Acoustics Parameters Estimation by Artificial Neural Networks

Noureddine Djarfour , Kamel Baddari*, Lab. physique de la terre,.*
Université de Boumerdés 35000, Algérie, E.mail:djarfour@usa.net

Abstract
In order to solve the geophysics inverse problem, the artificial neural networks of Elmen type were trained to extract acoustic parameters from seismic trace. This type of network offers an advantage of training simplicity by the Backpropagation conjugate gradient algorithm. The networks behaviour observed on training data is very close to the one observed on test data. The efficiency of these networks is tested with the noisy data, and the results were very encouraging.

Keywords:
neural networks; training; Elmen; acoustic parameters; Backpropagation

Introduction
In this work we consider the application of the **A**rtificial **N**eural **N**etworks (ANN) to solve the inverse problem in seismic, this emergent technology has demonstrated its applicability in different fields of the science and the engineering. Their development is carried through methods by which the man try to copy the nature and to replicate fashions of his own reasoning. The use of this technique is motivated by the fact that the ANN model presents a considerable advantage in systems analysis and design by including a priori available knowledge base regrouping a perceptual interpretation, an abstraction and a training[1]. When one nearly examines infinite possibilities of application of the ANN for the resolution of the geophysical problem, it seems very profitable to extract, in a first time, the primitive of training and adaptation. Possibilities of training and adaptation of the ANN model make it attractive for various applications in seismic as the first arrivals picking, traces edition, the detection of spikes[6], the filtering of the multiples, the seismic data compression[3]. In this paper we propose to investigate the use of the ANN model in acoustic parameters extraction from seismic traces. From the training diagram, we derive a certain relation between the seismic data and acoustic parameters witch well be seen as a non-linear mapping function. Finally, we illustrate the effectiveness of the ANN model in term of its capacity to approximate the complexity of the geological reality and the noisy data.

Neural network principles
Neural networks are constituted of the elementary neural (''agent'') connected between them through the intermediary of weights, that play the role of synapses. Information is carried by the value of these weights, while the structure of neural network only serves to treat this information, and to route it toward the output. These elements are inspired by biological nervous systems. the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

An ANN is constituted generally of three layers. The first is the one of the input, the second is said hidden layer and constitute the cur of the neural network, the third is the output layer.

The main contribution of the ANN model is twofold. First, it is characterised by a distributed and parallel mode in information processing that allows us to deal with uncertainties on data and even with local faults in the net structure. Second, because of the cohabitation property of net agents, it may be possible to realise an approximation of any mapping function.

A neural network operates in two steps. The first step consists of determining its parameters according to a backpropagation conjugate gradient algorithm witch in fact resume the training process. When its parameters being fixed, we use the obtained structure like a classic function [4].

Results and discussion

Synthetic tests and results

In order to extract the acoustic parameters from the seismic traces, we have adopted for net configuration of Elman type (feedback connection) (Fig.1). The estimated parameters are the velocity, the density and the acoustic impedance. These acoustics properties are used to generate the synthetic data that are of 70 traces with 501 samples for each trace. The signal used is a Ricker of 25Hz with central frequency (Fig 2).

We have opted for a Feedback dynamic structure. In order to achieve the network training, we introduce at each iteration a set of tuples constructed from inputs and desired output. During all experiences the input is the synthetic seismic data (example Shawn in Fig.3), the output selected is the distribution of the parameter to be estimated. The results obtained are illustrated on Fig. 6. 9.12. We got a satisfactory performance with a number of iterations variable. In the figures.4,7,10 we represent the output of ANN after the training, we presents him the seismic section used in the training, these figures are accompanied with the output wanted (Fig.5,8,11). While comparing the output of network after the training with data used for the calculation of the seismic section, we can notice easily that the network was able to performer a relation between data and parameters correspond. We chose to test the influence of the geometric shape of the reflector on the process of training of the ANN. For it one used a geological model constitutes of six layers (five reflectors) (Fig. 13), the results of different performances are given by the (Fig. 14,15,16). Three tests of training have been achieved with a variable noise percentage The (Fig. 17) represent the synthetic seismic section with percentage 5% of noise. In the same way, the (Fig. 18) represent the performance gotten after 2100 iterations. We increases the percentage of noise toward 15% (Fig. 19) and 50% (Fig.21), we got the performance given by the (Fig.20,22). the relatively reduced performances in relation to the ideal case (noise free). The objective of the last synthetic experience phase, is to test the possibility of generalisation of the use of ANN for the acoustics parameters estimation. To this effect, we achieved the training of network by a geological model, follows the efficiency of ANN is tested by the use of the synthetic data of another model different of the one used in training.. Results of this test are given by the (Fig.23,24), in which we represented log of velocity and acoustic impedance respectively estimated by the network and those used to generate data to the input of the network. results were extensively satisfactory in relation to the velocity and impedance.

Discussion

Elman neural networks were driven to allow the acoustics parameters evaluation from the seismic traces. In different tests, networks could establish a non-linear relationship between the seismic trace and parameters having served to the creation of this traces. If one examines the complexity of this relation established by networks through training processes and adaptation mechanism of this last. In following, we will explicit the process of the construction of a seismic trace. Let be d(t) double time density function, and v(t) the velocity function; I(t) the one of the acoustic impedance, and r(t) the reflectivity, w(t) the seismic Ricker-type wavelete, and finally T(t). The seismic trace. the seismic trace is calculated by the following stages:

- Calculation of the acoustic impedance

  I(t)=**F1**[d(t),v(t)].

  F1 : d(t), v(t) $\Longrightarrow$ I(t).

- Calculation of reflection coefficients r(t)=**F2**[I(t)].

  F2 : I(t) $\Longrightarrow$ r(t)

- Calculation of the seismic trace by the convolution of w(t) and r(t) given by the functional **F3** as T(t)=**F3**[w(t), r(t)]

  F3 :w(t),r(t) $\Longrightarrow$ T(t).

In order to solve the inverse problem consists of carrying up of the seismic trace T(t) to parameters acoustic d(t), v(t) and I(t), it is necessary to establish the following functional:

- The evaluation of impedance consists of finding the inverse operator of **F3** to pass from the seismic trace T(t) to reflectivity r(t), this problem is known in geophysics as the deconvolution. To solve it is necessary to arrange w(t) or an evaluation of this last. Finally, the passage from reflectivity to the acoustic impedance distribution makes by the application of the inverse operator of **F2** on r(t), this operation is known integration.

In the case of the realisation of a training where the input is the seismic traces and the output wanted is the acoustic impedance, the neural network established a relation non- linear between traces and impedance. This relation is equivalent has the evaluation of the inverse operators of **F3** and **F2**. In the same way for the case of the density and the velocity as another factor of complexity intervenes, the one of the evaluation of the inverse operator of **F1** after having estimated the inverse of **F3** and **F2**. In the case of noisy data before opting to the evaluation it is necessary to achieve filtering what has been made at the same time by the network, filtering and evaluation.

Conclusion

In this work the neural networks were driven for the evaluation of acoustics parameters from the seismic trace. Results show that networks could establish relationship between the trace and the acoustic parameters, thanks to their capacity of approximation, and of adaptation. The training of network can be considered like a means to synthesise automatically a function generally non-linear (control mapping)[5]. The obtained results, show that there is no need to use two hidden layers instead only one layer hidden for the complexity of network valued data by the number of weight used in the architecture of the network. Because neural networks of two hidden layers are more appreciable to problems of the local minimum during the training. The network of type feedback offers the advantage of a fast, and simple training while using an algorithm of Backpropagation conjugate gradient of the error. some authors [Carlos,Calderôn-Macias and al 2000] use a training by an hybridised algorithm compound by the Backpropagation and a genetic algorithm. As a fast optimisation method., in the case of the use of a type network feed forward. The efficiency of network is tested in relation to noisy data and results were extensively satisfactory, in the same way possibilities of generalisation of their use, because the training makes himself only one time.

References

[1] Carlos,Calderôn-Macias et al 2000, Artificial neural networks for parameter estimation in geophysics Geoph- Pros Volume No 40.

[2] Elman,J,L. 1990. Finding structure in time. Cognitive Science, Vol, 14.

[3] Epping,W.J.M. et A.R.L'ISTELLE 1992. Data compression of seismic images by neural networks Revue de l'IFP Vol.47. N° 3.

[4] Gondran,M et Corinne Muller1997. réseaux de neurones et apprentissage.

[5] Jean,M.R 1994. Algorithmes génétiques et réseaux de neurones. Edition HERMES

[6] MOUSSET,E 1992, Spikes filtering with neural networks. Revue de l'IFP Vol.47. N° 3.

[7] P.F.M.de Groof 1992 Neural Networks experiments on synthetic Seismic data Artificial intelligence in The petroleum industry. Edition Technip

list of figure

Summary picture of the hard training the models of the Fig.3

ANN	No of neural in every layer	The density		The velocity		Impedance	
		No of iter	performa	N of iter	perfoma	N of iter	performa
Number hidden layer layer1- layer2	**10**	179	$7.85\ 10^{-14}$	88	$6.89\ 10^{-16}$	**111**	**$1.40\ 10^{-15}$**
	15	175	$1.24\ 10^{-12}$	90	$8.98\ 10^{-16}$	87	$4.8\ 10^{-16}$
	20	185	$9.19\ 10^{-13}$	**74**	**$8.01\ 10^{-16}$**	106	$4.95\ 10^{-16}$
	30	172	$4.60\ 10^{-13}$	71	$6.3\ 10^{-16}$	120	$1.8\ 10^{-16}$
	40	186	$1.9\ 10^{-13}$	94	$5.28\ 10^{-16}$	84	$5.77\ 10^{-16}$
	5-5	225	$5.55\ 10^{-13}$	172	$4.16\ 10^{-18}$	167	$1.6\ 10^{-18}$
	10-10	195	$1.88\ 10^{-12}$	171	$3.26\ 10^{-17}$	173	$3.51\ 10^{-18}$
	10-15	**275**	**$1.929\ 10^{-11}$**	229	$3.8\ 10^{-17}$	213	$4.50\ 10^{-18}$
	50	168	$6.19\ 10^{-13}$	87	$9.29\ 10^{-16}$	81	$5.1\ 10^{-16}$
Input of ANN	Seismic section						
Transfer function	Linear						
Learning algorithm	Backpropagation						

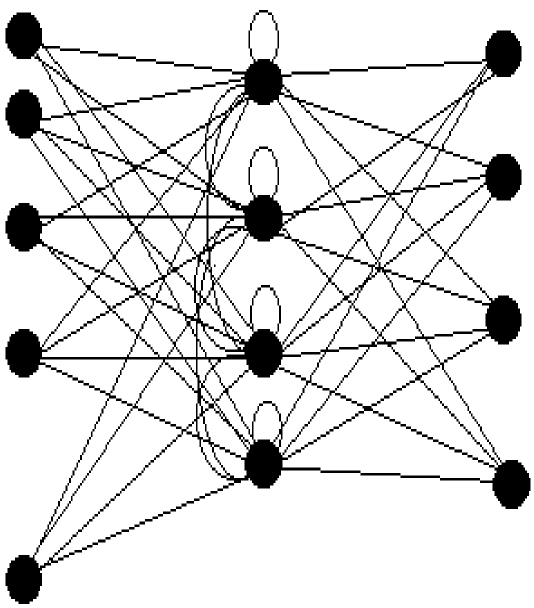

Fig.1

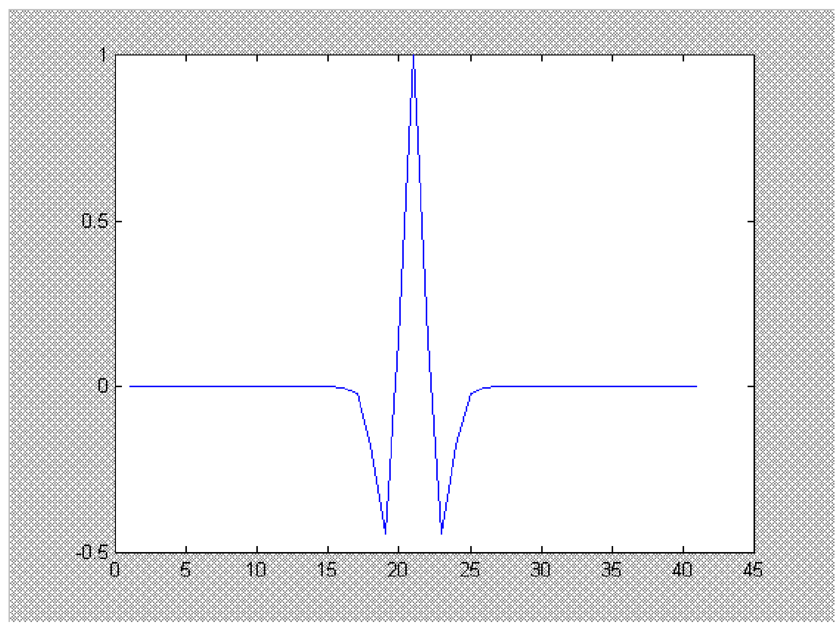

Fig.2

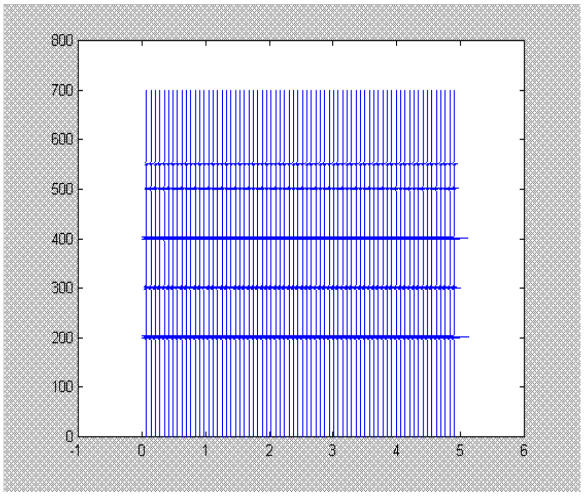

Fig.3

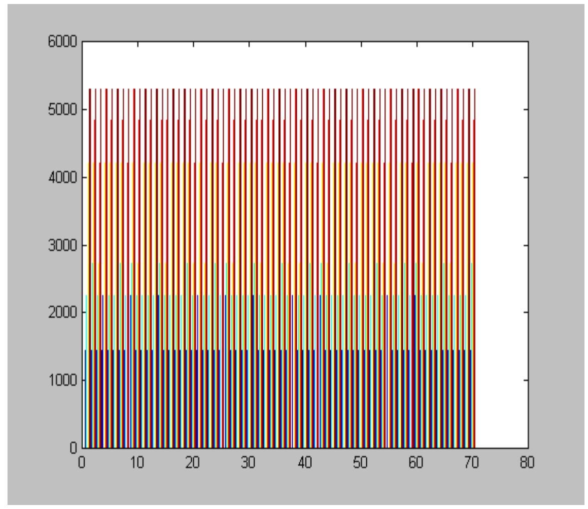

Fig.4

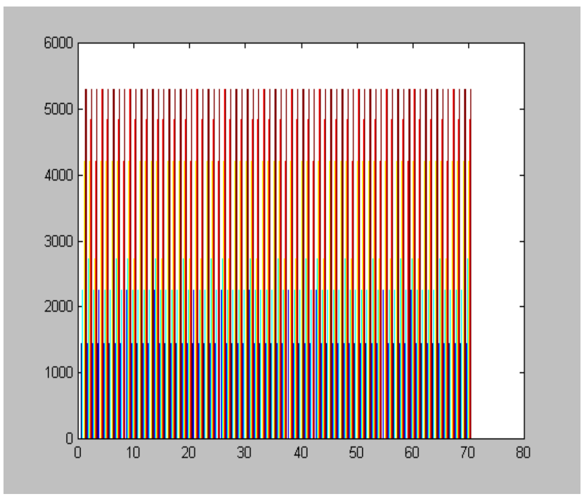

Fig.5

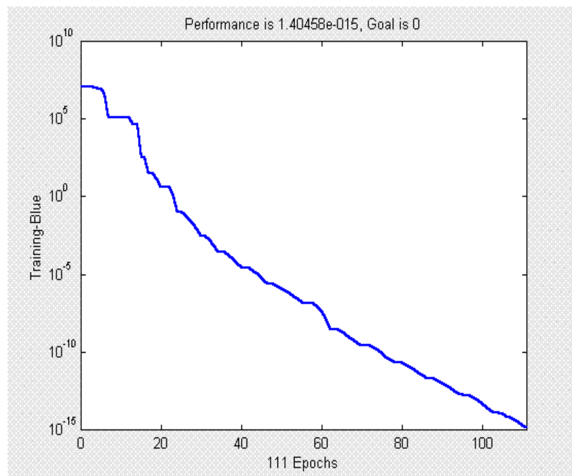

Fig.6

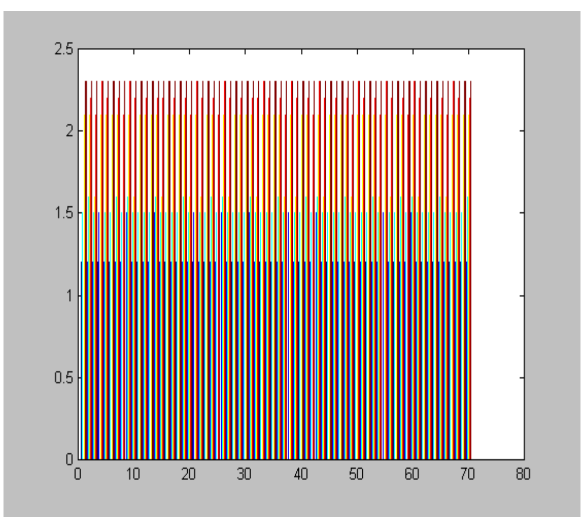

Fig. 7

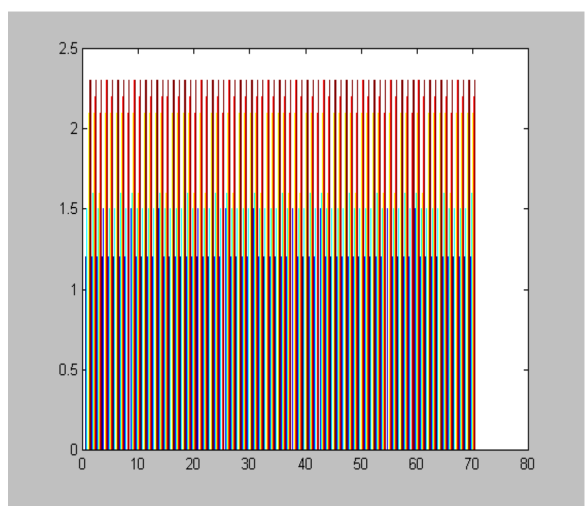

Fig.8

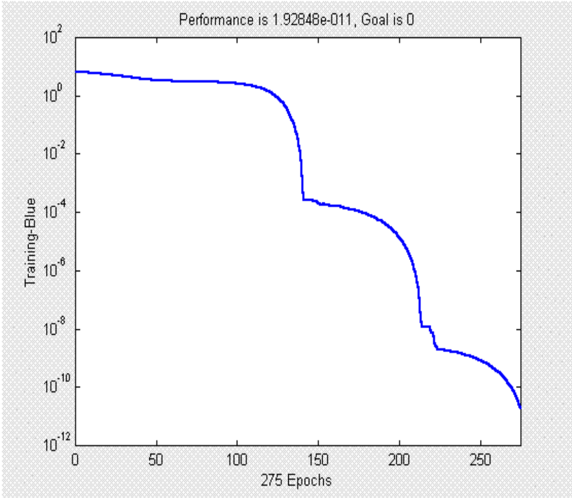

Fig.9

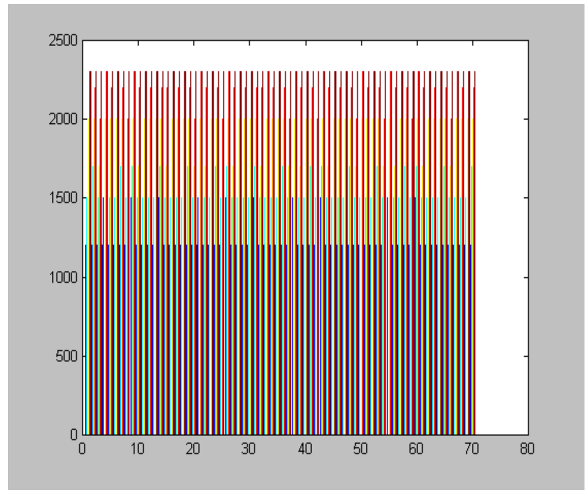

Fig.10

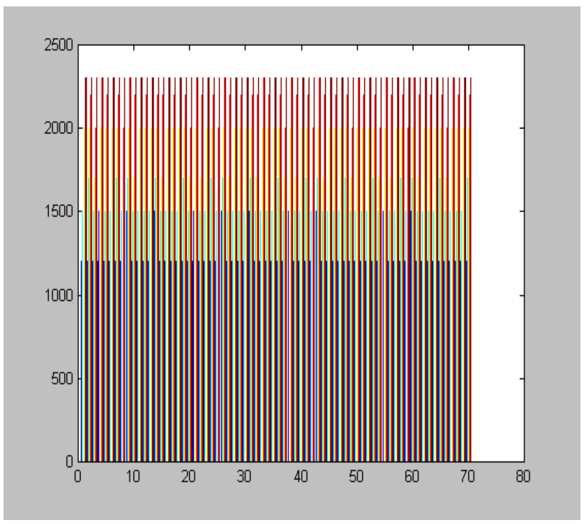

Fig.11

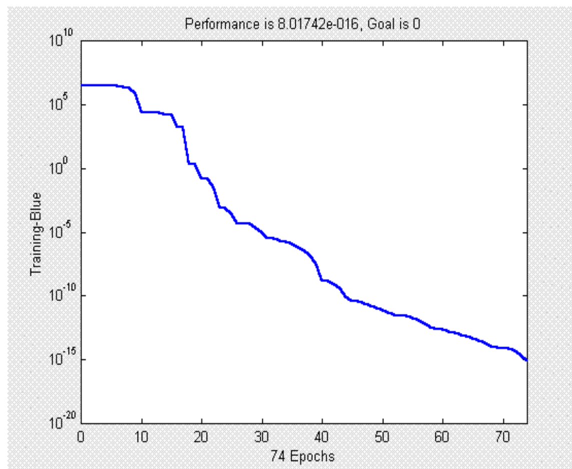

Fig.12

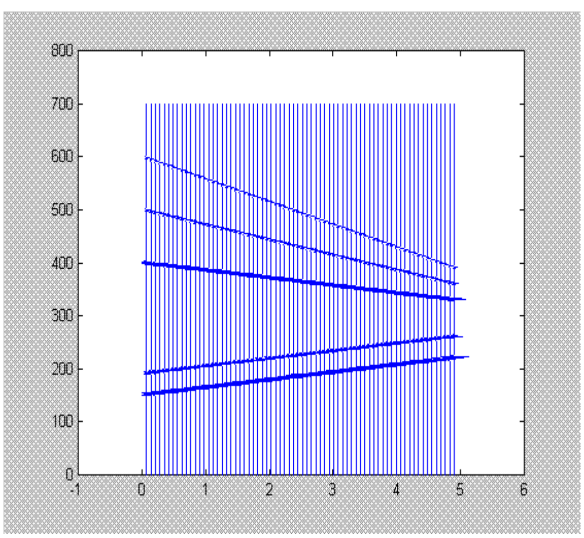

Fig.13

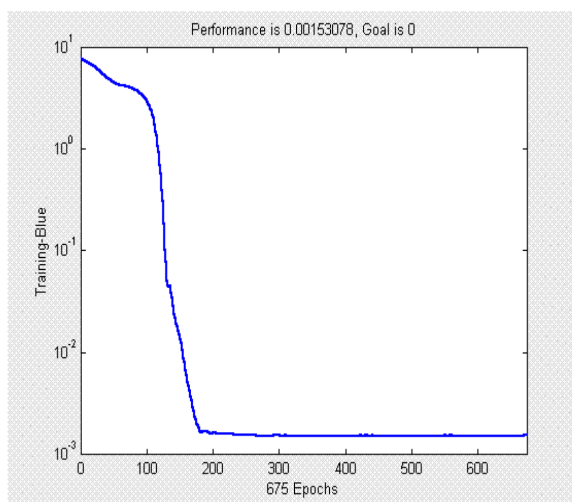

Fig.14

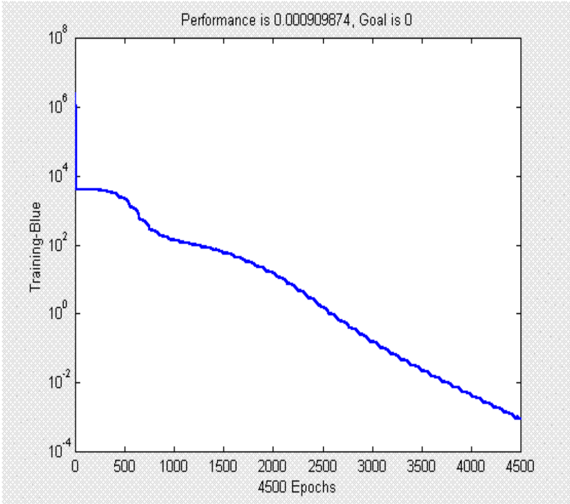

Fig .16

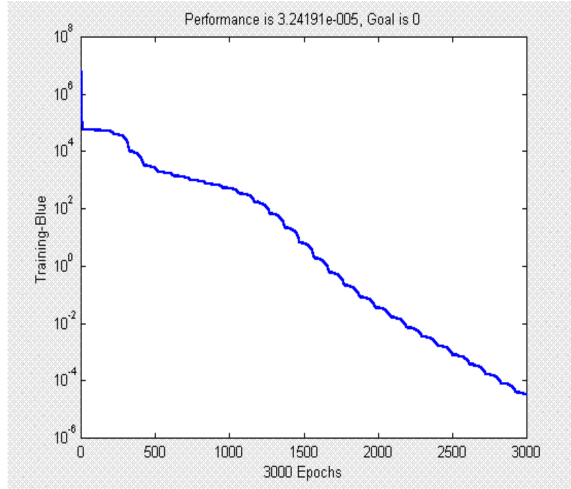

Fig.15

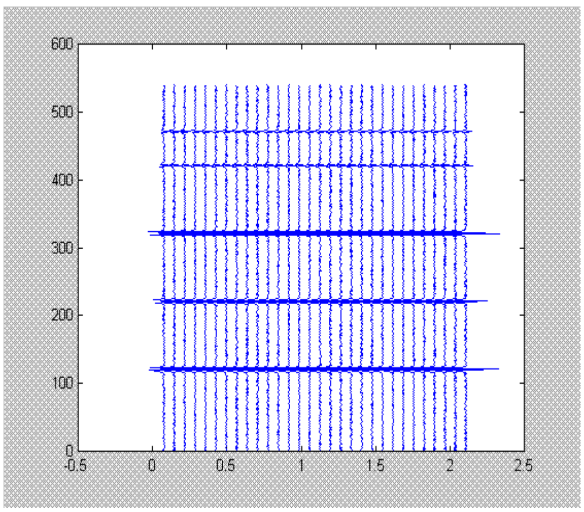

Fig.17

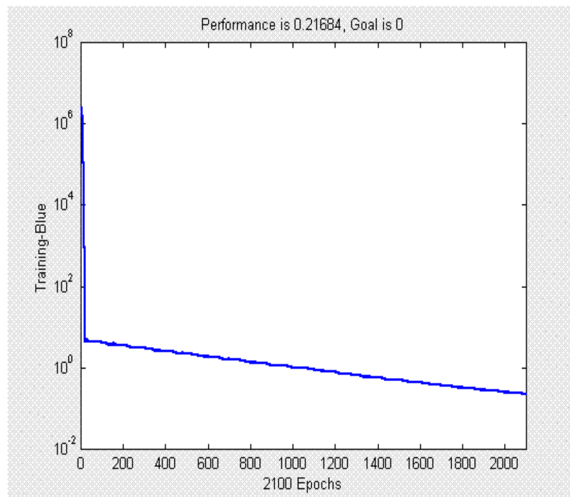

Fig.18

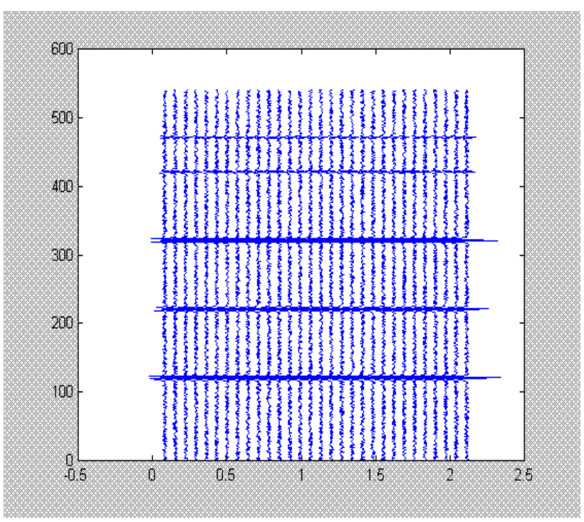

Fig.19

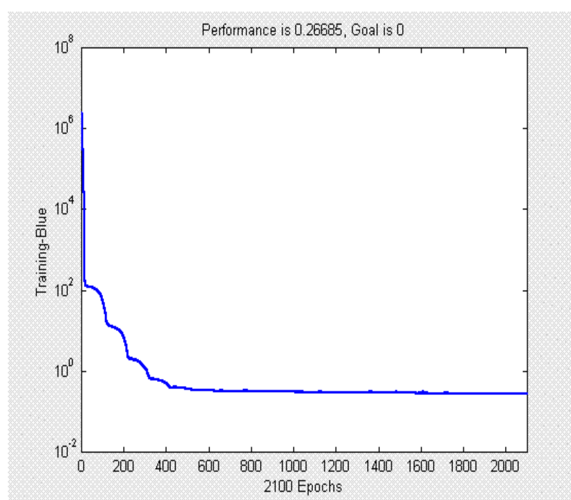

Fig.20

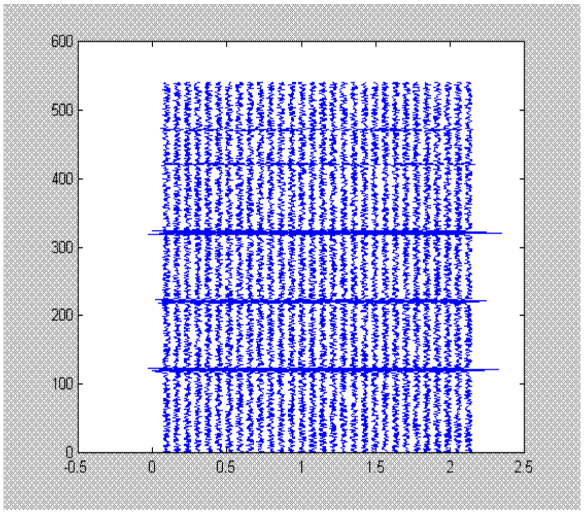

Fig.21

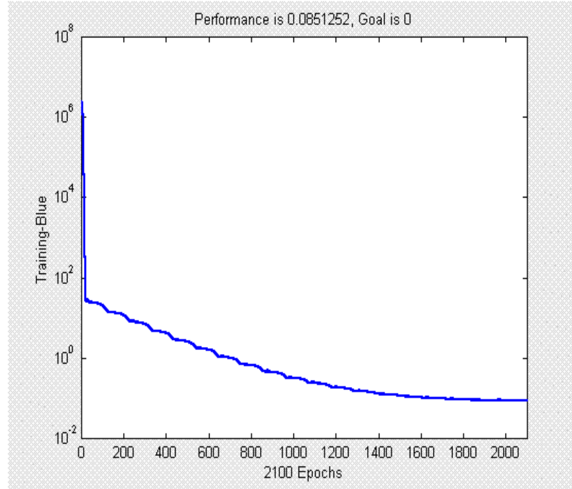

Fig.22

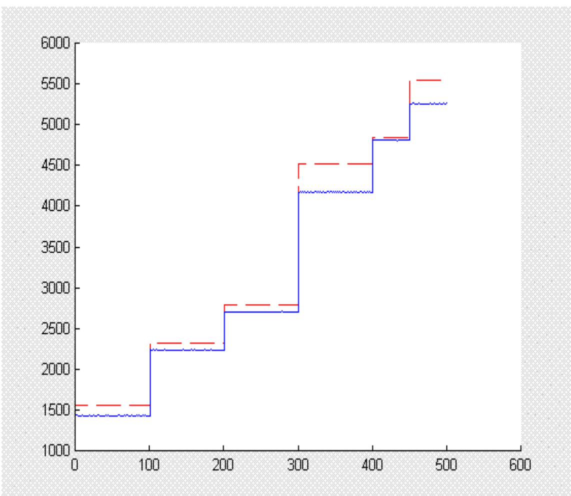

Fig.23

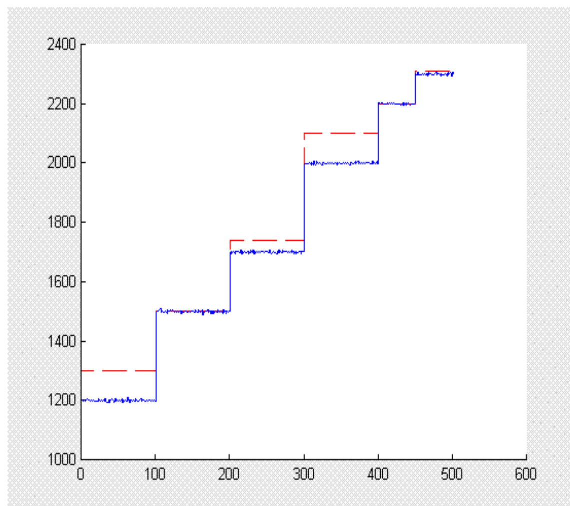

Fig.24