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# Load Shedding in Microgrid System with Combination of AHP Algorithm and Hybrid ANN-ACO Algorithm

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**Abstract**

This paper proposes a new load shedding method based on the application of intelligent algorithms, the process of calculating and load shedding is carried out in two stages. Stage-1 uses a backpropagation neural network to classify faults in the system, thereby determining whether or not to shed the load in that particular case. Stage-2 uses an artificial neural network combined with an ant colony algorithm (ANN-ACO) to determine a load shedding strategy. The AHP algorithm is applied to propose load shedding strategies based on ranking the importance of loads in the system. The proposed method in the article helps to solve the integrated problem of load shedding, classifying the fault to determine whether or not to shedding the load and proposing a correct strategy for shedding the load. The IEEE 25-bus 8-generator power system is used to simulate and test the effectiveness of the proposed method, the results show that the frequency of recovery is good in the allowable range.

**Keywords:** load shedding, ANN-ACO, BPNN, AHP, Microgrid

## 1. Introduction

Along with the development of economy and society, the load demand for electricity is also increasing. This requires the power system to develop in the direction of increasing scale and structure (Xu & Ma, 2021; Yin & Sun, 2021). Therefore, the number of loads and sources also increases rapidly, the number of faults in the system also increases. Serious problems sometimes unbalance the power and lead to frequency instability in the system. In the event of an incident that causes the generating power to be lower than the load's demand, shedding the load is the first necessary solution to quickly restore frequency stability.

There are many methods of shedding loads in the power system as in (Haes Alhelou & Hamedani Golshan, 2020; Sigrist & Echavarren, 2018) presents traditional shedding methods using under-frequency load shedding relays. These methods have the advantage of rapidly shedding the load which will help to restore the frequency to steady state. However, this sometimes leads to incorrect shedding situations, which results in losses for customers and power suppliers.

The methods of applying intelligent algorithms are also applied to load shedding (Padron & Hernandez, 2016), an online method is proposed to predict and adjust the possible load shedding problem by redistributing the load. This proposal uses artificial intelligence techniques, especially neural networks, to solve problems. A hybrid algorithm ABC-PSO is applied to provide more optimal solutions for load shedding problems with multi-objective functions (Kisengeu & Muriithi, 2021). A combined optimization method i.e., evolutionary particle swarm optimization is presented to determine the optimal amount of load power for load shedding (Usman & Amin, 2018). The proposed integration of Firefly Algorithm and Particle Swarm Optimization (FAPSO) is presented to apply scheduled and frequency reduction (Jallad & Mekhilef, 2018). A hybrid optimization algorithm between Particle Swarm Optimization and Bacterial Foraging (HPSBF) is presented to ensure security and the system's stability following faults and disturbances (Awad & Hafez, 2021). Besides, it also serves to optimize the operation of load shedding relays. The methods of using intelligent algorithms have the advantage of optimizing common problems in load shedding such as optimizing the amount of load shedding power, optimizing the load shedding schedule or optimizing the operation of load shedding relays.

The above load shedding methods have basically solved the key problems of load shedding. However, the classification of problems in the system to summarize which cases need or not to shed the load has not been mentioned. Besides, there are specific solutions for those cases.

In this paper, we propose a new load shedding method consisting of two stages. Stage-1 uses a backpropagation neural network to classify problems in the system, thereby determining whether or not to shed the load in that particular case. Stage-2 uses an artificial neural network combined with an ant colony algorithm (ANN-ACO) to determine a load shedding strategy. The AHP algorithm is applied to propose load shedding strategies based on ranking the importance of loads in the system. The proposed method in the article helps to solve the integrated problem of load shedding, classifying the fault to determine whether or not to shedding the load and proposing a correct strategy for shedding the load. The ACO algorithm with positive feedback leads to quick finding of good solutions, distributed computing avoids premature convergence and can be used in dynamic applications. From there, it helps to identify better load shedding strategies and achieve greater accuracy in training.

The effectiveness of the proposed method is simulated and tested on the IEEE 25-bus system with 8-generators. The simulation results show that the frequency recovery of the power system is positive, the frequency values quickly return to the allowable range when a fault occurs after the intervention of load shedding according to the proposed method. The proposed neural network adapts well to the simulated data of the system and achieves high performance in fault prediction.

## 2. Method

### *2.1 The Load Shedding Control Strategy Proposed Based on AHP Algorithm*

According to Saaty (1980) Analytic Hierarchy Process (AHP) is an approach to decision making. In this study, the AHP method is applied to calculate the priority weight of the load to rank the loads for the construction of a load shedding strategy. The steps are described in (Nguyen & Le, 2021).

### *2.2 Artificial Neural Network*

An artificial neural network is a computational model that simulates the structure and operation of biological neural networks. The structure of a simple artificial neural network consists of 3 layers including input layer, hidden layer and output layer. The number of neurons per layer depends on the trainer's decision to fit the training data.

Neural network training is essentially a process of finding the optimal set of weights for connections between neurons. From there, the neural network gives outputs that match the desired target value corresponding to each input. The backpropagation algorithm (Bala & Kumar, 2017), is a commonly used method in training neural networks to find the correct set of weights. Backpropagation is a supervised learning method. The inputs are passed into the neural network to produce the outputs. The calculated output is then compared with the desired target result to get error. Finally, the calculated error is used to adjust the weight so that it is minimized. This process is repeated until the error is within a criterion value.

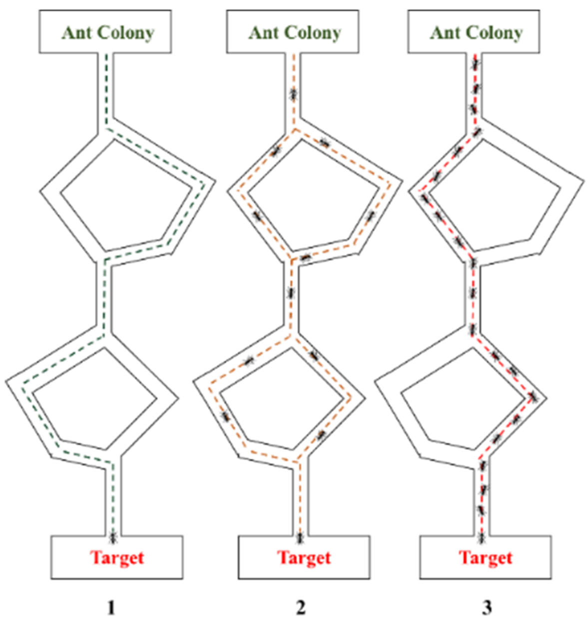



Figure 1. Ant Colony Optimization

*2.3 Ant Colony Optimization Algorithm*

Ant Colony Optimization (ACO) algorithm proposed by Marco Dorigo in 1996 (Dorigo & Maniezzo, 1996), inspired by the foraging behavior of ant colonies, helps ants find the shortest paths between food and the nest. The initial goal of the algorithm is to solve the traveling sales problem. It is a hyper-simulation approach to solving difficult optimization problems. In ACO, a group of artificial ants searches the space for the optimal solution to a problem. The ACO algorithm was born with the idea based on the behavior of ants that leave traces with pheromones to guide the paths traveled. From the saved path segments for analysis to find the optimal path to the goal, the process is depicted in Figure 1. The general flowchart of the algorithm is shown in Figure 2.

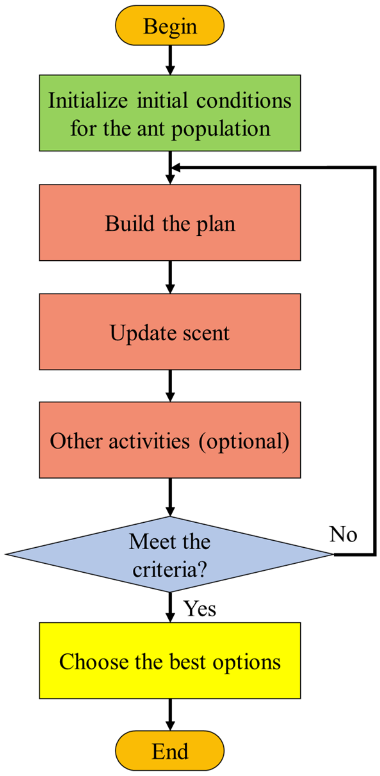



Figure 2. Flowchart of the ACO algorithm

The ACO algorithm has two forms, continuous and discrete. Depending on each specific problem, it is decided to use these two forms. The algorithm used in this project is of the continuous ACO type, because the spatial problem to be solved to find the optimal set of neural network weights is continuous.

*2.4 Backpropagation neural network combined with ant colony optimization algorithm*

The goal of the backpropagation algorithm is to adjust the link weights between the input nodes or data based on the error of the output with the target. According to Yann (2015), the author pointed out the shortcomings of the backpropagation algorithm in neural training such as instability and slow convergence due to local minimum entanglement. In order to overcome the shortcomings of neural training by back-propagation network, in this paper, it is proposed to use hybrid training method using ant colony optimization algorithm. The efficiency of the ACO algorithm is shown for an n-dimensional continuous optimization problem with n variables (Ojha & Abraham, 2014).

## 3. Simulation and Results

The proposed method is tested on the IEEE 25-Bus Microgrid diagram (Vergara & Lopez, 2019). This test system consists of 8 synchronous machines, 25 buses, 25 transmission lines, 9 transformers and 11 constant impedance loads, the system construction parameters are referenced from (Vergara & Lopez, 2019). The IEEE 25-Bus Microgrid system diagram is shown in Figure 3.

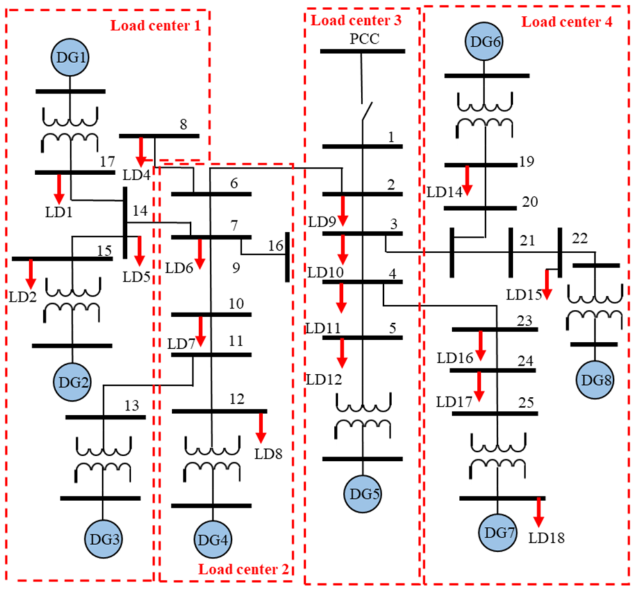



Figure 3. The IEEE 25-Bus Microgrid system diagram

The construction of the data set to train the ANN-ACO network is performed with loads from 50% to 100% of the load. For each load level, the test system is sampled with data for island operation cases and generator failure cases. The process of building a dataset to train ANN-ACO is shown in Figure 4.

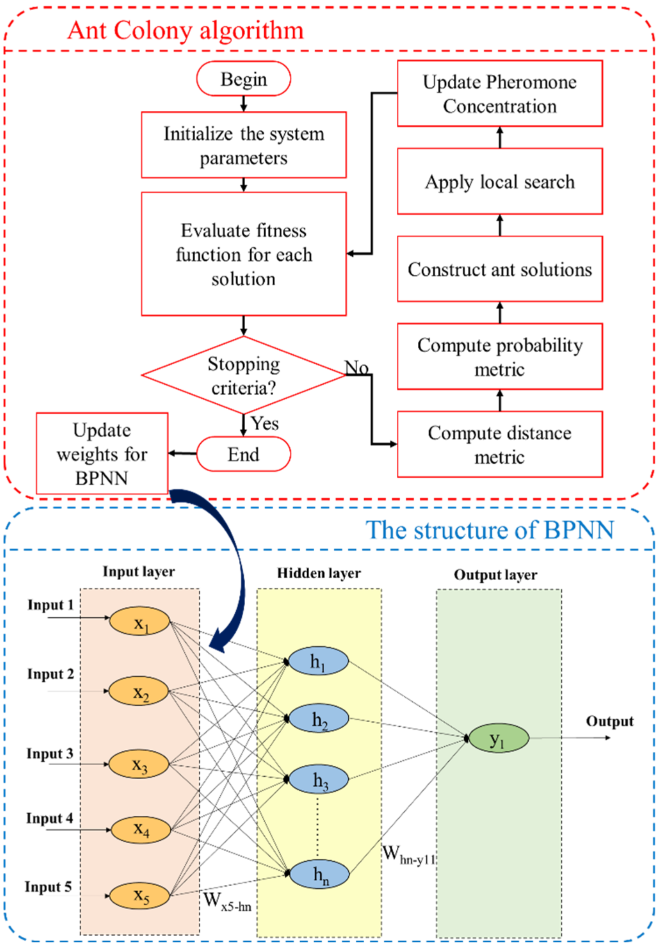


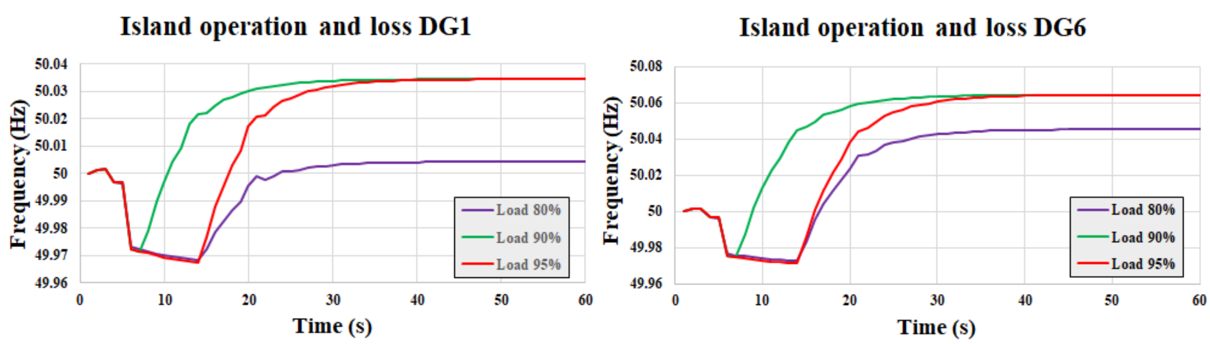

Figure 4. The process of building a dataset to train ANN-ACO

For the case of load shedding, each different load level will have a combination of loads and their shedding sequence is ranked in order of priority based on the AHP algorithm presented in section 2.1. The load shedding process is conducted based on the results of the load ratings and performed until the frequency is restored to the allowable range. The summary results of load shedding strategies for different load levels are presented in Table 1.

Table 1. STRATEGIES FOR LOAD SHEDDING ACCORDING TO THE AHP ALGORITHM

| Load shedding control strategy | Load |
|---|---|
| $LS_1$ | Load1, Load2, Load6, Load5, Load11, Load10 |
| $LS_2$ | Load1, Load2, Load6, Load5, Load11, Load10, Load7 |
| $LS_3$ | Load1, Load2, Load6, Load5, Load11, Load10, Load7, Load4 |
| $LS_4$ | Load1, Load2, Load6, Load5, Load11, Load10, Load7, Load4, Load17 |

The results of comparing recovery time and frequency value in DG1 and DG6 failure cases at 80%, 90% and 95% load level are shown in Figure 5. From there, implement the same load shedding strategy to consider frequency recovery into steady-state.




(a) (b)

Figure 5. System recovery frequency with failure (a) DG1 and (b) DG6

Table 2. Strategies for load shedding according to the AHP algorithm

| Load level | Island operation and loss DG1 | | Island operation and loss DG6 | |
|---|---|---|---|---|
| | Frequency recovery times (s) | Recovery frequency (Hz) | Frequency recovery times (s) | Recovery frequency (Hz) |
| 80%P tải | 19,08 | 50,004 | 19,08 | 50,045 |
| 90%P tải | 22,08 | 50,034 | 25,08 | 50,064 |
| 95%P tải | 25,07 | 50,048 | 25,08 | 50,073 |

The results of Table 2 show that, when the system operates with a higher load level, the frequency deviation from the rated frequency is higher and the recovery time is slower. As in the case of 90% $P_{load}$, the same fault DG1 is set to the same parameters, the same type of strategy is LS3, the frequency recovery time is 22.08 seconds, the recovery frequency is 50.034Hz. This result is 3 seconds slower than the 80% $P_{load}$ case and 2.99 seconds faster than the 95% $P_{load}$ case.

All data collected through the simulation process is used to train the ANN-ACO network. This data set includes 459 training samples, 123 input variables including five system parameters: line power, generator power, load power; frequency and voltage of each bus. The output of each training sample has 5 variables including: status of whether or not (1 or 0) load shedding and 4 suitable shedding strategies.

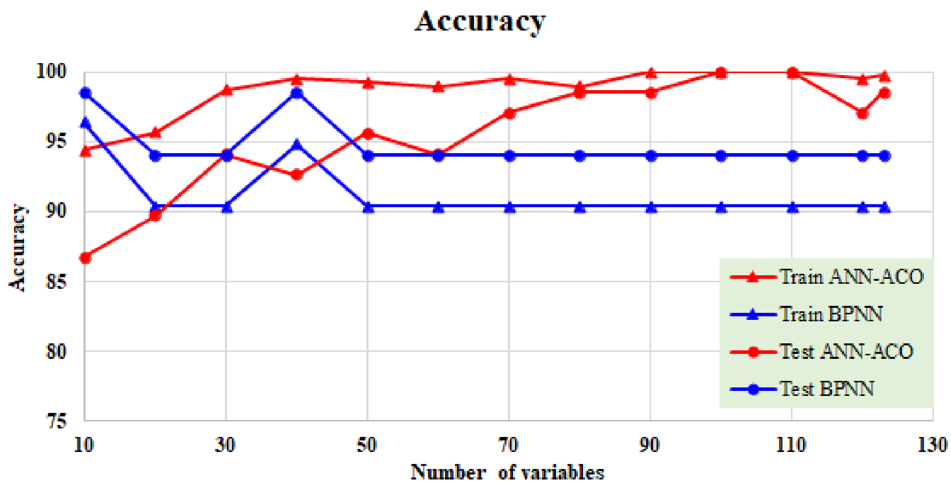



Figure 6. Comparison of training and test results between ANN-ACO and BPNN networks

The results of training and testing are shown in Figure 6. The results show that the ANN-ACO network is superior to BPNN, specifically with 90 input variables of the ANN-ACO network reaching 100% Train and 98.53% Test, while the BPNN network gets 90.4% Train and 94% Test. The training results show that using ANN-ACO network has better training and testing results, which contributes to increasing the accuracy and processing speed of the network.

## 4. Conclusion

The application of load shedding according to the proposed method with two stages helps to solve the integration problem in the load shedding problem. Quickly classifying the fault type and accurately determining the load shedding strategy helps the system frequency to recover better and quickly to the allowable range.

The application of AHP algorithm helps to make better decision on load ranking in the system. The opinions of experts in the system will be used to assess the importance of the loads, from which the rating will be appropriate to the actual situation of the system. This ensures accuracy for load shedding strategies.

The active recovery frequency when simulated on the IEEE 25-bus 8-generator system diagram shows the effectiveness of the proposed method.

In the future, the proposed load shedding method will improve and further solve the problem of optimizing the amount of load shedding power to ensure the minimum shedding power. Thereby reducing economic losses for electricity customers and electricity supply companies.

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