loss}(Kvar)$	59.70509	172.44191	242.13342	263.27637
VSM	0.68068	0.45002	0.39811	0.37488
$V_{min}(pu)$	0.95309	0.91661	0.90340	0.89757
Frequency (Hz)	59.56759	58.80188	58.30701	58.16513
Power load (Kw)	2709.02706	3509.07174	4696.9	4829.5
Load shedding (%)	43.90667	27.34088	2.74562	—
$P_{Loss}$ reduction	76.4 %	34.7 %	7.7 %	—
$V_{min}$ improvement	6.1 %	2.1 %	0.64 %	—

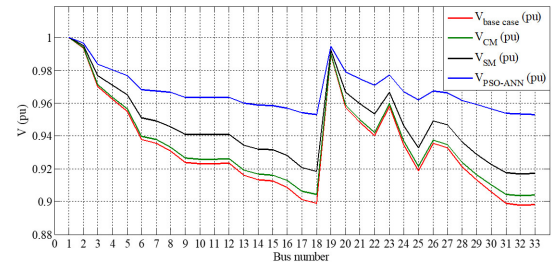


Fig. 9. Voltage profile at overload 30%.

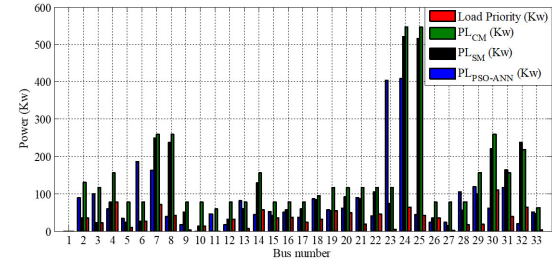


Fig. 10. Power remaining at overload 30%.

### 3) Overload 50%

In this case, the proposed method and other methods are applied after increasing the load by 50%. Table VI and Fig. 11 show the voltage profile and Table VII shows the comparison of the proposed technique with other methods for this case. Fig. 12 also shows the remaining load at this load increase.

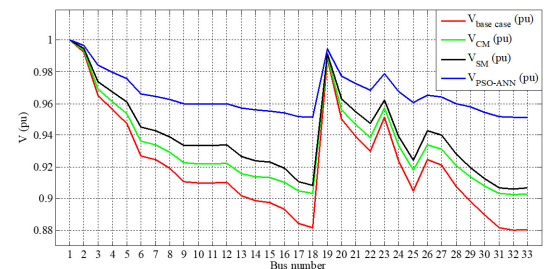


Fig. 11. Voltage profile at overload 50%.

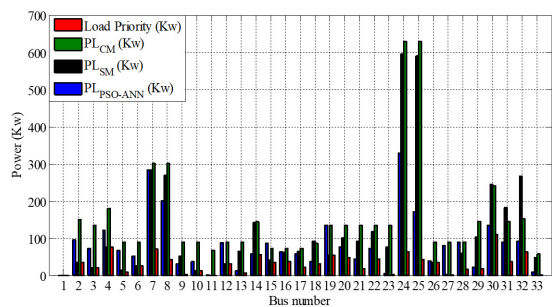


Fig. 12. Load remaining at overload 50%.

TABLE VI.  
VOLTAGE PROFILE AT OVERLOAD 50%

Bus number	$V_{PSO-ANN}$	$V_{(SM)}$	$V_{(CM)}$	$V_{Base\ case}$
2	0.99656	0.99457	0.99341	0.99257
3	0.98442	0.97386	0.96924	0.96515
4	0.97979	0.96723	0.96109	0.95593
5	0.97561	0.96084	0.95356	0.94729
6	0.96614	0.94495	0.93612	0.92702
7	0.96450	0.94283	0.93390	0.92467
8	0.96262	0.93884	0.92899	0.91889
9	0.95998	0.93350	0.92259	0.91073
10	0.95987	0.93359	0.92169	0.90978
11	0.95992	0.93363	0.92173	0.90981
12	0.96001	0.93372	0.92214	0.91020
13	0.95708	0.92647	0.91561	0.90150
14	0.95585	0.92378	0.91350	0.89841
15	0.95530	0.92295	0.91311	0.89751
16	0.95386	0.91898	0.91023	0.89299
17	0.95157	0.91073	0.90469	0.88413
18	0.95127	0.90804	0.90323	0.88142
19	0.99433	0.99123	0.98936	0.98802
20	0.97715	0.96279	0.95592	0.95007
21	0.97244	0.95472	0.94666	0.93942
22	0.96826	0.94753	0.93842	0.92981
23	0.97899	0.96225	0.95699	0.95110
24	0.96773	0.93912	0.93329	0.92362
25	0.96071	0.92401	0.91802	0.90468
26	0.96519	0.94292	0.93397	0.92440
27	0.96400	0.94021	0.93130	0.92106
28	0.95985	0.92793	0.92070	0.90743
29	0.95769	0.91936	0.91370	0.89817
30	0.95444	0.91262	0.90792	0.88976
31	0.95161	0.90672	0.90321	0.88138
32	0.95115	0.90581	0.90247	0.87987
33	0.95125	0.90669	0.90270	0.88035

TABLE VII.  
COMPARISON AT OVERLOAD 50%

Items	PSO-ANN	SM	CM	Base case
$P_{Loss}(Kw)$	94.12341	305.78789	367.99621	503.82723
$Q_{Loss}(Kvar)$	67.27464	220.22334	261.53784	361.56948
VSM	0.67186	0.40270	0.39658	0.31194
$V_{min}(pu)$	0.95115	0.90581	0.90247	0.87987
Frequency (Hz)	59.52938	58.47106	58.16001	57.48086
Power load (Kw)	2748.65147	3854.43989	5060.7	5572.5
Load shedding (%)	50.67471	30.83104	9.18438	—
$P_{Loss}$ reduction	81.3 %	39.3 %	26.9 %	—
$V_{min}$ improvement	8%	2.9 %	2.5 %	—

In the second scenario, the following cases are taken (Loss

of line 3, Loss of line 20):

1. Loss of line 3

In this case, line 3 is lost. Table VIII and Fig. 13 show the voltage profile and Table IX shows the comparison of the proposed technique with other methods for this case. The remaining load for each method is shown in Fig. 14.

TABLE VIII.  
VOLTAGE PROFILE AT LOSS OF LINE 3

Bus number	$V_{PSO-ANN}$	$V_{(SM)}$	$V_{(CM)}$	$V_{Base\ case}$
2	0.99772	0.99625	0.99529	0.99507
3	0.99167	0.98475	0.98141	0.98054
4	0.94875	0.92163	0.90470	0.89880
5	0.94921	0.92215	0.90525	0.89949
6	0.95088	0.92380	0.90724	0.90199
7	0.95175	0.92517	0.90879	0.90372
8	0.95696	0.93370	0.91871	0.91445
9	0.95551	0.93221	0.91628	0.91183
10	0.95613	0.93380	0.91753	0.91322
11	0.95635	0.93406	0.91785	0.91356
12	0.95677	0.93459	0.91869	0.91445
13	0.95351	0.92927	0.91277	0.90805
14	0.95247	0.92723	0.91064	0.90571
15	0.95222	0.92646	0.90996	0.90484
16	0.95135	0.92404	0.90768	0.90211
17	0.95016	0.91905	0.90335	0.89682
18	0.95009	0.91748	0.90213	0.89529
19	0.99542	0.99281	0.99099	0.99057
20	0.97595	0.96324	0.95440	0.95215
21	0.97044	0.95464	0.94390	0.94110
22	0.96614	0.94812	0.93588	0.93267
23	0.98580	0.97351	0.96821	0.96671
24	0.97382	0.95078	0.94195	0.93913
25	0.96312	0.93337	0.92131	0.91720
26	0.95113	0.92384	0.90734	0.90212
27	0.95167	0.92404	0.90771	0.90253
28	0.95453	0.92475	0.90980	0.90480
29	0.95710	0.92577	0.91208	0.90721
30	0.95399	0.92118	0.90698	0.90155
31	0.95102	0.91699	0.90238	0.89571
32	0.95027	0.91629	0.90152	0.89460
33	0.95022	0.91674	0.90170	0.89476

TABLE IX.  
COMPARISON AT LOSS OF LINE 3

Items	PSO-ANN	SM	CM	Base case
$P_{Loss}(Kw)$	71.20822	190.94855	276.11971	308.37182
$Q_{Loss}(Kvar)$	58.60759	151.83859	220.83401	247.18030
VSM	0.80128	0.64166	0.60216	0.57875
$V_{min}(pu)$	0.94875	0.91629	0.90152	0.89460
Frequency (Hz)	59.64395	59.04525	58.61940	58.45814
Power load (Kw)	1771.03256	2720.07106	3565	3715
Load shedding (%)	52.32752	26.78139	4.03768	—
$P_{Loss}$ reduction	76.9 %	38 %	10.45 %	—
$V_{min}$ improvement	6.05 %	2.4 %	0.77 %	—

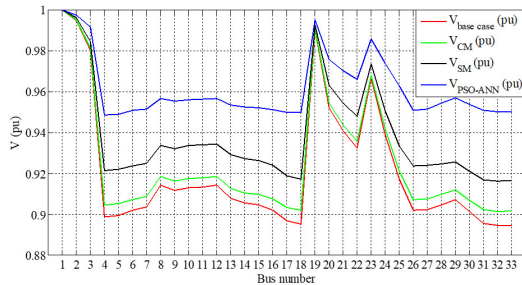


Fig. 13. Voltage profile at loss of line 3.

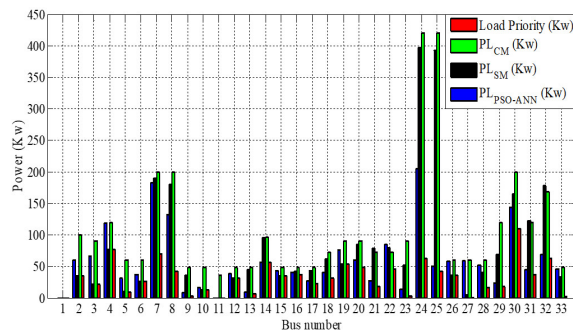


Fig. 14. Load remaining at loss of line 3.

## 2. Loss of line 20

In this case, line 20 is lost. Table X and Fig. 15 show the voltage profile and Table XI shows the comparison of the proposed technique with other methods for this case. Fig. 16 shows the remaining load in each method.

TABLE X.  
COMPARISON AT LOSS OF LINE 20

Bus number	$V_{PSO-ANN}$	$V_{(SM)}$	$V_{(CM)}$	$V_{Base\ case}$
2	0.99752	0.99624	0.99544	0.99507
3	0.98557	0.97734	0.97291	0.97060
4	0.98059	0.97030	0.96442	0.96126
5	0.97603	0.96341	0.95621	0.95217
6	0.96491	0.94600	0.93637	0.93018
7	0.96171	0.94091	0.93107	0.92415
8	0.95186	0.92414	0.91234	0.90199
9	0.94940	0.91943	0.90689	0.89522
10	0.94808	0.91733	0.90421	0.89187
11	0.94789	0.91703	0.90389	0.89146
12	0.94755	0.91648	0.90345	0.89091
13	0.94690	0.91445	0.90171	0.88881
14	0.94667	0.91401	0.90141	0.88848
15	0.94704	0.91468	0.90215	0.88948
16	0.94712	0.91426	0.90195	0.88934
17	0.94778	0.91391	0.90210	0.88991
18	0.94850	0.91437	0.90286	0.89100
19	0.99720	0.99590	0.99502	0.99465
20	0.99594	0.99410	0.99311	0.99274
21	0.94851	0.91841	0.90635	0.89447
22	0.94749	0.91710	0.90485	0.89260
23	0.98071	0.96806	0.96242	0.95932
24	0.97068	0.94938	0.94171	0.93698
25	0.96329	0.93602	0.92661	0.92027
26	0.96419	0.94475	0.93489	0.92861
27	0.96341	0.94314	0.93303	0.92663
28	0.96061	0.93585	0.92558	0.91868
29	0.95907	0.93083	0.92063	0.91335
30	0.95528	0.92505	0.91439	0.90612
31	0.95128	0.91784	0.90689	0.89642
32	0.95017	0.91609	0.90504	0.89398
33	0.94928	0.91519	0.90392	0.89246

TABLE XI.  
COMPARISON AT LOSS OF LINE 20

Items	PSO-ANN	SM	CM	Base case
$P_{Loss}(Kw)$	74.66021	199.94839	263.12473	320.79488
$Q_{Loss}(Kvar)$	50.49341	136.02154	176.81385	217.85780
VSM	0.64627	0.47526	0.43638	0.39021
$V_{min}(pu)$	0.94667	0.91391	0.90141	0.88848
Frequency (Hz)	59.62669	59.00025	58.68437	58.39602
Power load (Kw)	1915.6150	2719.17707	3460	3715
Load shedding (%)	48.43566	26.80546	6.86406	—
$P_{Loss}$ reduction	76.7%	37.67 %	18 %	—
$V_{min}$ improvement	6.55 %	2.25 %	1.45 %	—

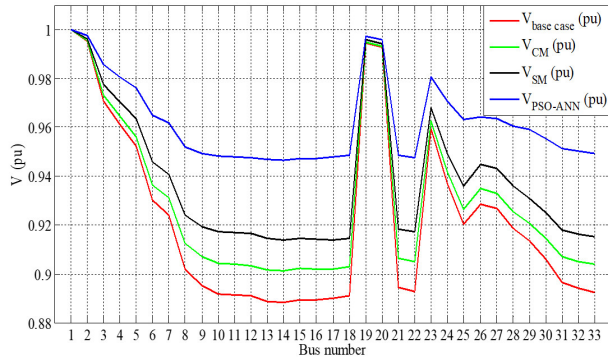


Fig. 15. Voltage profile at loss of line 20.

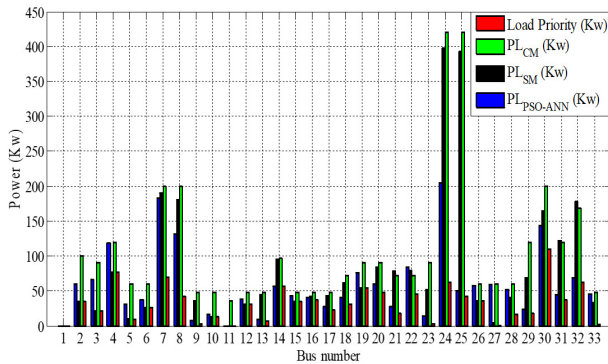


Fig. 16. Load remaining at loss of line 20.

The results for the first scenario in the base case (no overload) when applying the proposed method show an improvement in VSM from (0.484364) to (0.647825), active power losses decreased from (207.93496) to (92.60952), frequency improved from (58.96032) to (59.53695), minimum voltage was (0.95100), and load shedding percent was (27.84289). When compared with other methods, it became clear that the proposed method was much better, as explained in Table III and Fig. 7. It is also noted in this case when applying the proposed method that the amount of load shedding does not exceed the load priority limits for each bus, as explained in Fig. 8.

The results for the first scenario in the case of overload 30% likewise show an improvement in VSM from (0.37488) to (0.68068), active power losses decreased from (366.97212) to (86.48142), frequency improved from (58.16513) to (59.56759), minimum voltage was (0.95309), and load shedding percent was (43.90667). Also, when compared with other methods, the proposed method was much better, as explained in Table V and Fig. 9.

In the case of overloading 50%, there was an improvement in VSM from (0.31194) to (0.67186), active power losses decreased from (503.82723) to (94.1234), frequency improved from (57.48086) to (59.52938), minimum voltage was

(0.95115), and load shedding percent was (50.67471). Also, when compared with other methods, the proposed method was much better, as explained in Table VII and Fig. 11.

The results in the second scenario, when line 3 is lost, when applying the proposed method show an improvement in VSM from (0.57875) to (0.80128), active power losses decreased from (308.37182) to (71.20822), frequency improved from (58.45814) to (59.64395), minimum voltage was (0.94667), and load shedding percent was (52.32752). When compared with other methods, it became clear that the proposed method was much better, as explained in Table IX and Fig. 13.

The results in the second scenario when line 20 is lost likewise show an improvement in VSM from (0.39021) to (0.64627), active power losses decreased from (320.79488) to (74.66021), frequency improved from (58.3960) to (59.62669), minimum voltage was (0.95309), and load shedding percent was (48.43566). Also, when compared with other methods, the proposed method was much better, as explained in Table XI and Fig. 15.

It is also noted for all cases when applying the proposed method that the amount of load shedding does not exceed the load priority limits for each bus, as explained in Fig. 10 and Fig. 12 when overload is 30% and 50%, Fig. 14 and Fig. 16 when loss is lines 3 and 20, respectively.

The comparison tables show the percentage of improvement in reducing the amount of power loss and increasing the minimum voltage when using the proposed method. The active and reactive losses for the cases with the highest losses (a 50% increase in load and cutting line No. 20) have been reduced by a large percentage when using the proposed method. In the case of a 50% increase in load, the active power losses were reduced by 81.3%, and in the case of cutting line No. 20 has decreased by 76.7%. Likewise, the minimum voltage value in the case of a 50% load increase was improved by 8%, and in the case of disconnecting line 20 by 6.55% using proposed method.

## VII. CONCLUSION

The PSO algorithm-trained feed-forward ANN model used in this paper presents an optimal UVLS approach for determining the optimal load-shedding quantity for a distribution network to avoid voltage collapse after a disturbance occurs (overload, line loss) while taking into account the remaining load and the load priority limits for each bus. The PSO-ANN algorithm performs accurately in different overload and line loss conditions due to the implementation of a proper database of contingencies for training the neural network, which depends on the PSO algorithm.

The results obtained using the PSO-ANN algorithm were compared with the SM and CM algorithms in terms of the

overall voltage profile (VSM), the remaining load, load shedding amount, power loss, and the minimum bus voltage in the system for all the scenarios. It was shown that UVLS employing the PSO-ANN algorithm performs better than SM and CM by considerably improving the network's voltage profile during an emergency, avoiding voltage collapse or blackout, providing a higher remaining load, and reducing power losses while maintaining priority loads. Future studies might extend this article to include the following issues:

1. Network study in multiple emergencies.
2. Applying the proposed method to a part of the Iraqi distribution networks.

### CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article

### LIST OF ABBREVIATIONS

Abbreviation	Meaning
PSO	Particle swarm optimization
ANN	The artificial neural network
VSM	Voltage stability margin
MATLAB	Matrix Laboratory
IEEE	Institute of Electrical and Electronics Engineers
UVLS	Under-voltage load shedding
CITs	Computational intelligence techniques
GA	Genetic algorithm
ABC	Artificial bee colonies
BHA	The black hole algorithm
MFO	Moth flame optimization
FVSI	The fast voltage stability index
BP	Back-Propagation
MSE	The mean squared error

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