

Article

Wavelet Energy Fuzzy Neural Network-Based Fault Protection System for Microgrid

Cheng-I Chen ^{1,*}, Chien-Kai Lan ², Yeong-Chin Chen ³, Chung-Hsien Chen ⁴ and Yung-Ruei Chang ⁵

¹ Department of Electrical Engineering, National Central University, Taoyuan 32001, Taiwan

² Department of Mechatronics Engineering, National Changhua University of Education, Changhua 50074, Taiwan; lnjakigu@gmail.com

³ Department of Computer Science and Information Engineering, Asia University, Taichung 41354, Taiwan; ycchenster@gmail.com

⁴ Metal Industries Research and Development Centre, Taichung 40768, Taiwan; jacky@mail.mirdc.org.tw

⁵ Institute of Nuclear Energy Research, Taoyuan 32546, Taiwan; raymond@iner.gov.tw

* Correspondence: cichen@ee.ncu.edu.tw; Tel.: +886-3-4227151 (ext. 34526)

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Abstract: To perform the fault protection for the microgrid in grid-connected mode, the wavelet energy fuzzy neural network-based technique (WEFNNBT) is proposed in this paper. Through the accurate activation of protective relay, the microgrid can be effectively isolated from the utility power system to prevent serious voltage fluctuation when the power quality of power system is disturbed. The proposed WEFNNBT can be divided into three stages—feature extraction (FE), feature condensation (FC), and disturbance identification (DI). In the FE stage, the feature of power signal at the point of common coupling (PCC) between microgrid and utility power system would be extracted with discrete wavelet transform (DWT). Then, the wavelet energy and variation of singular power signal can be obtained according to Parseval Theorem. To determine the dominant wavelet energy and enhance the robustness to the noise, the feature information is integrated in the FC stage. The feature information then would be processed in the DI stage to perform the fault identification and activate the protective relay if necessary. From the experimental results, it is realized that the proposed WEFNNBT can effectively perform the fault protection of microgrid.

Keywords: fault protection; power quality; wavelet energy fuzzy neural network-based technique; microgrid; voltage fluctuation

1. Introduction

Due to advantages of reducing the investment of new energy costs in power systems, providing the compensation of reactive power, regulating the frequency of power system, increasing the system backup capacity, and improving the stability of power system, the distributed generation has become popular in recent years [1,2]. In this way, the traditional unidirectional transmission of the passive distribution network has translated into the intelligent active network with bidirectional power transmission, which is called the microgrid. The structure of the microgrid is similar to that of a traditional large power grid. The only difference is that the sizes of the power supply and the load in the microgrid are relatively small. For a place where the traditional utility power system is difficult to provide power supply, the microgrid can resolve this problem for these remote areas or the systems with special requirements.

The microgrid is usually connected to the utility power system through the protective relay [3–5]. Under normal circumstances, the microgrid is operated in parallel with the utility power system, which is in

the grid-connected mode. However, when a fault occurs in the utility power system or inside the microgrid, the protective relay switches off and the microgrid is turned into the island operation mode. When the fault is removed, the microgrid can be reconnected to the utility power system. With the estimation of the voltages, phase angles, and frequencies, on both sides of the point of common coupling, the microgrid is considered to be synchronized with and reconnected to the utility power system if the measured values on both sides are the same or if the difference is within the specification. If the microgrid and the utility power system are not synchronized, the direct reconnection will lead to current surge, overvoltage, system instability, etc., and even equipment damage. Therefore, the accurate fault protection system is necessary to isolate the microgrid from the utility power system to prevent serious voltage fluctuation when the power quality of power system is disturbed [6].

In order to detect power disturbances, many wavelet transform-based techniques have been proposed in the literature due to their advantage of feature extraction for the singular signals. The multiresolution characteristics of wavelet analysis and traditional neural network have been applied to the fault detection and localization in the microgrid, where the high-level wavelet coefficients are required [7]. The wavelet neural network-based detection method has been proposed in [8], which can accurately estimate the dominant lower-order harmonics in the presence of interference with only half-cycle data. In reference [9], many power disturbances, such as instantaneous interruptions, capacitor switching, voltage sags, swells, harmonic distortion, and flickers, can be detected and effectively classified by feeding the results of wavelet transform into the neural network. The wavelet-based deep neural network is used to perform the fault detection in the microgrid system, where many features are required to help the training of neural network [10]. In addition to the neural networks, the fuzzy systems can also be applied to power quality analysis and identification systems to improve the drawbacks of traditional power quality analysis and evaluation methods [11]. In reference [12], the power quality disturbances can also be identified by a deep learning neural network. From the above techniques, it is found that the accuracy of power disturbance identification is dependent on the structures of classifiers. In this way, the complexity of classifier has been dramatically increased and then the hardware requirements for the implementation have been critical. To resolve this problem, the feature condensation based on the wavelet energy and variation of singular power signal is proposed in this paper to integrate the feature information. Then, the dominant features can be enhanced for the identification of power disturbance and reduce the required complexity of classifier. This is because all the minor features from the noise interference can be removed or merged in the fuzzy inference. The proposed wavelet energy fuzzy neural network-based technique (WEFNNBT) can be divided into three stages, including feature extraction (FE), feature condensation (FC), and disturbance identification (DI). According to the above-mentioned analysis mechanism, the main contributions of proposed fault protection system are as follows:

- (1) The required features for the identification can be reduced. In this way, the complexity of neural network-based classifier can be simplified and then the hardware requirements for the implementation will also be mitigated.
- (2) The noise interference can be effectively removed due to the fuzzy inference.
- (3) The dominant features for the identification of power disturbance can be enhanced and the recognition accuracy will be increased.
- (4) According to the revisions of IEEE Std. 1159-2019 [13], the identification mechanism of proposed fault protection system can be easily and flexibly adjusted without taking hardware requirements into account.

The organization of this paper is as follows. In Section 2, the identification mechanism of proposed WEFNNBT for the microgrid fault protection is introduced. Some comprehensive case studies are designed and analyzed with implementation on the microcontroller to verify the recognition performance of proposed WEFNNBT fault protection strategy in the field experiments of Section 3. The performance discussion will be displayed in Section 4.

2. Proposed Wavelet Energy Fuzzy Neural Network-Based Microgrid Fault Protection Strategy

Figure 1 depicts the architecture of microgrid fault protection system, where the power signal at PCC between microgrid and utility power system is extracted via voltage/current sensors. The proposed WEFNNBT implemented on the microprocessor is used to perform the identification of power disturbances. Once the fault is recognized, the microprocessor triggers the driver to switch off the protective relay and the microgrid is be turned onto the island operation mode. The solution procedure of proposed WEFNNBT is shown in Figure 2 and the details of fault identification are then addressed.

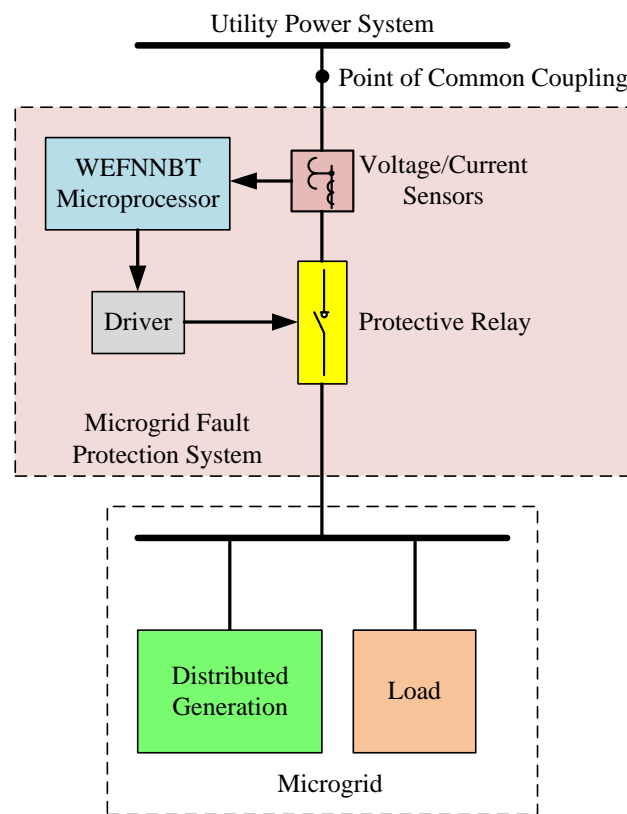


Figure 1. Architecture of microgrid fault protection system.

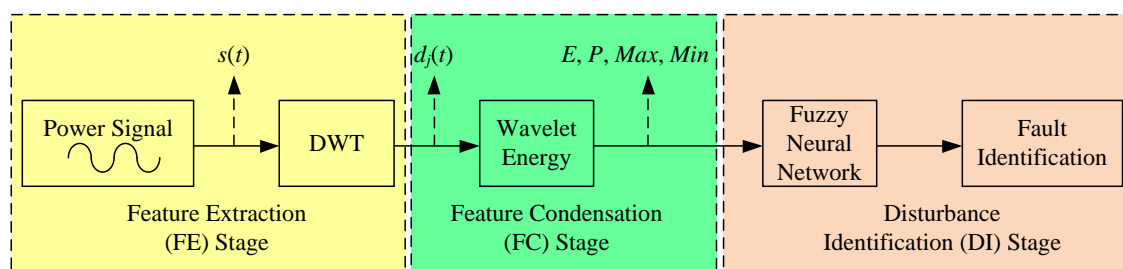


Figure 2. Solution procedure of proposed wavelet energy fuzzy neural network-based technique (WEFNNBT).

2.1. Feature Extraction (FE)

Due to the multiresolution analysis of DWT, the singular features of power signal $s(t)$ can be easily extracted with Equation (1), where $\Phi(t)$ and $\Psi(t)$ are called scaling function and wavelet function, c_{j0} and d_j are scaling coefficient and wavelet coefficient, j is the index for the wavelet analysis level and j_0 is the fundamental level, and t and k are the time indices, respectively.

$$s(t) = \sum_k c_{j_0}(k) 2^{-j_0/2} \Phi(2^{-j_0}t - k) + \sum_k \sum_{j=j_0} d_j(k) 2^{-j/2} \Psi(2^{-j}t - k) \quad (1)$$

In general, the singular features of fault signal can be observed in the wavelet coefficients. For example, a power signal suffered from the 1.2-pu voltage swell during 0.01 s and 0.07 s, the 0.75-pu voltage sag during 0.0332 s and 0.06 s, and the voltage interruption at 0.083 s, as shown in Figure 3. It is found that the singular features of power events defined in IEEE Std. 1159-2019 can be detected in the signals of wavelet coefficients d_1 , d_2 , and d_3 [13]. According to the experimentation in this paper, the Daubechies Wavelet (DB4) is used for the feature extraction. However, the extracted features could not be used to identify the power disturbances directly. As a result, the obtained features were processed in the stages shown in Figure 3.

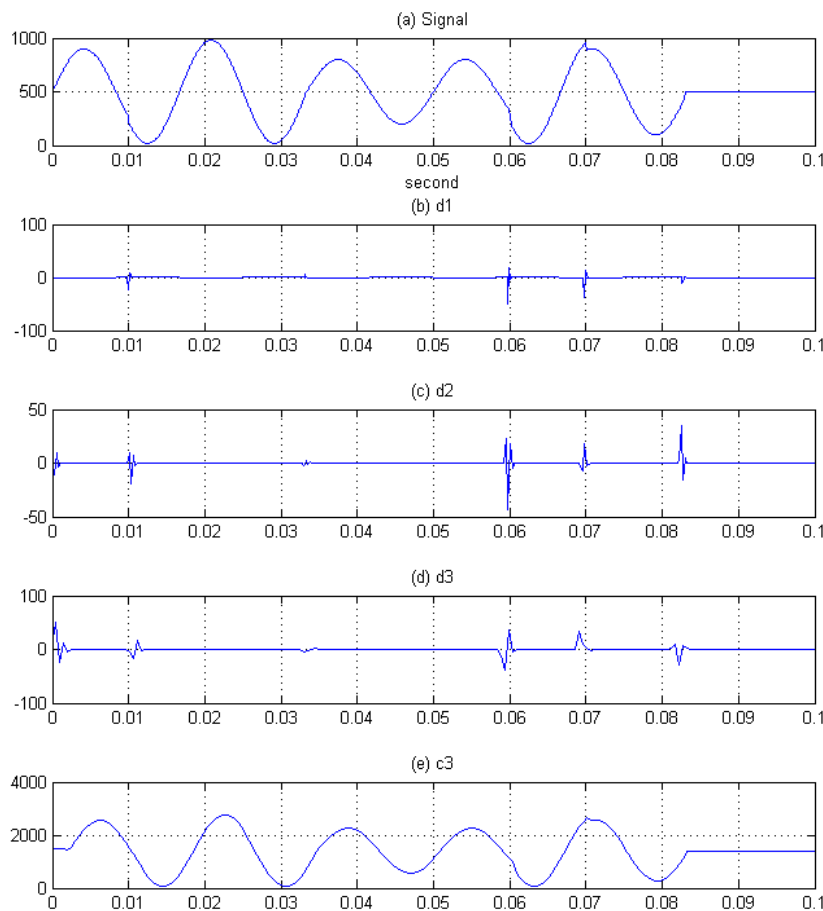


Figure 3. (a) Distorted power signal, (b) signal of wavelet coefficient d_1 , (c) signal of wavelet coefficient d_2 , (d) signal of wavelet coefficient d_3 , and (e) signal of scaling coefficient c_3 .

2.2. Feature Condensation (FC)

To realize the severity of power events, the energy of wavelet coefficients is evaluated. According to Parseval Theorem, the energy of power signal in the time domain would be the same with that in the frequency domain, as represented in Equation (2) [13].

$$\int |s(t)|^2 dt = \sum_k |c_{j_0}(t)|^2 + \sum_k \sum_{j=1} |d_j(t)|^2 \quad (2)$$

Through the definition of wavelet coefficient energy E_j in Equation (3), the energy in different wavelet analysis levels can be compared and used to activate the protective relay.

$$E_j = \sum_k |d_j(t)|^2 \quad (3)$$

In this paper, each 0.25-cycle voltage and current signals are analyzed with DWT and the energy of wavelet coefficients are calculated. After testing numerous power signals, four indices in Equations (4)–(7) are selected as the important features for the fault identification of proposed fuzzy neural network-based technique.

$$E = E_1 + E_2 \quad (4)$$

$$P = \frac{E_1}{E_1 + E_2} \quad (5)$$

$$Max = \frac{\max(d_2)}{\sqrt{\sum \|E_2\|^2}} \quad (6)$$

$$Min = \frac{\min(d_2)}{\sqrt{\sum \|E_2\|^2}} \quad (7)$$

where E is the total energy of two high-frequency wavelet analysis levels, P is the ratio between E_1 and E , and Max and Min determine the variation of power signal. Since E contains the event features and noises, five classes are defined to distinguish the fault signal from the interference. If P is larger than 1, it means that the main event feature is significant. The ratios between the maximum or minimum of d_2 and E_2 can be used to realize the intensity of power signal variation. The membership functions of E , P , Max , and Min are displayed in Figure 4 and Table 1, according to the experimentation. The membership function of fuzzy output is shown in Figure 5 and Table 2.

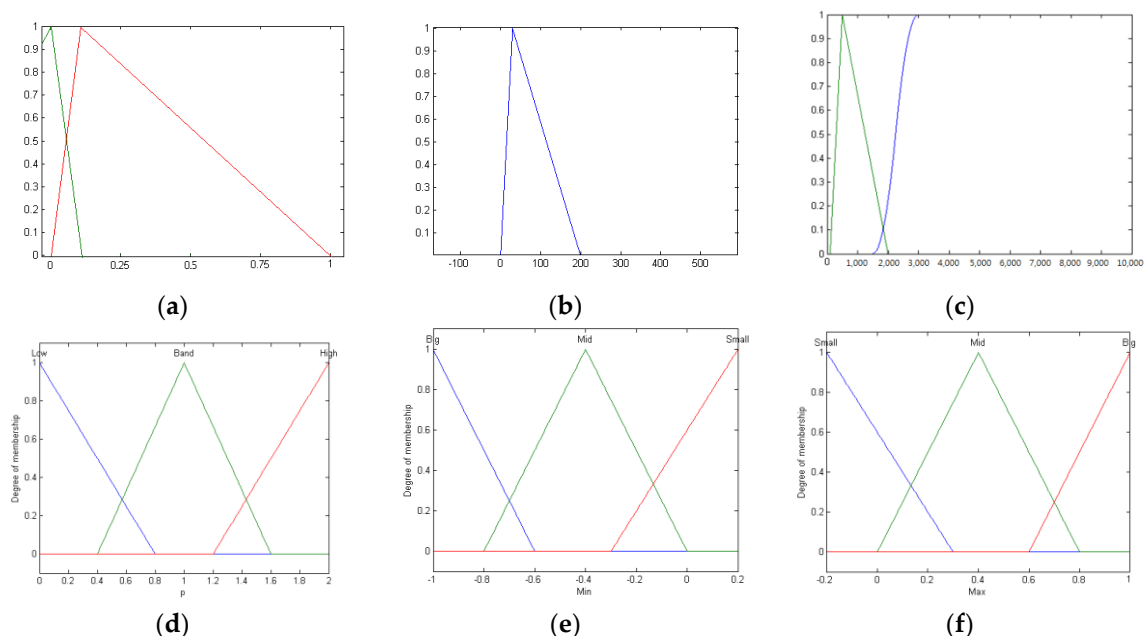
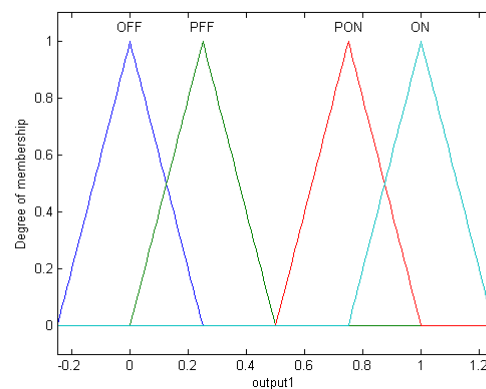


Figure 4. Membership functions of (a) E -MF1 and MF2, (b) E -MF3, (c) E -MF4 and MF5, (d) P , (e) Min , and (f) Max .

Table 1. Membership functions of E , P , Min , and Max .

Membership Function	Name	Range
E -MF1	Zero	(−1000, 0.001, 0.1)
E -MF2	Decimal	(0, 0.1, 1)
E -MF3	Digit	(0.1, 30, 200)
E -MF4	Hundred	(100, 500, 2000)
E -MF5	Thousand	(1499, 2999, 10,000)
P -MF1	Low	(−0.8, 0, 0.8)
P -MF2	Band	(0.4, 1, 1.6)
P -MF3	High	(1.2, 2, 2.8)
Min -MF1	Big	(−1.48, −1, −0.6)
Min -MF2	Mid	(−0.8, −0.4, 0)
Min -MF3	Small	(−0.3, 0.2, 0.68)
Max -MF1	Small	(−0.68, −0.2, 0.3)
Max -MF2	Mid	(0, 0.4, 0.8)
Max -MF3	Big	(0.6, 1, 1.48)

**Figure 5.** Membership function of fuzzy output.**Table 2.** Membership functions of fuzzy output (POFF and PON means probably off and probably on).

Membership Function	Name	Range
MF1	OFF	(−0.25, 0, 0.25)
MF2	POFF	(0, 0.25, 0.5)
MF3	PON	(0.5, 0.75, 1)
MF4	ON	(0.75, 1, 1.25)

2.3. Disturbance Identification (DI)

Through the extracted features of fuzzy analysis, the identification of power quality disturbances based on the fuzzy neural network is established for the fault protection of microgrid, as depicted in Figure 6. In this way, the output of neural network can be used to determine the state of protective relay. In this paper, Levenberg-Marquardt algorithm is applied for the training of neural network and the evaluation index in the training process is based on the mean-squared error (MSE) [8,9]. According to the experimentation in this paper, the original 135 fuzzy rules ($5 \times 3 \times 3 \times 3$) can be reduced to 27, as listed in Table 3.

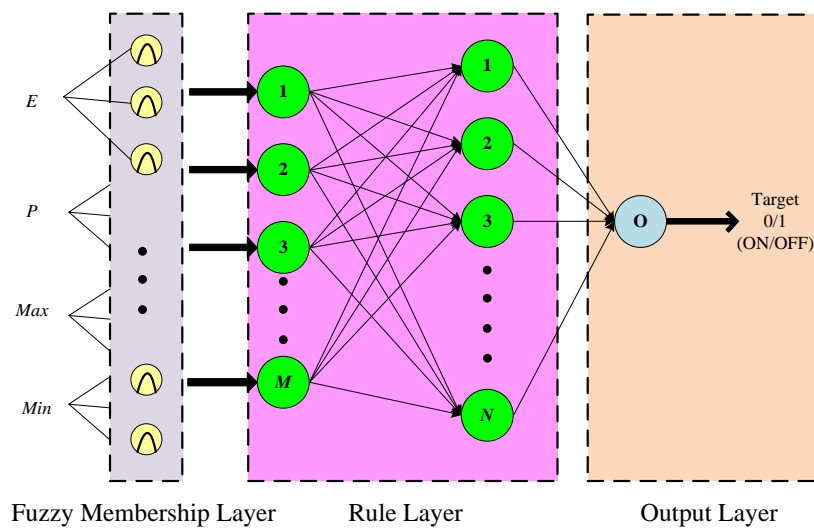


Figure 6. Structure of fuzzy neural network for disturbance identification.

For the fuzzy membership layer, the i th output node x_i would be the membership function output MFO_k , as addressed in Equation (8), where M is the number of features.

$$x_i = f_i(MFO_k), i = 1, 2, \dots, M, k \in \{E, P, Max, Min\} \tag{8}$$

In the rule layer, the j th output node y_j would be

$$y_j = f_j(\prod_i w_{ij}x_i) = \prod_i w_{ij}x_i, j = 1, 2, \dots, N \tag{9}$$

where \prod means the multiplication of input signals and output of the results of product, w_{ij} is the weight between the fuzzy membership layer and rule layer, and N is the number of rules with complete rule connection.

In the output layer, the single output node O would be the absolute value of the summation of all input signals, as shown in Equation (10), where w_j is the weight associated with j th rule.

$$O = f(\sum_j w_j y_j) = \left| \sum_j w_j y_j \right|, j = 1, 2, \dots, N \tag{10}$$

Table 3. Fuzzy rules for fault identification and trigger of protective relay.

Rule	IF				THEN
	<i>P</i>	<i>Max</i>	<i>Min</i>	<i>E</i>	Output
1	High	Mid	Mid	Thousand	PON
2	High	Mid	Mid	Hundred	ON
3	High	Mid	Mid	Digit	ON
4	High	Mid	Mid	Decimal	ON
5	High	Big	Small	Thousand	OFF
6	High	Big	Small	Hundred	PON
7	High	Big	Small	Digit	ON
8	High	Big	Small	Decimal	ON
9	High	Small	Big	Thousand	OFF

Table 3. Cont.

Rule	IF				THEN
	<i>P</i>	<i>Max</i>	<i>Min</i>	<i>E</i>	Output
10	High	Small	Big	Hundred	PON
11	High	Small	Big	Digit	ON
12	High	Small	Big	Decimal	ON
13	Band	Big	Small	Thousand	OFF
14	Band	Big	Small	Hundred	PON
15	Band	Big	Small	Digit	ON
16	Band	Big	Small	Decimal	ON
17	Band	Big	Small	Zero	ON
18	Band	Small	Big	Thousand	OFF
19	Band	Small	Big	Hundred	PON
20	Band	Small	Big	Digit	ON
21	Band	Small	Big	Decimal	ON
22	Band	Small	Big	Zero	ON
23	Low	Mid	Mid	Thousand	OFF
24	Low	Mid	Mid	Hundred	OFF
25	Low	Mid	Mid	Digit	OFF
26	Low	Mid	Mid	Decimal	POFF
27	Low	Mid	Mid	Zero	ON

3. Case Studies

To examine the performance of proposed WEFNNBT for microgrid fault protection, the experimental setup in Figure 7 is implemented. For the training of microgrid fault protection system, 1000 noisy power signals extracted from this setup are used. The detection results of normal power signal and interruption are displayed in Figures 8 and 9, respectively. According to numerous experimental tests, the proposed method can deal with most identification of power events correctly compared with the threshold method (TM) in [14], the traditional fuzzy analysis (FA) in [15], and the traditional back-propagation neural network (BPNN) in [16], as listed in Table 4.

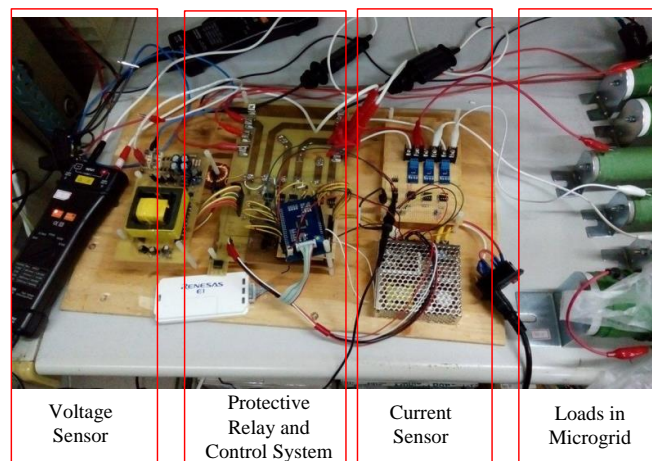


Figure 7. Experimental setup.

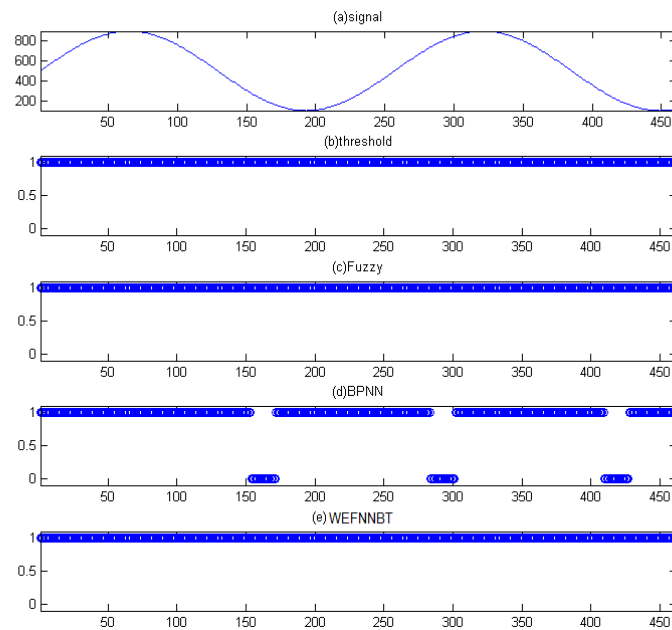


Figure 8. (a) Waveform of normal power signal, (b) state of protective relay based on identification with threshold method (TM) for normal power signal, (c) state of protective relay based on identification with fuzzy analysis (FA) for normal power signal, (d) state of protective relay based on identification with back-propagation neural network (BPNN) for normal power signal, and (e) state of protective relay based on identification with proposed WEFNNBT for normal power signal.

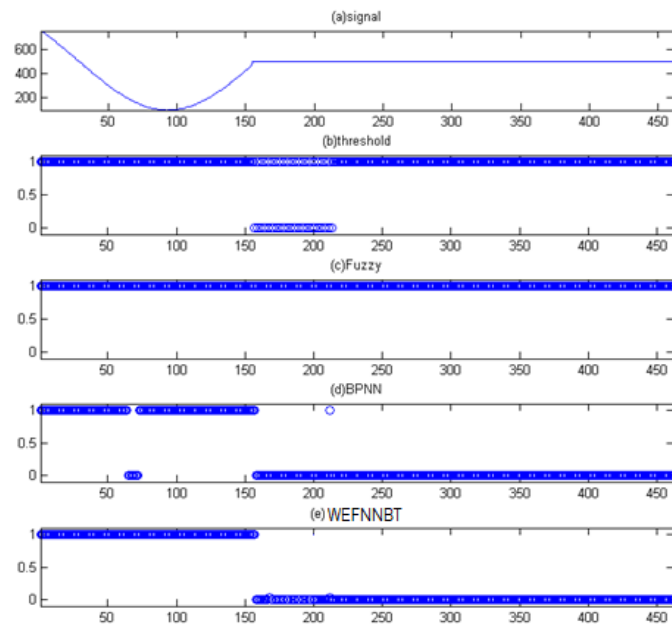


Figure 9. (a) Waveform of interruption, (b) state of protective relay based on identification with TM for interruption, (c) state of protective relay based on identification with FA for interruption, (d) state of protective relay based on identification with BPNN for interruption, and (e) state of protective relay based on identification with proposed WEFNNBT for interruption.

Table 4. Comparison of identification accuracy.

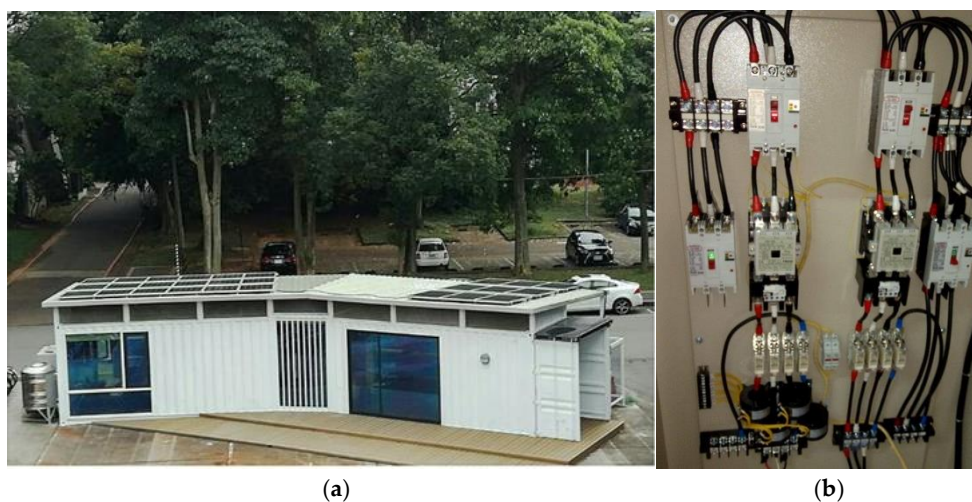
Event \ Method	TM	FA	BPNN	Proposed WEFNNBT
Normal	97.5%	98.1%	67.8%	99.2%
Sag	97.1%	16.1%	97.8%	98.8%
Swell	96.8%	17.5%	97.6%	98.6%
Harmonic	13.7%	96.4%	97.1%	99.1%
Impulse Transient	86.3%	95.8%	96.9%	98.2%
Oscillation	84.5%	95.2%	96.4%	97.7%
Interruption	12.8%	15.2%	97.7%	98.9%

The incorrect identification for the normal power signal with BPNN resulted from the inefficient robustness of DWT to the noise. In the proposed method, the drawback of DWT would be modified with the fuzzy analysis to largely reduce the interference of noise.

To examine the practical performance of proposed WEFNNBT in the field measurement, the microgrid system in National Central University, Taiwan is tested. The system information and photo are displayed in Table 5 and Figure 10. A 0.75-pu and 180 degree, a sag event occurs and is quickly removed. The testing results for the identification with TM, FA, BPNN, and proposed WEFNNBT are revealed in Figure 11. It is easily found that the TM and FA could not recognize the power event due to the short duration. The incorrect protection command is triggered in BPNN, since the noisy interference is present in DWT. The proposed WEFNNBT can accurately detect the event time and activate the protective relay correctly with the advantages of robustness in FE, FC, and DI stages.

Table 5. System information of microgrid in National Central University, Taiwan.

Building Size	4 20-foot containers	
Load Demand	10 kWh/day	
Solar Generation	7.4 kW; the total power generation per day is $7.4 \text{ kW} \times 3.9 \text{ h} = 28.86 \text{ kWh}$ 3.9 h is the average sunshine hour in National Central University, Taiwan	
Storage System	Lithium-ion Battery	21.6 kWh
	Fuel Cell	5 kW
Power Inverter	Three-phase 15 kW, AC output voltage is 220 V	

**Figure 10.** (a) Microgrid system and (b) protective relay for the system.

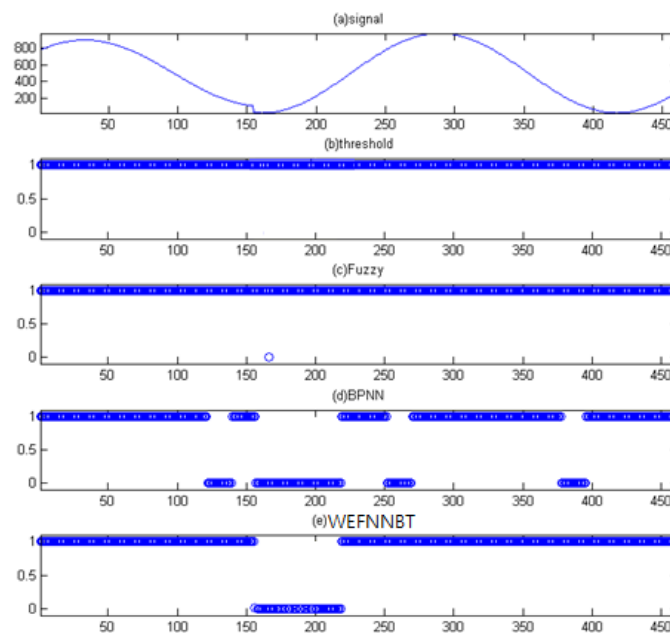


Figure 11. (a) Waveform of 0.75-pu and 180 degree sag, (b) state of protective relay based on identification with TM for sag, (c) state of protective relay based on identification with FA for sag, (d) state of protective relay based on identification with BPNN for sag, and (e) state of protective relay based on identification with proposed WEFNNBT for sag.

4. Discussions

According to the testing results, it is found that the TM will lead to misclassification by simply setting the threshold value. If the threshold value is unsuitably adjusted, the originally detected faults may be ignored. In addition, the difference of phase angle will interfere with the determination of threshold value. There is a hard trade-off between misjudgment and interference neglect. Therefore, it is difficult for the TM to get a balance point that is sufficient for all situations.

For the faults of voltage swells, sags, and interruptions, its frequency-domain energy is closely related to the phase of event occurrence and value of variations in pu. Similar to the TM, it is difficult to determine the suitable membership functions for the FA to prevent misjudgment or achieve interference neglect.

The performance of BPNN in [8] is dependent on the level of DWT, type of wavelet, size of neural network, learning rate of neural network, and so on. The incorrect identification for the normal power signal with BPNN in Table 4 results from the inefficient robustness of DWT to the noise. Therefore, it is necessary to find out the suitable combination of DWT level, wavelet type, size, and parameters of neural network to mitigate the noise interference. This process to determine the suitable combination is time-consuming and not suitable for practical applications.

For the proposed WEFNNBT, the problem of DWT can be modified with the fuzzy analysis to largely reduce the interference of noise. Compared with the direct usage of wavelet coefficients in BPNN, four indices in Equations (4)–(7) and corresponding membership functions can effectively mitigate the noise interference and condense the size of neural network with several dominant features. In this way, the influence of wavelet type can be mitigated and then only signals of two high-frequency wavelet analysis levels will be necessary. From the testing results, it is realized that the proposed WEFNNBT can perform the fault identification accurately and suitably trigger the protective relay.

5. Conclusions

In this paper, a robust system based on the wavelet energy fuzzy neural network-based technique for fault identification and protection in the microgrid is developed. Through four defined energy indices, the dominant singular features of fault signals can be correctly extracted by the fuzzy analysis. According to the testing for 1000 noisy power signals, the maximal computational time for the proposed system is 2.94 m/s. The experimental results reveal that the proposed method can effectively perform the fault identification and then activate the protection relay to isolate the microgrid from the utility power system in the real-time manner.

Author Contributions: C.-I.C. designed and developed the main parts of the research work, including theory derivation and analyses of the obtained results. C.-K.L. contributed in the implementation of analysis algorithm and testing experiments. Y.-C.C. was mainly responsible for preparing the contents of the feature extraction and disturbance identification. C.-H.C. contributed in the performance examination of fault protection system and compliance with the limits of standards. Y.-R.C. contributed in the field experiments. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations and Symbols

WEFNNBT	wavelet energy fuzzy neural network-based technique
FE	feature extraction
FC	feature condensation
DI	disturbance identification (DI)
PCC	point of common coupling
DWT	discrete wavelet transform
POFF	probably off
PON	probably on
MSE	mean-squared error
TM	threshold method
FA	fuzzy analysis
BPNN	back-propagation neural network

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