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A Comparative Performance Analyses of Training Algorithms Employed in Artificial Neural Networks Based Modulation Recognition Systems

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Abstract – The performances of learning algorithms employed in artificial neural networks (ANNs) have been analyzed for classifying baseband signals that are subjected to additive white Gaussian noise (AWGN) and frequency selective Rayleigh fading channel in this paper. The high order cumulants of the received signals have been utilized in the ANN classifier. Different learning algorithms have been used in finding the optimal weight set which directly affects the performance of artificial neural networks. The performances of Levenberg Marquardt (LM) and scaled conjugate gradient (SCG) algorithm, the most widely employed learning algorithms, have been compared for training of artificial neural networks. Computer simulation results have demonstrated that the LM-ANN classifier can reach much better classification accuracy than the SCG-ANN recognizer in even low training steps.

Keywords - *Modulation recognition, SCG-ANN, LM-ANN, High order cumulant.*

1 Introduction

An automatically recognition of modulation type of a received signal is extremely vital in civilian and military communication systems. Automatic Modulation recognition has a high importance especially in military electronic counter/counter-counter measures such as target detection, monitoring and jamming operations. Attempts have been made since the early 1960s to classify digital modulation types in various types of propagation channels and noise, and using various features of the signals of interest.

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So far the developed modulation classifiers are basically divided into two groups. Likelihood based classifiers, developed over the likelihood function of signal, offer the best solution, but the computational complexity is high. Therefore, feature-based classifier methods, offering lower computational complexity and solution of the close to the best, have been developed. Feature based modulation recognition includes feature extraction and decision-making stages. Statistics of the complex envelope and instant components of the signal, wavelet transform of the signal, Fourier transform of the signal can be demonstrated as an example of features that are generally used. In decision making phase, decision tree, neural networks, support vector machines are preferred structures of decision [1].

The signals used in communication systems, in terms of modulation types and frequencies are spread over a wide area. It is required to identify and monitor these signals for both cooperative and non-cooperative communication applications such as signal confirmation, interference identification, spectrum management, software defined radio, cognitive radio, intelligent modem for civilian purposes and electronic warfare, surveillance, target detection and threat analysis for military purposes [1, 2].

There is a tendency for the use of the "learning machines" as a decision making structure after the features are extracted from the received signal in solve the problem of feature based automatic modulation recognition. Multi-layer artificial neural networks are used in many studies as a decision-making structure [3-7]. In [3], for the first time, Ghani and Lamontagne proposed using a multi-layer perceptron (MLP) neural network with back-propagation (BP) learning algorithm for automatic signal type identification. In [4], Nandi and Azzouz introduced two classifiers: neural network classifier and fixed threshold classifier, for analog and digital modulation recognition. In [5], Sehier proposed an identifier based on cyclic spectral features and artificial neural networks for identification of analog and digital modulation. In [7], Ebrahimzadeh and Seyedin proposed a wavelet packet analysis as a feature extractor and a MLP neural network with back propagation learning algorithm as a classifier for modulation recognition. Additionally, support vector machines (SVM) are also employed in many studies in a decision-making structure [8, 9]. Wang and Ren developed a new digital modulation classification algorithm combining high order cumulants and SVM [9]. However, while the above classifiers give appropriate results for SNR > 5 dB when SNR value is smaller than 0 dB the performance of classifiers has decreased.

Although the literature shows that the use of artificial neural networks (ANNs) as the classifier has better performance than alternatives [3-7], there are some problems with regard to effectiveness of ANNs; for example ANNs have limitations on generalization ability in low SNRs [7]. These problems depend on the learning method used during training of ANN and in order to solve this problem many optimization techniques have been tried and their results revealed in the literature [10, 11]. Genetic algorithm, particle swarm optimization algorithm, evolutionary algorithm, artificial bee colony (ABC) algorithm and etc. algorithms were used in the training of artificial neural networks as both individually and hybrid. In this paper, multi-layer artificial neural networks have been employed as a modulation classifier using fourth, sixth and eighth order cumulants as an effective features for the recognition of digital communication signals. In order to analyze the impacts of training algorithms on the performance of the classifier, the most widely used in literature Levenberg Marquardt (LM) algorithm and Scaled Conjugate Gradient (SCG) algorithm has been tested.

The rest of the paper is organized as follows: Section 2 summarizes extraction of signal features for modulation recognition. The ANN based modulation recognition method is introduced in detail in Section 3. Section 4 evaluates the obtained performances to verify the feasibility and robustness of the training algorithms and finally, the paper is concluded in Section 5.

2 Feature Extraction of Signal for Classifier

In digital communication systems, according to the changes in the information parameters, there are main digital signal types, frequency shift keying (FSK), amplitude shift keying (ASK), phase shift keying (PSK) and quadrature amplitude modulation (QAM) that most of them are used in M-ary form [12]. Different types of digital signal have different characteristics. Therefore finding the proper features for identification of them, particularly in case of higher order or non-square types, is a serious problem. Choosing bad features may make it impossible even for an advanced classifier to perform a simple task, while choosing good features may make it possible for simple classifier to solve complex problems [1, 13].

In this study, the considered digital signal types are: binary phase shift keying (BPSK), 4-QAM, 4-ASK, 8-PSK, 8-ASK, 16-PSK, 16-QAM and 64-QAM. High order statistics are very interesting features to solve the problem of automatic modulation recognition. Cumulants can provide a good way to define the format of the probability density function of the signal. In addition, cumulants have been used for the classification of M-PSK and M-QAM signals in Gaussian noise environments. The third and higher order cumulants of Gaussian distribution random variables are zero and they are the most widely used features, the cumulant of the sums of independent random variables is equal to their the sum of cumulants. The most adopted features are high order statistics, including moments and cumulants. Cumulants are preferred due to their favorable properties. The main reasons for using cumulants are to resist the AWGN by all zeros property of high order cumulants of Gaussian distribution and the time domain analysis property without any transform. In this study, because of the advantages the fourth, sixth and eighth order cumulants of complex envelope of the received signal are used for classification of the above mentioned digital signal types. The use of the ANN is considered as a decision making structure.

In the light of information on the moments and cumulants [1], using the relationship between moment and cumulant more simple definitions of the fourth, sixth and eighth order cumulants are given by equation (1), (2) and (3):

$$C_{42} = M_{42} - |M_{20}|^2 - 2M_{21}^2 \tag{1}$$

$$C_{63} = M_{63} - 6M_{20}M_{41} - 9M_{21}M_{42} + 18M_{20}^2M_{21} + 12M_{21}^3 \tag{2}$$

$$C_{80} = M_{80} - 35M_{40}^2 - 630M_{21}^4 + 420M_{20}^2M_{40}^2 \tag{3}$$

Computed theoretical values of the fourth, sixth and eighth order cumulants for the digital modulated signals that are considered in this study are shown in Table 1. These values are computed under the constraint of unit variance in noise free and normalized by theoretical signal power and obtained assuming the signal is clean and of infinite length.

Table 1. Theoretical values of the fourth, sixth and eighth order cumulants for the employed digital modulated signal in study.

C_{pq}	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
C_{42}	-2	-1	-1.36	-1	-1.22	-1	-0.68	-0.618
C_{63}	16	4	8.32	4	7.81	4	2.2	1.72
C_{80}	-244	-34	-30.08	1	9.56	0.0016	-13.95	-11.595

3 Artificial Neural Networks (ANN) Based Modulation Classifier

Today, field named as artificial neural networks, looking for answers to the mathematical and philosophical problems, has become a science. Even though artificial neural networks could not pass stage can compete with the human brain in terms of decision speed, because of the complex mappings can be implemented in a sensitive manner and structural robustness, they have been expanding increasingly applications. In this sense, while working on the artificial neural networks issue, a network structure could solve the problem of space, it would be quite a restricted subset of the human brain can solve problem of space should not be overlooked [14].

Artificial Neural Networks (ANNs) are being successfully applied to solving problems in pattern classification, function approximation, optimization, pattern matching and associative memories [15]. Broad applicable areas of artificial neural networks, pattern recognition is one of the most important applications in such problems: speech synthesis, diagnostic problems, medicine, finance, robotic control, signal processing, computer vision, modulation recognition of communication signals and many other problems that fall under the category of pattern recognition [3]. Among many different neural network classifiers, the multilayer feed-forward networks have been mainly used for solving classification tasks, due to their well-known universal approximation capabilities [16, 17].

The success of neural networks largely depends on their architecture, their training algorithm, and the choice of features used in training. All these make design of artificial neural networks a difficult optimization problem [5]. Researchers have been studying to train the networks by choosing suitable architecture and/or training algorithm and/or the transfer functions and/or finding the weights and the biases based on some training data [6-11]. In many approaches, the topology and transfer functions are held fixed, and the space of possible networks is spanned by all possible values of the weights and biases [12]. In this paper, we focused on the problem of finding optimal weight set.

In principle, a neural network can be designed to solve any given problem, provided that non-limited network size and infinite available data. However, in practice, resources are limited and should be relied on the generalization abilities of the network [13, 16]. In fact, when fixing the structure of the network, i.e. determining the number of hidden layers and the number of nodes in each hidden layer, then the network tries to adjust weights until the optimal weight set is obtained. In many practical pattern recognition problems, networks do not tend to converge the corresponding weight set. To alleviate this problem (finding the optimum weight set), a variety of network optimization approaches have been proposed [17-20].

Block diagram of the artificial neural networks based automatic modulation recognizer is given in Figure 1 in this study.

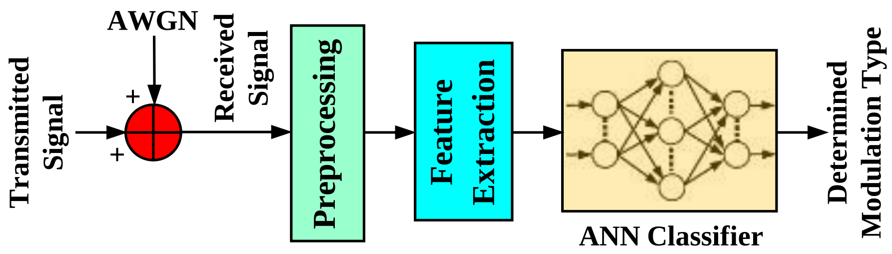

Figure 1. The block diagram of ANNs based modulation recognizer in AWGN channel.

In Figure 1, a data sequences are transmitted and corrupted by additive white Gaussian noise (AWGN). In preprocessing block, operations are performed such as symbol rate, carrier frequency, bandwidth estimation and recovery of complex envelope etc. High order statistics of the received signal are computed in feature extraction block. In this study, the fourth, sixth and eighth order cumulants are calculated. Multi-layer artificial neural networks, using extracted features, are employed in ANNs classifier block. SCG and LM training algorithms have been used to find the optimal weight set in the training of artificial neural networks in ANNs classifier block.

3.1 The Training of Artificial Neural Networks

The general function of ANNs is to produce an output data when given a particular input data. This concept is taken from the brain's ability to recollect on the basis of certain input datas. Learning these mappings is done in conceptually the same way as the brain, which is generalizing from a number of examples. ANNs consist of a number of fairly simple computational devices that resemble the neurons in the brain, interconnected with weighted connections that resemble dendrites and axons [21].

An ANN consists of a set of processing elements (Figure 2), also known as neurons or nodes, which are interconnected with each other [22]. Typically, multi-layer feedforward ANN consists of the input layer, hidden layer and output layer. The training problem of feed-forward ANN can be seen as a limited non-linear problem [16]. The output value corresponding to a given set of input vectors are calculated by ANN training method. Then, the optimal connection weights between neurons that will allow each other to get closer to the calculated output values and the expected output values are calculated. When inter iterations optimal connection weights approached to a certain "the expected output and the calculated output" difference sensitivity (<=0.01), it has been concluded learning of ANN.

In this paper, LM and SCG training algorithm is used to evolve the weights of the feedforward neural network with three layered structure. Figure 2 shows the structure of a three layered feedforward neural network; supposed that the input layer has n nodes; the hidden layer has h hidden nodes and output layer has o output nodes [17].

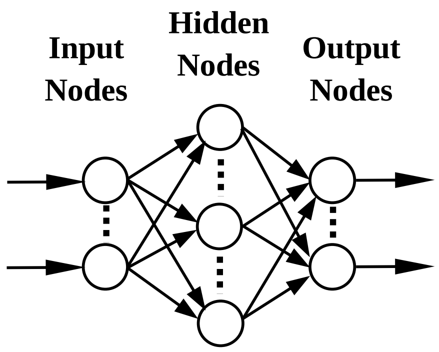

Figure 2. A three-layered feedforward neural network structure.

In the Feed Forward neural network models each node receives a signal from the nodes in the previous layer and each of those signals is multiplied by a separate weight value. The weighted inputs are summed and passed through a limiting function which scales the output to a fixed range of values and then, the output is sent to all of the nodes in the next layer [23]. The formula of the calculated output and the minimized error function has been given in equation (4) and equation (5), respectively.

$$Y_i = f_i\left(\sum_{j=1}^{n} \boldsymbol{w_{ij}} * \boldsymbol{x_j} + \boldsymbol{\theta_i}\right) \quad (4)$$

where Y_i is the output of the node, x_j is the *j*th input from the hidden layer, W_{ij} is the connection weight from the *j*th node of hidden layer to the *i*th node of output layer. θ_i is the threshold (or bias) of the node and f_i is the transfer function which is chosen sigmoid function in the experiments.

In the training process of ANNs, sigmoid function is employed as a transfer function and mean square error (MSE) is used as a learning error, which is calculated by Equation (5);

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\sum_{k=1}^{K}(d_k - o_k)^2 \quad (5)$$

where *N* is the number of total training samples; d_k and o_k represent the *k*th desired output and the actual output, respectively and *K* is the number of output nodes (number of class).

In the test process, Classification Error Percentage (CEP), the percentage of incorrectly classified patterns, is reported as in Equation (6).

$$CEP = 100\,\frac{Number\ of\ Misclassified\ Patterns}{Number\ of\ Test\ Patterns} \quad (6)$$

The patterns are classified by the winner-takes-all method, in which output with the largest value defines the class. The assigned class is compared with the desired output and if they are not same, the pattern is separated as incorrectly classified. It is calculated for all the test data and the total incorrectly classified pattern number is percentaged to the size of the test data set, as described by Equation (6) [17].

4 Computer Simulation Results

In order to analyze the performances of the modulation recognizers, the computer simulation studies have composed of two stages. In the first stage studies are performed using AWGN channel. In the second stage studies are also implemented employing AWGN and frequency selective Rayleigh fading channels. The performances of the LM-ANN and SCG-ANN classifier are analyzed with confusion matrices over 1000 test data for two stages.

4.1 Simulation Results of AWGN Channel

In the first stage, in order to verify the performance of the ANNs based modulation recognition method in AWGN channel, classifier given by Figure 1 is implemented in computer environment. It is assumed that the received signals are subjected to AWGN channel in the input of the modulation classifier. A 24000 random baseband signal, composed of a 1000 samples for each modulation type, is produced at seven different SNR levels. Sampling frequency is 1 MHz, symbol rate is 25 kHz, the number of symbol is 8000 and pulse shape is selected as a rectangular. It is assumed that carrier frequencies were estimated correctly. Thus, it is only considered complex baseband signals.

ANN classifier is composed of input layer using 3 features, a hidden layer of 25 neurons and an output layer of 8 neurons recognized 8 different modulation types. The LM-ANN and SCG-ANN modulation recognizers are tested with ANN classifier using LM and SCG algorithm as a learning algorithm during the ANN based classifier training stage. A total 8000 signals, composed of a 1000 samples of each modulation type, were used during the training stage of LM-ANN and SCG-ANN classifier and simulation results were recorded with 10 runtimes. The trainings were stopped at the end of the 10000 loops of training data set in the training of LM-ANN and SCG-ANN model. The performances of LM-ANN and SCG-ANN classifiers are shown with confusion matrices over 1000 test data.

The correct classification ratios of BPSK, 4-QAM, 4-ASK, 8-PSK, 8-ASK, 16-PSK, 16-QAM and 64-QAM modulated signals are given with confusion matrices for SCG-ANN in Table 2 and LM-ANN method in Table 3 for -5 dB of SNR value [24, 25].

Table 2. The performance of SCG-ANN classifier for -5 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%15.32**	%17.50	%13.51	-	-	%8.10	%4.65	%40.92
4-QAM	%0.31	**%4.38**	%5.01	%8.48	%2.87	%12.41	%25.29	%41.25
4-ASK	%1.26	%11.52	**%5.63**	%2.48	%1.55	%8.43	%32.06	%37.07
8-PSK	%7.18	%2.79	%0.31	**%11.30**	%0.31	%3.12	%23.84	%51.15
8-ASK	-	%10.95	%4.35	%22.67	**%4.42**	%3.74	%22.50	%31.37
16-PSK	-	%6.52	%4.40	%12.10	%5.33	**%8.75**	%39.50	%23.40
16-QAM	-	%1.25	-	%17.78	-	%5.78	**%25.84**	%49.35
64-QAM	%0.31	%1.24	%2.19	%13.16	%0.62	%15.01	%59.08	**%8.39**

Table 3. The performance of LM-ANN classifier for -5 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%11.87**	%12.83	%5.62	-	-	%28.48	%7.13	%34.07
4-QAM	-	**%3.42**	%0.62	%13.19	%3.19	%13.68	%35.25	%30.65
4-ASK	%0.32	%9.64	**%0.93**	%3.41	%0.31	%18.15	%25.13	%42.11
8-PSK	-	%0.31	%0.62	**%16.93**	%1.24	%9.98	%28.53	%42.39
8-ASK	-	%6.23	%3.11	%18.63	**%8.18**	%14.95	%16.57	%32.33
16-PSK	-	%6.20	%3.15	%12.09	%7.23	**%11.57**	%38.55	%21.21
16-QAM	-	%0.62	%0.62	%9.96	%0.31	%9.65	**%33.29**	%45.51
64-QAM	-	-	-	%24.11	-	%11.55	%55.33	**%9.01**

It is clearly seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK, 4-QAM and 4-ASK modulation types. It can be easily seen from the Table 2 and the Table 3 that 4-QAM and 4-ASK modulated signals are mostly confused with another modulation types and the hardest to be recognized with ANN classifier.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 4 and LM-ANN method in Table 5 for 0 dB of SNR value [24, 25].

Table 4. The performance of SCG-ANN classifier for 0 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%54.69**	-	%20.61	-	%7.19	-	-	%17.51
4-QAM	-	**%21.22**	-	%0.64	%8.46	%39.37	%12.77	%17.54
4-ASK	%0.31	%0.93	**%23.28**	-	%75.16	-	-	%0.32
8-PSK	%0.32	%1.25	%2.50	**%38.80**	%8.42	%22.15	%12.79	%13.77
8-ASK	-	-	%0.31	-	**%99.69**	-	-	-
16-PSK	-	%1.24	%0.95	%26.93	%7.23	**%43.41**	%18.38	%1.86
16-QAM	-	-	-	%10.27	-	%1.55	**%33.68**	%54.50
64-QAM	-	-	-	%15.76	-	%1.55	%50.50	**%32.19**

Table 5. The performance of LM-ANN classifier for 0 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%73.17**	-	%9.97	-	%4.08	%0.62	-	%12.16
4-QAM	-	**%27.73**	-	%0.32	%6.91	%29.38	%14.98	%20.68
4-ASK	%0.31	-	**%19.22**	-	%78.89	%0.62	-	%0.96
8-PSK	-	-	%0.31	**%31.65**	%8.43	%18.11	%25.91	%15.59
8-ASK	-	-	-	-	**%100**	-	-	-
16-PSK	-	-	%0.96	%13.29	%6.56	**%47.52**	%27.30	%4.37
16-QAM	-	-	%0.62	%6.85	%0.31	%4.05	**%37.71**	%50.46
64-QAM	-	-	-	%10.09	%0.32	%3.13	%49.22	**%37.24**

It is obviously seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for 4-ASK and 8-PSK modulation types. It can be easily seen from the Table 4 and the Table 5 that 4-QAM and 4-ASK modulated signals are mostly confused with another modulation types and the hardest to be classified with ANN recognizer.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 6 and LM-ANN method in Table 7 for 5 dB of SNR value [24, 25].

Table 6. The performance of SCG-ANN classifier for 5 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%81.87**	-	%10.00	-	-	-	-	%8.13
4-QAM	-	**%64.33**	%0.62	-	-	%18.18	-	%16.87
4-ASK	%3.42	-	**%70.65**	-	%11.23	%1.88	-	%12.82
8-PSK	-	%0.32	-	**%32.56**	%0.64	%59.32	-	%7.16
8-ASK	-	-	%10.00	%1.55	**%84.41**	-	-	%4.04
16-PSK	-	%2.19	%0.94	%11.59	%1.24	**%79.33**	%0.95	%3.76
16-QAM	%3.76	%0.94	-	-	-	%2.19	**%25.30**	%67.81
64-QAM	%5.64	-	-	%1.87	-	%4.05	%28.48	**%59.96**

Table 7. The performance of LM-ANN classifier for 5 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%75.92**	-	-	-	-	-	-	%24.08
4-QAM	-	**%82.74**	-	-	-	%6.31	%2.51	%8.44
4-ASK	-	-	**%79.07**	-	%7.77	%10.34	-	%2.82
8-PSK	-	-	-	**%41.33**	-	%36.83	%21.84	-
8-ASK	-	-	-	%0.62	**%95.66**	-	-	%3.72
16-PSK	-	-	-	%12.49	-	**%70.92**	%16.59	-
16-QAM	-	-	-	-	-	-	**%25.31**	%74.69
64-QAM	-	-	-	-	-	-	%36.76	**%63.24**

It is clearly seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK and 16-PSK modulation types. It can be easily seen from the Table 6 and the Table 7 that 8-PSK and 16-QAM modulated signals are mostly confused with another modulation types and the hardest to be recognized with ANN classifier.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 8 and LM-ANN method in Table 9 for 10 dB of SNR value [24, 25].

Table 8. The performance of SCG-ANN classifier for 10 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%85.94**	-	%10.00	-	-	-	-	%4.06
4-QAM	%0.31	**%88.73**	-	-	-	%9.69	-	%1.27
4-ASK	-	-	**%99.07**	-	%0.93	-	-	-
8-PSK	-	-	-	**%45.04**	-	%53.10	-	%1.86
8-ASK	%9.07	-	-	%0.93	**%90.00**	-	-	-
16-PSK	-	-	-	%17.81	-	**%82.19**	-	-
16-QAM	%0.64	-	-	-	-	%1.87	**%50.65**	%46.84
64-QAM	%10.98	-	-	%3.42	-	%0.62	%13.04	**%71.94**

Table 9. The performance of LM-ANN classifier for 10 dB of SNR value in AWGN channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%93.75**	-	-	-	-	-	-	%6.25
4-QAM	-	**%99.36**	-	-	-	-	-	%0.64
4-ASK	-	-	**%97.83**	-	%1.86	-	-	%0.31
8-PSK	-	-	-	**%53.53**	-	%46.47	-	-
8-ASK	-	-	-	-	**%100**	-	-	-
16-PSK	-	-	-	%11.90	-	**%88.10**	-	-
16-QAM	-	-	-	-	-	-	**%43.49**	%56.51
64-QAM	-	-	-	-	-	-	%11.16	**%88.84**

It is obviously seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for 4-ASK and 16-QAM modulation types. It can be easily seen from the Table 8 and the Table 9 that 8-PSK and 16-QAM modulated signals are mostly confused with another modulation types and the hardest to be classified with ANN recognizer.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 10 and LM-ANN method in Table 11 for 15 dB of SNR value [24, 25].

Table 10. The performance of SCG-ANN classifier for 15 dB of SNR value in AWGN channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	**%90.00**	-	%10.00	-	-	-	-	-
4-QAM	%0.31	**%89.68**	%0.62	-	-	%9.07	-	%0.32
4-ASK	%3.76	-	**%80.00**	-	%0.62	-	-	%15.62
8-PSK	-	-	-	**%48.16**	-	%51.84	-	-
8-ASK	%12.80	-	%4.38	-	**%80.00**	-	-	%2.82
16-PSK	-	-	-	%18.76	-	**%79.37**	-	%1.87
16-QAM	-	-	-	-	-	-	**%80.00**	%20.00
64-QAM	%7.20	-	-	-	-	-	%7.76	**%85.04**

Table 11. The performance of LM-ANN classifier for 15 dB of SNR value in AWGN channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	**%99.37**	-	-	-	-	-	-	%0.63
4-QAM	-	**%100**	-	-	-	-	-	-
4-ASK	-	-	**%99.69**	-	-	-	-	%0.31
8-PSK	-	-	-	**%67.60**	-	%32.40	-	-
8-ASK	-	-	-	-	**%100**	-	-	-
16-PSK	-	-	-	%3.12	-	**%96.88**	-	-
16-QAM	-	-	-	-	-	-	**%84.71**	%15.29
64-QAM	-	-	-	-	-	-	%3.72	**%96.28**

It is clearly seen that when compared with SCG-ANN, LM-ANN method has decided with high accuracy for all modulation types. It can be easily seen from the Table 10 that 8-PSK modulated signal is mostly confused with another modulation types and the hardest to be recognized with SCG-ANN classifier.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 12 and LM-ANN method in Table 13 for 20 dB of SNR value [24, 25].

Table 12. The performance of SCG-ANN classifier for 20 dB of SNR value in AWGN channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	**%90.00**	-	%10.00	-	-	-	-	-
4-QAM	-	**%70.00**	%0.63	-	-	%6.57	-	%22.80
4-ASK	%4.38	-	**%80.00**	-	%0.31	-	-	%15.31
8-PSK	-	-	-	**%52.52**	-	%47.48	-	-
8-ASK	%12.49	-	%4.38	-	**%80.00**	-	-	%3.13
16-PSK	-	-	-	%20.00	-	**%80.00**	-	-
16-QAM	-	-	-	-	-	-	**%87.44**	%12.56
64-QAM	%7.19	-	-	-	-	-	%2.81	**%90.00**

Table 13. The performance of LM-ANN classifier for 20 dB of SNR value in AWGN channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	%100	-	-	-	-	-	-	-
4-QAM	-	%100	-	-	-	-	-	-
4-ASK	-	-	%100	-	-	-	-	-
8-PSK	-	-	-	%84.15	-	%15.85	-	-
8-ASK	-	-	-	-	%100	-	-	-
16-PSK	-	-	-	-	-	%100	-	-
16-QAM	-	-	-	-	-	-	%96.80	%3.20
64-QAM	-	-	-	-	-	-	-	%100

It is obviously seen that when compared with SCG-ANN, LM-ANN method has decided with high accuracy for all modulation types. It can be easily seen from the Table 12 that 8-PSK modulated signal is mostly confused with another modulation types and the hardest to be recognized with SCG-ANN classifier.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 14 and LM-ANN method in Table 15 for 25 dB of SNR value [24, 25].

Table 14. The performance of SCG-ANN classifier for 25 dB of SNR value in AWGN channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	%90.00	-	%10.00	-	-	-	-	-
4-QAM	%10.00	%70.00	-	-	-	%4.06	-	%15.94
4-ASK	%12.83	-	%70.00	-	%14.03	-	-	%3.14
8-PSK	-	-	-	%56.28	-	%43.72	-	-
8-ASK	%10.00	-	%10.00	-	%80.00	-	-	-
16-PSK	-	-	-	%10.00	-	%90.00	-	-
16-QAM	-	-	-	-	-	%5.32	%88.08	%6.60
64-QAM	%11.88	-	-	%1.55	-	-	%6.57	%80.00

Table 15. The performance of LM-ANN classifier for 25 dB of SNR value in AWGN channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	%100	-	-	-	-	-	-	-
4-QAM	-	%100	-	-	-	-	-	-
4-ASK	-	-	%100	-	-	-	-	-
8-PSK	-	-	-	%98.76	-	%1.24	-	-
8-ASK	-	-	-	-	%100	-	-	-
16-PSK	-	-	-	-	-	%100	-	-
16-QAM	-	-	-	-	-	-	%100	-
64-QAM	-	-	-	-	-	-	-	%100

It is clearly seen from the Table 15 that when compared with SCG-ANN, LM-ANN method has decided with the highest accuracy for all modulation types. It can be easily seen from the Table 14 that 8-PSK modulated signal is mostly confused with another modulation types and the hardest to be recognized with SCG-ANN classifier.

The performances of probability of correct classification (PCC) of LM-ANN and SCG-ANN classifier are shown in Figure 3 for 4-QAM, 4-ASK and 16-PSK modulated signals given in the Tables 2-15 [24, 25].

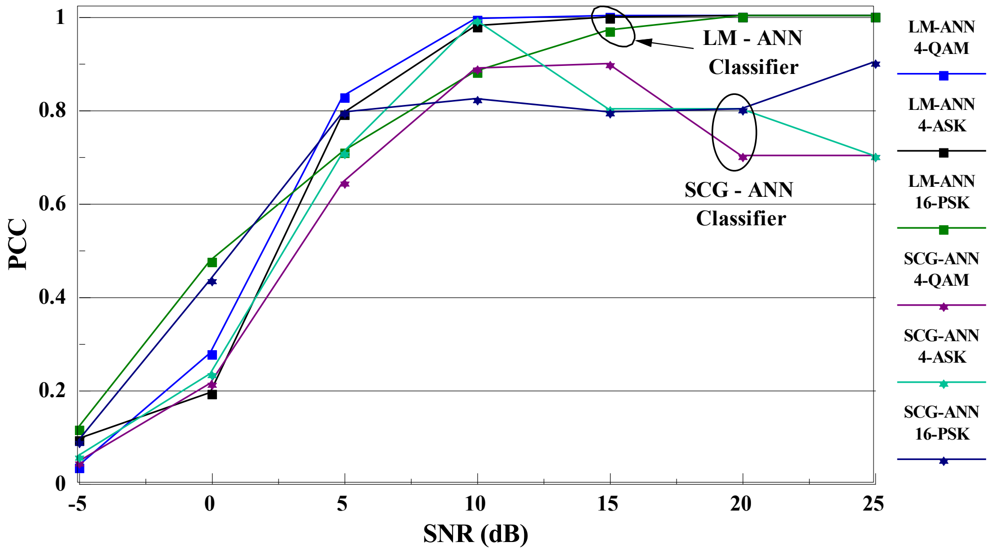

Figure 3. The performances of correct classification of SCG-ANN and LM-ANN recognizers in AWGN channel.

As can be easily seen from the Figure 3 when compared with SCG-ANN classifier, the LM-ANN method is able to recognize the signals with higher accuracy for all SNR values.

4.2 Simulation Results of AWGN and Frequency Selective Rayleigh Fading Channel

In the second stage, in order to verify the performance of the ANN based modulation recognition method in AWGN and frequency selective Rayleigh fading channel, classifier given by Figure 4 is implemented in computer environment.

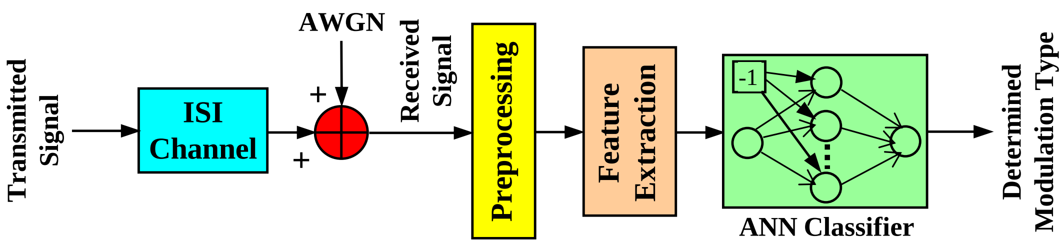

Figure 4. The block diagram of ANN based modulation recognizer in AWGN and frequency selective Rayleigh fading channel.

It is assumed that the received signals are subjected to AWGN and frequency selective Rayleigh fading channel in the input of the modulation classifier. In this study, a three taps channel profile with average coefficient amplitudes given by (0.407, 0.815, 0.407), which is defined by Proakis, is used [26]. The same ANN recognizer techniques have been employed in order to assess the same modulation types for the same SNR levels. It is assumed that carrier frequencies were estimated correctly and symbol synchronization was done properly.

The correct classification ratios of BPSK, 4-QAM, 4-ASK, 8-PSK, 8-ASK, 16-PSK, 16-QAM and 64-QAM modulated signals are given with confusion matrices for SCG-ANN in Table 16 and LM-ANN method in Table 17 for 0 dB of SNR value [24, 25].

Table 16. The performance of SCG-ANN classifier for 0 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%10.65**	%1.57	%20.66	%0.31	%39.30	%1.24	-	%26.27
4-QAM	%4.99	**%10.06**	%1.24	%10.91	%9.03	%10.91	%21.23	%31.63
4-ASK	%6.56	%11.56	**%5.30**	%18.16	%13.48	%14.94	%8.98	%21.02
8-PSK	%6.85	%9.39	%1.88	**%19.10**	%11.49	%4.41	%12.16	%34.72
8-ASK	%3.42	%6.66	%0.96	%22.48	**%12.75**	%11.22	%16.02	%26.49
16-PSK	%5.02	%7.19	%4.36	%18.13	%8.72	**%7.75**	%12.88	%35.95
16-QAM	%2.50	%3.14	%0.64	%22.46	%3.13	%5.30	**%43.98**	%18.85
64-QAM	%1.55	%2.81	%0.62	%20.02	%4.06	%9.65	%22.76	**%38.53**

Table 17. The performance of LM-ANN classifier for 0 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%0.00**	%0.31	%26.34	%0.62	%41.48	%9.97	-	%21.28
4-QAM	-	**%5.33**	%0.62	%20.29	%5.89	%17.45	%33.75	%16.67
4-ASK	-	%11.25	**%5.28**	%38.47	%3.17	%13.40	%3.95	%24.48
8-PSK	-	%10.02	%0.93	**%38.45**	%4.03	%4.41	%34.39	%7.77
8-ASK	-	%4.10	-	%37.18	**%8.99**	%8.10	%9.24	%32.39
16-PSK	-	%8.10	%1.24	%32.23	%0.93	**%9.96**	%20.74	%26.80
16-QAM	-	%0.32	-	%33.70	-	%4.38	**%52.72**	%8.88
64-QAM	-	%1.24	-	%27.81	-	%9.35	%13.67	**%47.93**

It is obviously seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK, 4-QAM, 4-ASK and 8-ASK modulation types. It can be easily seen from the Table 16 and the Table 17 that BPSK, 4-QAM and 4-ASK modulated signals are mostly confused with another modulation types and the hardest to be classified with ANN recognizer.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 18 and LM-ANN method in Table 19 for 5 dB of SNR value [24, 25].

Table 18. The performance of SCG-ANN classifier for 5 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%1.26**	-	%13.75	-	%51.60	%1.56	-	%31.83
4-QAM	-	**%41.87**	%5.61	%0.31	%0.93	-	-	%48.49
4-ASK	-	-	**%10.00**	%46.89	%35.28	-	%3.44	%4.39
8-PSK	%0.31	%10.04	%9.05	**%22.54**	%15.29	%15.85	%1.28	%25.64
8-ASK	-	-	%10.00	%42.19	**%27.21**	%0.62	%8.39	%11.59
16-PSK	-	%11.89	%9.96	%11.89	%7.81	**%7.18**	-	%51.27
16-QAM	-	%10.97	%1.24	%15.31	%3.73	%3.73	**%15.51**	%51.05
64-QAM	%0.93	%9.06	%2.83	%11.30	%0.93	%0.93	%13.42	**%58.09**

Table 19. The performance of LM-ANN classifier for 5 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%0.63**	-	%12.48	-	%47.83	%2.49	-	%36.57
4-QAM	-	**%31.91**	%0.31	-	%0.93	%4.65	-	%62.20
4-ASK	-	-	**%0.00**	%62.81	%19.98	-	%14.37	%2.84
8-PSK	-	%1.55	%0.93	**%33.86**	%10.25	%5.26	%6.30	%4.85
8-ASK	-	-	-	%65.01	**%9.47**	%0.62	%15.86	%9.04
16-PSK	-	%5.32	%0.93	%12.83	%7.82	**%16.22**	-	%56.88
16-QAM	-	%3.44	-	%25.13	-	%1.24	**%27.98**	%42.21
64-QAM	-	%2.18	-	%8.78	-	%0.95	%17.80	**%70.29**

It is clearly seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK, 4-QAM, 4-ASK and 8-ASK modulation types. It can be easily seen from the Table 18 and the Table 19 that BPSK and 4-ASK modulated signals are mostly confused with another modulation types and the hardest to be recognized with ANN classifier.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 20 and LM-ANN method in Table 21 for 10 dB of SNR value [24, 25].

Table 20. The performance of SCG-ANN classifier for 10 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%1.88**	-	%9.99	-	%49.08	-	-	%39.05
4-QAM	%0.62	**%41.57**	%1.87	-	-	-	-	%55.94
4-ASK	-	-	**%10.00**	%41.25	%30.01	-	%9.06	%9.68
8-PSK	%0.62	%1.58	%12.50	**%19.73**	%34.33	%8.08	-	%23.16
8-ASK	-	-	%10.00	%45.64	**%25.92**	-	%11.54	%6.90
16-PSK	-	%8.75	%18.75	%0.31	%0.93	**%13.42**	-	%57.84
16-QAM	-	%11.86	%0.32	%1.55	%0.31	%0.31	**%0.00**	%85.65
64-QAM	%0.31	%8.73	%0.62	%0.64	%1.26	%0.95	-	**%87.49**

Table 21. The performance of LM-ANN classifier for 10 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%0.31**	-	%7.80	-	%44.08	%0.31	-	%47.50
4-QAM	-	**%28.12**	-	-	-	-	-	%71.88
4-ASK	-	-	**%0.00**	%82.81	%0.94	-	%16.25	-
8-PSK	-	%0.95	%3.11	**%19.44**	%30.00	%15.27	-	%31.23
8-ASK	-	-	-	%75.34	**%0.62**	-	%24.04	-
16-PSK	-	%4.06	%7.21	-	%2.17	**%31.86**	-	%54.70
16-QAM	-	%4.38	-	%2.79	-	%1.25	**%3.11**	%88.47
64-QAM	-	%1.26	-	%0.96	-	%0.98	%1.68	**%96.54**

It is obviously seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK, 4-QAM, 4-ASK and 8-ASK modulation types. It can be easily seen from the Table 20 and the Table 21 that BPSK, 4-ASK and 8-ASK modulated signals are mostly confused with another modulation types and the hardest to be classified with ANN recognizer. The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 22 and LM-ANN method in Table 23 for 15 dB of SNR value [24, 25].

Table 22. The performance of SCG-ANN classifier for 15 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%7.49**	-	%0.31	-	%51.57	%0.31	-	%40.32
4-QAM	%14.05	**%27.19**	%10.00	-	-	%9.38	-	%39.38
4-ASK	%3.76	-	**%0.00**	%50.00	%30.00	-	%10.00	%16.24
8-PSK	%6.56	-	%3.10	**%9.69**	%66.60	%3.76	-	%10.29
8-ASK	%8.44	-	-	%37.21	**%30.00**	-	%13.10	%11.25
16-PSK	%9.06	%14.38	%12.82	-	%0.31	**%3.14**	-	%60.29
16-QAM	%9.38	%10.62	-	-	-	-	**%0.00**	%80.00
64-QAM	%8.13	%10.00	-	-	-	-	-	**%81.87**

Table 23. The performance of LM-ANN classifier for 15 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%0.00**	-	%5.31	-	%45.01	-	-	%49.68
4-QAM	-	**%28.45**	-	-	-	-	-	%71.55
4-ASK	-	-	**%0.00**	%79.39	-	-	%20.61	-
8-PSK	-	%0.31	%1.55	**%13.77**	%50.65	%8.13	-	%25.59
8-ASK	-	-	-	%68.74	**%0.00**	-	%31.26	-
16-PSK	-	%3.43	%8.12	-	%0.31	**%36.92**	-	%51.22
16-QAM	-	%6.87	-	-	-	%0.31	**%2.50**	%90.32
64-QAM	-	%1.88	-	-	-	-	%1.88	**%96.24**

It is clearly seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK and 8-ASK modulation types. It can be easily seen from the Table 22 and the Table 23 that BPSK, 4-ASK and 8-ASK modulated signals are mostly confused with another modulation types and the hardest to be recognized with SCG-ANN and LM-ANN classifiers. The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 24 and LM-ANN method in Table 25 for 20 dB of SNR value [24, 25].

Table 24. The performance of SCG-ANN classifier for 20 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%18.43**	-	-	-	%34.07	-	-	%47.50
4-QAM	%4.69	**%36.24**	%8.75	-	-	-	-	%50.32
4-ASK	%11.87	-	**%0.00**	%40.27	%19.39	-	%8.15	%20.32
8-PSK	%18.14	-	%2.79	**%15.33**	%44.13	%0.31	-	%19.30
8-ASK	%14.99	-	-	%31.55	**%10.95**	-	%22.82	%19.69
16-PSK	-	%11.87	%13.78	-	-	**%8.45**	-	%65.90
16-QAM	%0.94	%11.87	-	-	-	-	**%0.00**	%87.19
64-QAM	%0.63	%10.31	%0.31	-	-	-	-	**%88.75**

Table 25. The performance of LM-ANN classifier for 20 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	**%0.00**	-	%4.04	-	%45.34	-	-	%50.62
4-QAM	-	**%27.20**	-	-	-	-	-	%72.80
4-ASK	-	-	**%0.00**	%79.37	-	-	%20.63	-
8-PSK	-	%0.62	%0.93	**%13.77**	%56.32	%7.15	-	%21.21
8-ASK	-	-	-	%63.11	**%4.37**	-	%32.52	-
16-PSK	-	%2.81	%7.82	-	%0.31	**%41.91**	-	%47.15
16-QAM	-	%6.54	-	-	-	-	**%2.19**	%91.27
64-QAM	-	%1.56	-	-	-	-	%1.56	**%96.88**

It is obviously seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK, 4-QAM, 8-PSK and 8-ASK modulation types. It can be easily seen from the Table 24 and the Table 25 that BPSK and 4-ASK modulated signals are mostly confused with another modulation types and the hardest to be recognized with SCG-ANN and LM-ANN classifiers.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 26 and LM-ANN method in Table 27 for 25 dB of SNR value [24, 25].

Table 26. The performance of SCG-ANN classifier for 25 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	**%20.0**	-	-	-	%43.45	-	-	%36.55
4-QAM	%13.75	**%37.19**	%0.63	-	-	-	-	%48.43
4-ASK	-	-	**%0.00**	%41.88	%9.69	-	%28.43	%20.0
8-PSK	%9.69	-	%10.93	**%15.01**	%50.35	%14.02	-	-
8-ASK	-	%3.12	-	%40.0	**%10.0**	-	%30.0	%16.88
16-PSK	%10.0	%6.88	%13.14	-	%0.94	**%15.63**	-	%53.41
16-QAM	%10.0	%11.56	-	-	-	-	**%0.00**	%78.44
64-QAM	%10.0	%10.62	-	-	-	-	-	**%79.38**

Table 27. The performance of LM-ANN classifier for 25 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	4-QAM	4-ASK	8-PSK	8-ASK	16-PSK	16-QAM	64-QAM
BPSK	**%0.00**	-	%2.18	-	%46.58	-	-	%51.24
4-QAM	-	**%26.88**	-	-	-	-	-	%73.12
4-ASK	-	-	**%0.00**	%79.05	-	-	%20.95	-
8-PSK	-	-	%1.24	**%13.14**	%56.30	%1.24	-	%28.08
8-ASK	-	-	-	%67.80	**%0.00**	-	%32.20	-
16-PSK	-	%2.81	%8.13	-	-	**%42.21**	-	%46.85
16-QAM	-	%5.91	-	-	-	-	**%2.19**	%91.90
64-QAM	-	%2.50	-	-	-	%0.31	%1.25	**%95.94**

It is clearly seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK, 4-QAM, 8-PSK and 8-ASK modulation types. It can be easily seen from the Table 26 and the Table 27 that BPSK and 8-ASK modulated signals are mostly confused with another modulation types and the hardest to be classified with SCG-ANN and LM-ANN recognizer.

The correct classification ratios of the same modulated signals are given with confusion matrices for SCG-ANN in Table 28 and LM-ANN method in Table 29 for 30 dB of SNR value [24, 25].

Table 28. The performance of SCG-ANN classifier for 30 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%20.0**	-	%37.18	-	%42.82	-	-	-
4-QAM	%14.06	**%36.88**	%0.63	-	-	-	-	%48.43
4-ASK	-	-	**%0.00**	%41.88	%9.69	-	%28.43	%20.0
8-PSK	%10.0	-	%10.62	**%13.14**	%49.72	-	-	%16.52
8-ASK	-	%3.12	-	%40.0	**%10.0**	-	%30.0	%16.88
16-PSK	%9.68	%6.87	%14.39	-	%1.57	**%15.02**	-	%52.47
16-QAM	%10.0	%11.56	-	-	-	-	**%0.00**	%78.44
64-QAM	%10.0	%10.62	-	-	-	-	-	**%79.38**

Table 29. The performance of LM-ANN classifier for 30 dB of SNR value in AWGN and frequency selective Rayleigh fading channel.

	BPSK	**4-QAM**	**4-ASK**	**8-PSK**	**8-ASK**	**16-PSK**	**16-QAM**	**64-QAM**
BPSK	**%0.00**	-	%1.56	-	%47.51	-	-	%50.93
4-QAM	-	**%26.57**	-	-	-	-	-	%73.43
4-ASK	-	-	**%0.00**	%78.74	-	-	%21.26	-
8-PSK	-	-	%0.93	**%12.52**	%61.92	%0.31	-	%24.32
8-ASK	-	-	-	%67.49	**%0.00**	-	%32.51	-
16-PSK	-	%3.12	%8.48	-	-	**%41.25**	-	%47.15
16-QAM	-	%5.92	-	-	-	-	**%1.88**	%92.20
64-QAM	-	%2.18	-	-	-	%0.31	%1.57	**%95.94**

It is obviously seen that when compared with SCG-ANN, LM-ANN method has decided with better accuracy for all modulation types except for BPSK, 4-QAM, 8-PSK and 8-ASK modulation types. It can be easily seen from the Table 28 and the Table 29 that BPSK and 4-ASK modulated signals are mostly confused with another modulation types and the hardest to be recognized with SCG-ANN and LM-ANN classifier.

The performances of PCC of LM-ANN and SCG-ANN classifier are shown in Figure 5 for 4-QAM, 16-PSK and 64-QAM modulated signals, subjected to AWGN and frequency selective Rayleigh fading channels, given in the Tables 16-29 [24, 25].

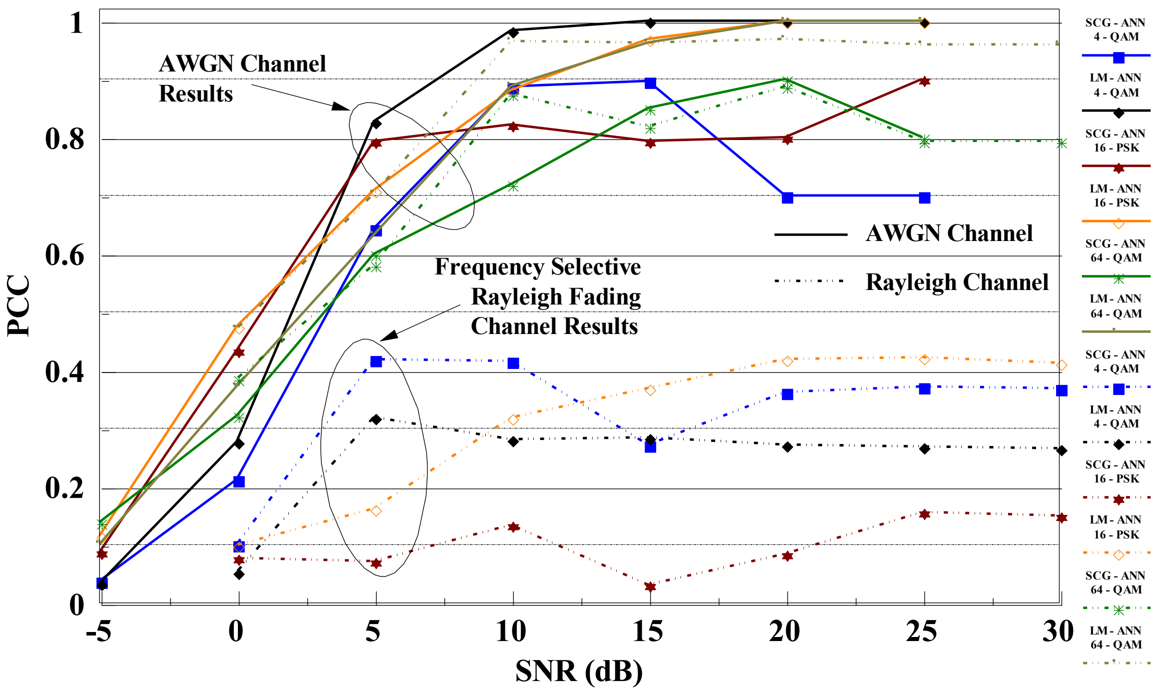

Figure 5. The performances of correct classification of SCG-ANN and LM-ANN recognizers in AWGN channel and frequency selective Rayleigh fading channels.

As can be easily seen from the Figure 5 when compared with SCG-ANN classifier, the LM-ANN method is able to recognize the signals with higher accuracy for all SNR values. Additionally, it can be seen that the results of AWGN channel much better than the results of frequency selective Rayleigh fading channel.

5 Conclusions

Automatic modulation recognition has a great importance especially in military communication systems. This process is also very difficult with the number of modulation types and the effect of multipath fading channel. Since the correct classification is carried out with features obtained high order cumulants of the baseband signal, firstly three high order statistics is selected as features in this study. In this paper, multi-layer artificial neural networks, using these features, are employed as a modulation classifier. In order to test the performance of the classifier, the performances of ANN classifiers trained with SCG and LM algorithm are compared during the training stage. Successful results are obtained with the investigated recognizers for classification of M-PSK and M-QAM modulated signals in especially low training steps of as 10000. Computer simulation results have demonstrated that LM-ANN technique has reached much better classification accuracy than SCG-ANN classifier even at 0 dB of SNR value. Additionally, computer simulation results have shown that as SNR value increases, both recognizers reached better recognition accuracy.

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