ACOUSTIC EMISSION IDENTIFICATION OF FAILURE MECHANISMS IN FIBER REINFORCED PLASTIC MATERIALS BY NEURAL NETWORKS

N. Ativitavas[1], T. J. Fowler[2]
[1] PTT Public Company Limited, Bangkok, Thailand; [2] The University of Texas at Austin, Texas, USA

Abstract: The paper presents a new approach to categorize failure mechanisms of fiber reinforced plastic (FRP) by pattern recognition of neural networks from acoustic emission (AE) data. The research began with a compilation of AE database from FRP materials. Specifically, a series of pultruded FRP specimen testing with AE monitoring was conducted throughout the research program. Failure mechanisms of representative tests were analyzed and identified by assistance of scanning electron microscope. With known failure mechanisms, typical AE correlations were plotted. Each plot was arranged into a form of data arrays which were applied as an input to the network system. It was found that the developed network system could well recognize failure mechanisms of a testing data set, in which its performance was 97 % accuracy. This shows that the approach of using AE correlation plot for the input is a key to successfully apply the neural network for this particular problem.

Introduction: Acoustic emission (AE) has been a key for monitoring integrity of fiber reinforced plastic (FRP) components.(1) Being a global technique and capability to examine discontinuities in the complex micro structures of FRP, acoustic emission has developed into a mature nondestructive testing method. In addition, AE is fast, less labor intensive than competitive evaluation techniques and, in many cases, able to be performed without a service shutdown.

Currently, many AE standard procedures for various structural components are widely available. One drawback of these procedures is that none of them provides a method to determine the type of defects. If this information is needed, other NDT methods must be used. Many researchers have developed techniques to accurately perform defect characterization using AE data. Unfortunately, these techniques still need further study.

The paper presents an application of neural networks for performing pattern recognition of failure mechanisms in FRP structures. The input data set used to train the networks was collected from AE data from a variety of testing. The approach was implemented such that the input data were arranged from typical AE correlation plots. It was found that the developed network system showed a very satisfactory performance.

Background: Several researchers have found that the occurrence of fiber breaks in FRP was associated with high amplitude and high signal strength AE hits.(2-5) This was confirmed by a research study, which used scanning electron microscope to extensively observe the number of fiber breaks in FRP coupons and corresponded with the number of high-amplitude AE hits and cumulative signal strength. The confirmation led to the development of low-amplitude filtering technique, in which low-amplitude hits (associated with non-fiber breaks) were removed from the AE data until the cumulative plot of the remaining hits with respect to the loads coincided with the plot of cumulative signal strength.(6,7) The lowest amplitude remaining after filtering was denoted as the borderline between the fiber break and non-fiber break hits.

The low-amplitude filtering was then applied to several other FRP specimens, which were made of different fiber and resin materials. It was found that this technique was very reliable and the borderline amplitudes for three FRP materials were estimated as presented in Table 1.

Table 1. Summary of low-amplitude filtering results (6,7)

Material	Average borderline amplitude (dB)
Glass/isopthalic polyester	76
Glass/vinyl ester	81
Hybrid/vinyl ester	68

When the AE data and its known failure mechanisms are obtained, this database is ready for feeding to the neural network system. A neural network is a computerized program that arranges its structure based on a database and is able to give the "most-likely" correct answer.[8] For example, if a record of weather in the past 200 years is available, neural networks can learn the pattern of weather, and be able to predict the pattern of the future weather based on the pattern of the present and immediately preceding weather. Therefore, larger databases are preferred to achieve better accuracy. Neural networks not only can perform prediction problems, but they can also solve pattern recognition, classification, and optimizing problems. One of the most suitable training methods for the pattern recognition application is backpropagation.[8] This method allows networks to compare the output result with the real answer for every set of training input. The difference between the output and the answer is called "error". The computer will adjust the network configuration in such a way to reduce the error. After many cycles of training, the error will be reduced to minimum.

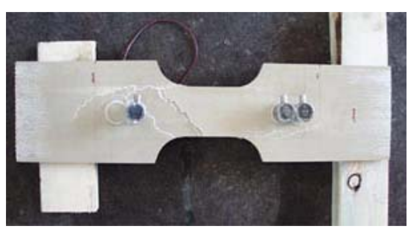
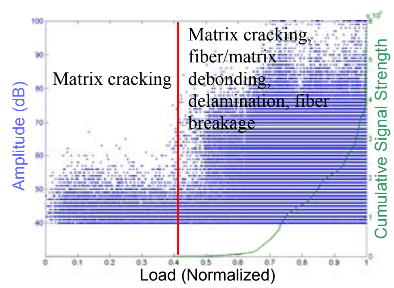
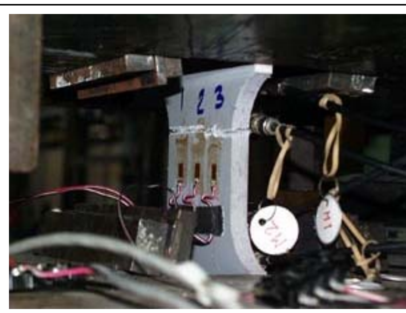
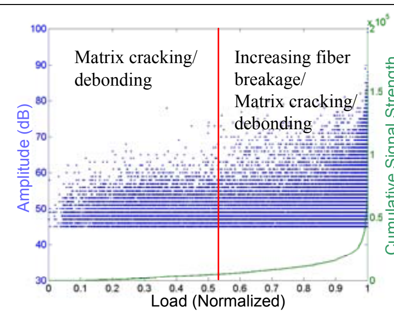
Database Collection: The AE data were obtained from experimental testing of the following test setups. These setups were chosen based on different types of failure mode occurring during the test.[6]

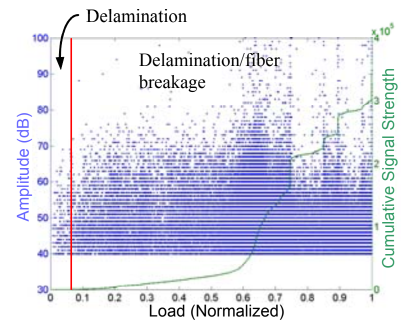
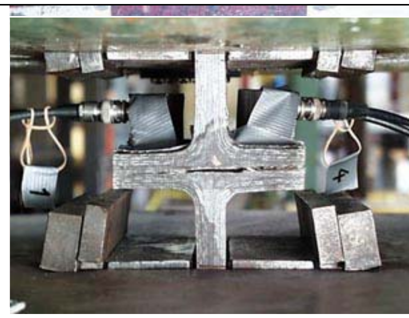
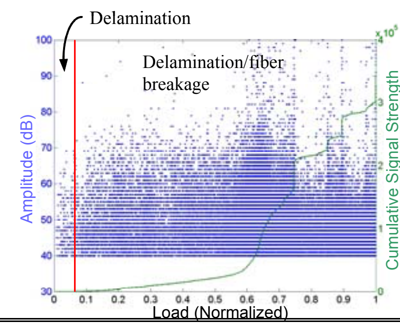
1. Tension test of unidirectional specimens in the direction parallel to the fibers. The specimens include coupons and full-scale components.
2. Tension test of unidirectional specimens in the direction perpendicular to the fibers
3. Short beam shear test of coupon specimens
4. Tension test of "T" specimens

The specimens for these tests were made of three fiber/resin combinations including glass/isopthalic polyester, glass/vinyl ester, and glass-carbon hybrid/vinyl ester. Four 150 kHz AE sensors were mounted on all specimens except the short beam shear specimens, which were monitored by only two sensors. The pictures of representative specimens, their associated amplitude vs. load AE plots, and short descriptions are presented in Table 2.

After the borderline amplitudes in Table 1 were applied to all AE data along with the observation of SEM, failure mechanisms of these AE data were determined. Table 2 also shows the failure mechanism information on the AE plots.

Table 2. Representative specimens and amplitude vs. load AE plot [6]

Description	Picture	Amplitude vs. load plot
Unidirectional specimens tested in parallel to fibers AE data can be separated into 2 portions: 1. matrix cracking 2. matrix cracking/ debonding/ delamination/ fiber breakage		
Unidirectional specimens tested perpendicular to fibers AE data can be separated into 2 portions: 1. matrix cracking/ debonding 2. matrix cracking/ debonding/ fiber breakage		

Short beam shear AE data can be separated into 2 portions: 1. delamination 2. delamination/ fiber breakage		
Short beam shear AE data can be separated into 2 portions: 1. delamination 2. delamination/ fiber breakage		

Neural Network Modeling: The network system consists of two levels of network. The network in the first level is called primary network, while the network in the second level is called secondary network. A flow chart of a network system including primary and secondary networks is shown in Fig. 1.

A primary network receives data input that is arranged from the AE database. There are many ways to model the AE data to the network input. In this research program, the AE data are organized in the form of AE correlation plots. The plots are then arranged into arrays of numbers and used as the primary network input. This is from the concept that AE correlation plots have been shown to have a capability for visualization of failure mechanism dissimilarities.[3,4] In the similar way, the network will learn to recognize the dissimilarities from the AE plots with known failure mechanisms and is then able to identify unknown failure mechanisms. Nine AE correlation plots are initially selected and, therefore, nine primary networks are constructed to receive the input from each plot. The AE plots are chosen such that they cover a number of the important AE parameters, which are amplitude, duration, historic index, severity, and signal strength. After training and testing, the performance of every primary network will be evaluated. The primary networks associated with poor performance will be eliminated from the system.

Each selected primary network has strengths and weaknesses in determining each type of failure mechanism and the networks are complementary to one another. As a result, a secondary network is developed as a supplement to the primary networks. This secondary network is trained using outputs from the primary networks as its input. The mechanism of the secondary network combines strengths of each primary network, leading to a higher performance of the network system.

All of the networks in this analysis are generated and trained using NeuralWork® Professional II/PLUS software version 5.51. Only AE data from 45 dB to 100 dB are used for training.

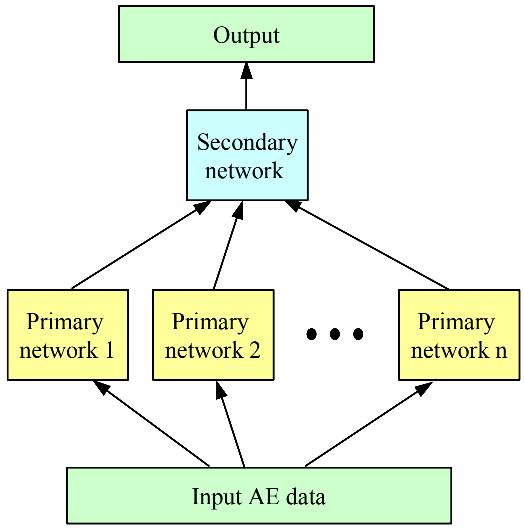


Figure 1. Flow chart of network system consisting of primary and secondary neural networks

Primary Network Architecture

The network consists of three layers: input, output, and hidden layers (see Fig. 2). The input layer consists of a group of input neurons that represent the AE plots. The input layer also consists of three additional input neurons representing material information of a specimen: glass/isopthalic polyester, glass/vinyl ester, and hybrid/vinyl ester (e.g. 1,0,0 represents glass/isopthalic polyester). There are six neurons in the output layer. Based on mechanisms found during the tests, these output neurons represent the six failure mechanism combinations, which are:

Combination 1. Matrix cracking
Combination 2. Matrix cracking/ debonding/ delamination/ fiber break
Combination 3. Matrix cracking/ debonding
Combination 4. Matrix cracking/ debonding/ fiber break
Combination 5. Delamination
Combination 6. Delamination/ fiber break

AE data from each sensor and specimen are plotted at every 10% of the ultimate load. AE is not generated at zero loads. Accordingly, the first plot is for 10% of ultimate load. Each AE plot is arranged into an array of numbers. This gives the total of 720 data arrays for each type of AE plot (72 sensors from all AE tests x 10 levels of load = 720 data arrays). From these 720 data arrays, 550 data arrays or 76% are statistically selected as a training data set and the remaining data arrays become a testing data set. Figure 2 also describes the steps to prepare input data for a primary network using an example of an amplitude distribution plot to arrange the network input.

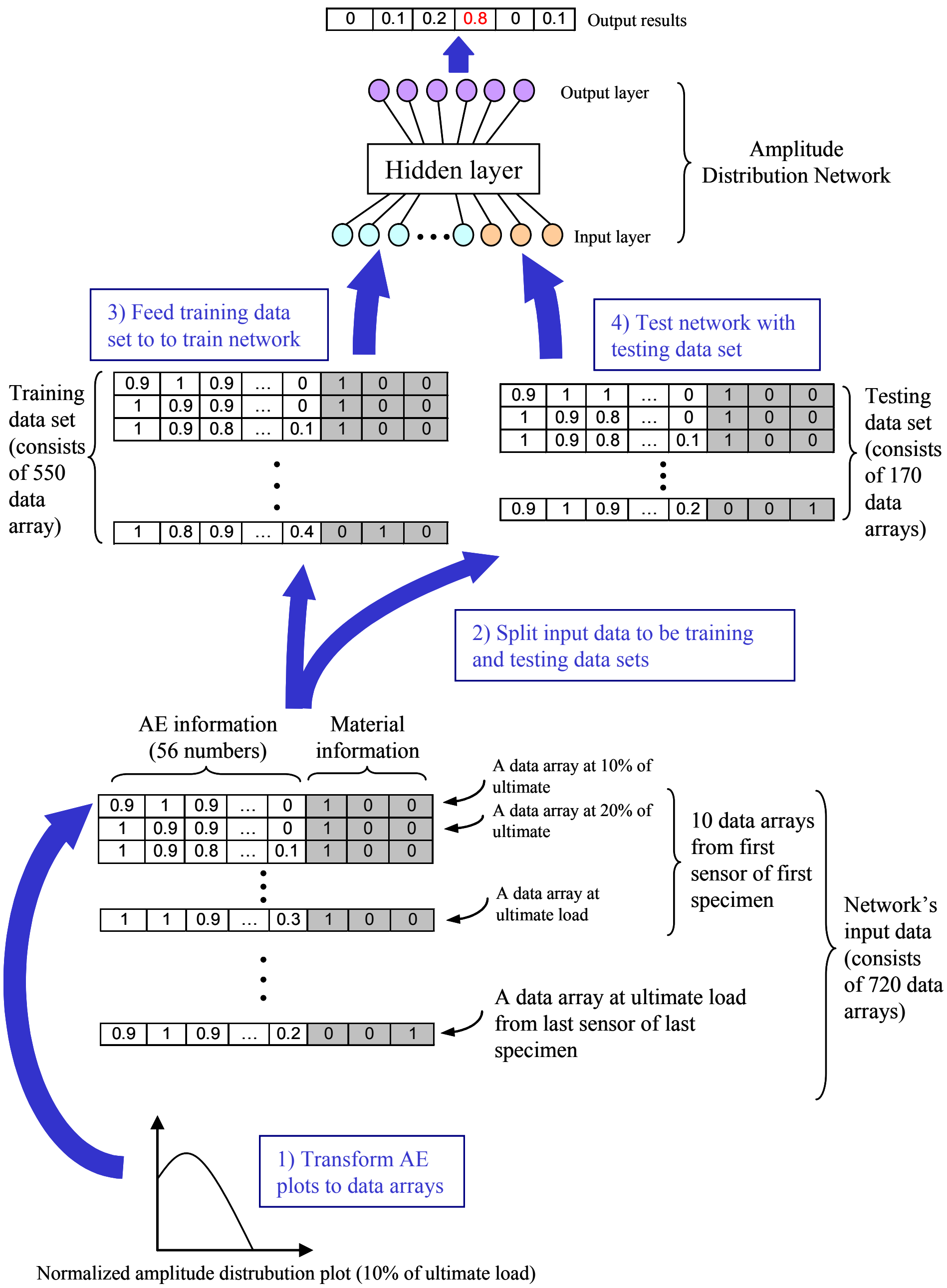


Figure 2. Process of preparing input data for a primary network

As mentioned earlier, nine primary networks are developed based on typically-used AE plots. The description of each network is explained below:

1. **Differential Amplitude Distribution Network 1:** This network uses each point in the differential amplitude distribution AE plot as the base input. Such numbers are normalized by dividing all the numbers with the maximum number of the plot.
2. **Differential Amplitude Distribution Network 2:** This network is similar to the network in item 1 but each number is divided by the summation of the numbers for normalization (area under the plot is equal to one).

3. **Cumulative Amplitude Distribution Network 1:** The base input of the network is obtained from each point in the cumulative amplitude distribution AE plot and all numbers are divided by the maximum number of the plot for normalization.
4. **Cumulative Amplitude Distribution Network 2:** Similar to the network in item 3 but all numbers are divided by the summation of the numbers for normalization.
5. **Amplitude vs. Duration Network:** The AE data from the amplitude vs. duration plot are mapped into 12 x 14 matrix. The number of each cell of the matrix is the number of hits that fall into a specified amplitude and duration interval. The number in each cell is then normalized using the total number of hits as a reference.
6. **Amplitude vs. Duration with Linear Conversion Network:** The mapping scheme of the network in item 4 is used. The normalized numbers are linearly converted to be in a simpler range (0 to 11).
7. **Amplitude vs. Duration with Log Conversion Network:** The mapping scheme of the network in item 4 is used, but the normalized numbers are exponentially converted to be in a simpler range (0 to 11).
8. **Historic Index and Severity Network:** Two input neurons are used as the base input including the maximum value of historic index from the beginning until a specific level of load and the value of severity at that specific level of load.
9. **Cumulative Signal Strength Network:** The cumulative signal strength vs. load plot is normalized using the maximum cumulative signal strength as a reference value. Then the network input is taken from 20 numbers of the plot (each at 5% increment of the maximum load).

Secondary Network Architecture

After obtaining the outputs from the primary networks (failure mechanism identification), the outputs from each primary network are combined and used as the input data for the secondary network (see Fig. 3). However, to achieve the optimized performance, the outputs from primary networks that perform poorly may not be used. Trial and error method is performed to select the primary network combination that yields the highest secondary network performance.

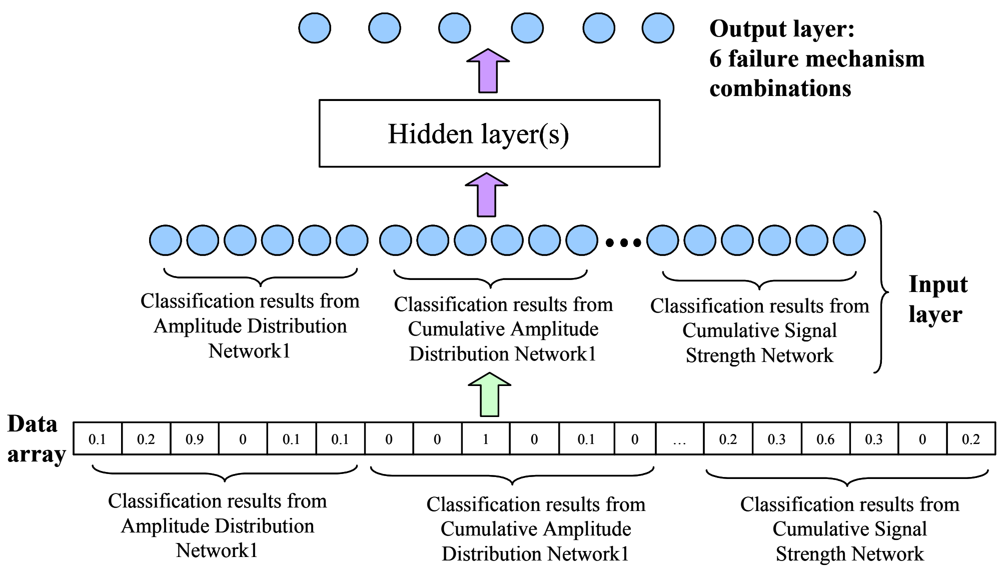


Figure 3. Secondary neural network diagram

Therefore, the number of the input neurons for the secondary network is different depending on what combination of the selected primary networks is used. Like the primary network, there are six output neurons for the secondary network. A total of 170 data arrays are used as the training set.

Results: After trained by the training data set, the primary networks are checked their ability to identify failure mechanisms with the testing data set. Table 3 presents the performance results by failure mechanism of each primary network. Note that the performance is calculated from the number of data arrays that are correctly identified in a failure mechanism combination divided by the total number of the data arrays in that failure mechanism combination. The overall performance is calculated from the number of data arrays in all failure mechanism categories divided by the total number of data arrays in the testing data set.

It is observed that Historic Index and Severity Network yields the performance of 54% and 91% accuracy in failure mechanism combinations 5 and 6 respectively, while the performance is 0% in three other combinations. This means the network tends to determine all the failure mechanisms to be only failure mechanism combinations 5 and 6. This behavior can be called "bias" and thus the outputs from the Historic Index and Severity Network are not qualified to use for the secondary network.

Table 3. Summary of primary neural network testing performance

Primary networks	Overall Performance (%)	Performance by failure mechanism (%)					
		1	2	3	4	5	6
Amplitude Distribution1	71.7	79.3	75.6	66.7	83.3	84.9	40.5
Amplitude Distribution2	49.7	69.0	70.7	0	33.3	84.9	40.5
Cumulative Amplitude Distribution1	52.9	75.9	70.7	0	50.0	66.7	54.1
Cumulative Amplitude Distribution2	51.5	75.9	65.9	0	50.0	60.6	56.8
Amplitude vs. Duration	78.6	75.9	87.8	83.3	91.7	54.6	78.4
Amplitude vs. Duration with Linear Conversion	83.7	65.5	85.4	88.9	100	75.8	86.5
Amplitude vs. Duration with Log Conversion	83.8	75.9	82.9	77.8	100	84.9	81.1
Historic Index and Severity	29.3	0	29.3	0	0	54.6	91.9
Cumulative Signal Strength	46.6	65.5	65.9	16.7	0	42.4	89.1

Note: Failure Mechanism combinations
1 = Matrix cracking
2 = Matrix cracking/ debonding/ delamination/ fiber break
3 = Matrix cracking/ debonding
4 = Matrix cracking/ debonding/ fiber break
5 = Delamination
6 = Delamination/ fiber break

For the secondary network, it is found that the combination that yields the best secondary network performance requires the output from the following primary networks.

1. Amplitude Distribution Network 1
2. Cumulative Amplitude Distribution Network 1
3. Amplitude vs. Duration Network
4. Amplitude vs. Duration Network with Linear Conversion Network
5. Amplitude vs. Duration Network with Log Conversion Network
6. Cumulative Signal Strength Network

The performance of secondary network based on above output combination is summarized in Table 4. The output of the secondary network represents the output of the entire network system. Therefore, the performance of the secondary network is the performance of the network system as well.

Table 4. Summary of secondary neural network testing performance

Overall Performance (%)	Performance by failure mechanism (%)					
	1*	2*	3*	4*	5*	6*
97.1	93.1	95.1	94.4	100	100	100

* is defined as noted in Table 3

Discussion: The primary networks that yield the three highest performances are all related to the amplitude vs. duration AE plot. Their overall performances are all above 78% accuracy. The Amplitude Distribution Network 1 also gives satisfactory results.

The low performance and the bias behavior of the Historic Index and Severity Network are as expected. This is because both historic index and severity are created only for the structural severity assessment purpose. Obviously, these two parameters are not meaningful for failure mechanism characterization.

Each network has unique strengths and weaknesses and can be complementary to one another for classifying failure mechanisms. An example of this is the Amplitude Distribution Network 1, which performs with high accuracy in identifying failure mechanism combination 1, while it performs poorly in combination 6. On the other hand, the Amplitude vs. Duration with Linear Conversion Network gives a lower performance for failure mechanism combination 1 but yields much higher performance in recognizing combination 6. The secondary network combines these strengths. This is proven by the significantly higher overall performance of the secondary network (also the network system) than those of the primary networks. The secondary network even recognizes three out of six failure mechanism combinations with a perfect accuracy.

Conclusions: In order to train the neural networks, a considerable number of data inputs are needed to guarantee good network performance. A number of coupons and full-scale FRP components were tested. These specimens were made of three different fiber/resin combinations. Four types of testing were carried out to obtain a diverse group of failure mechanisms occurred in the specimens. With the SEM examination and the low-amplitude filtering technique, failure mechanisms associated with AE data of each specimen were identified.

The AE database with known failure mechanisms is applied to the network system. In particular, the data inputs are arranged from typical AE plots. Material information is also used as an input. The network system consists of two levels including primary networks and secondary network. Initially, there are nine primary networks developed, requiring nine different AE plots as the network input. The output of the primary networks are arranged and used as the input for the secondary network. The performance results of the network system are determined

From the study, it is found that the outputs from only six primary networks yield the best network system performance. This performance is as high as 97% accuracy. The reason of the satisfactory results is attributed to the secondary network, which combines strengths of all primary networks together.

Training the network by inputs, which are arranged from typical AE plots is another factor to achieve this high network efficiency. Moreover, it is proven that the evaluation of AE hits in groups (burst) is likely to be a key to overcome the pattern recognition problem rather than focusing on only a single hit.

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