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An Effective Performance of Sigmoidal Activation Function in Neural Network Architecture

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Abstract

In this paper, we will analyze a program that allows you to and train a neural network to generate the code on c as the most sophisticated simulation programs. in that program will present special tools that will allow us to investigate some issues and training techniques advanced relating to neural networks, among which the overcoming of local training with sigmoidal function. The fields of application of neural networks are typically those where classic algorithms, because of their inherent stiffness (need to have accurate inputs), they fail. In general, the problems that have imprecise inputs are those for which the number of possible variations input is so high that it cannot be classified. As we will see, a neural network trained with the data of a complex phenomenon will be able to make predictions also on its frequency components, and this means that realized inside a Fourier transform There are cases in which the elementary historical sequences (those that represent an example) must be composed of many consecutive data to get good results and this entails the need to use networks with a number of inputs very high: it is possible to do this but, sometimes, you prefer to use 'recurrent networks' that are equipped with neural networks "memoirs on inputs" such that each variable can have only one physical input but the network at any instant t is conditioned not only by the input The neural networks discussed in the previous chapters were a Associative Memory and Error Back Propagation, two paradigms completely different as regards use and operating principles but had, actually, something in common: both were using a type of learning.

Index Terms: FPGA, Neural Networks, Sigmoid Activation Function, Schematic Tools.

1. INTRODUCTION

In the digital network, the process of execution occurs based on the activation invoking signals. The behavior of the activation function in network varies with the function. It is based on brain interface neuron inducing signals. The invoking signals such as normalized sigmoid mathematical function used to process the execution in the networks. It improves the system performance based on various mathematical models. In multilayer perceptron or radial basis functions, the sigmoid function considered as the most utilized factors to analyze the input procedure. It includes binary sigmoidal function and bipolar sigmoidal functions. Generally, it various based on the allocated sigmoid curve range over the output layer of various networks. Based on the Lipchitz-continuous activation functions, the stability and non-delaying of the neural networks are analyzed [1]. The absolute stability (ABST) is the essential condition to validate the neuron activation functions in both Hopfield-type and composite neural networks. The robust activation function realistic performance improves wide range of applications over the neural networks Similarly, the concept of extreme learning machine in neural network improves the facilities for various sophisticated complex applications. The extreme training in the network deals with the analysis of output weights based on random assumption of arbitrarily preferred input weights for a finite set. Based on the observation through appropriate learning of single hidden layer feed forward neural network (SLFN), the level of observation increased and the error range also decreased. It is due to the mathematical scheming of Moore-Penrose inverse method for the hidden neurons in the neural network for various unique training samples. The simulation results shows the learning rate increase through the intense training of the algorithm. But, the excess trained neurons cause proximity errors that

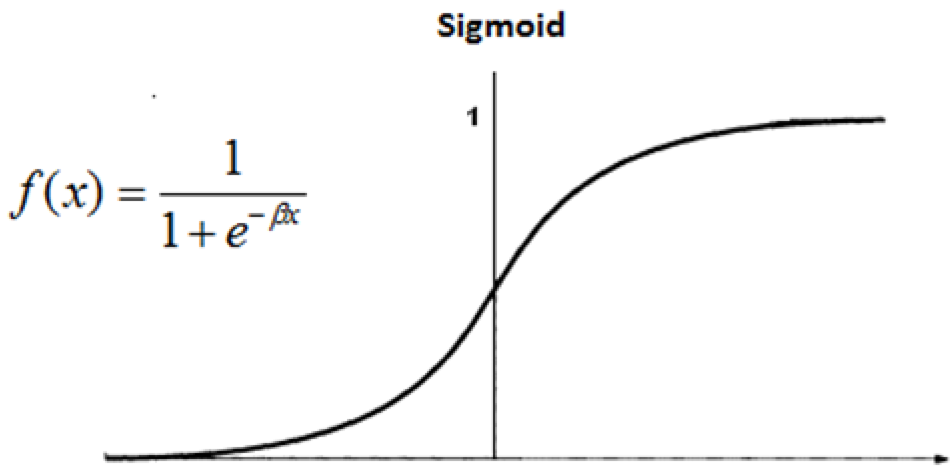

Fig 1 The shape of sigmoidal function.

In neural network. In neural networks, the global asymptotic stability analyze the time delay through the equilibrium point. In [3], the distributed and discrete delays that occurs in neural networks based on activation functions are analyzed. The assumptions shows the linear matrix inequality (LMI) reduce the monotonicity parameters. The Matlab LMI toolbox solves the formulated interior point problem that deals with the delayed connection weight matrix. The time series predication in dynamic systems for scrutinize the convergence of the recurrent fuzzy neural network (RFNN) structure is established in [4]. One way to retrieve concentrations of coastal water constituents, such as phytoplankton pigment, suspended matter and gelbst off, from remotely sensed radiance reflectance is to use the inverse modelling technique. The procedure requires a radiative transfer model, an optimization procedure and the specific optical properties of the sea water constitutions as used in the model. By using a two-flow radiative transfer formulation, this technique was first applied to radiance spectra. In order to reduce the computational effort, direct application of the inverse model on a pixel-by-pixel basis has to be avoided. Since the range of concentrations of water constituents in the sea is limited, the possible reactance spectra can be computed in advance with a radiative transfer model. The result of this computation, i.e. the inverse relationship between concentrations and reactance, can be stored in form of a table and/or expressed by polynomials or a Neural Network (NN) and used for retrieval.

The inhibition may not be absolute, but such as to decrease by one the sum of the activation values for each variable inhibitory active. And 'possible to associate a weight (integer) to each input variable. The variable will be taken as a number equivalent to the It's weight of var. Booleans, which they all behave in the same way. The potential of neural networks together with the low computational costs have allowed for a massive development of such techniques that have been applied in various fields. Neural networks, in fact, if properly conceived and defined allow us to reconstruct the cause-effect relationships that are the basis of multivariable complex systems. For this reason, these new methods have already stimulated numerous applications not only academic but also by the industry that have shown how these techniques prove advantageous and fast implementation in many areas such as process, the control of complex systems and signal processing. The issues pertaining to the field of road are, as is well known, highly complex is not easy for the determination of the many variables in play that for the consequent need for a systemic approach to their management. At present, research suggest that the application of neural networks to study some complex issues in the field of road and transport terms are numerous. In Specifically, this technique has been used to develop models for analysis and prediction in accident interpreting the relationships of cause and effect that generate such Paranormal In addition, these approaches have proven useful for the management maintenance of road surfaces and as a tool for prediction of their conditions as an operational tool. For the problems in this study, the use of artificial intelligence techniques can be a useful tool for the prediction of functional parameters of the pavement which is also a necessary step to define the temporal evolution in relation to the operating conditions.

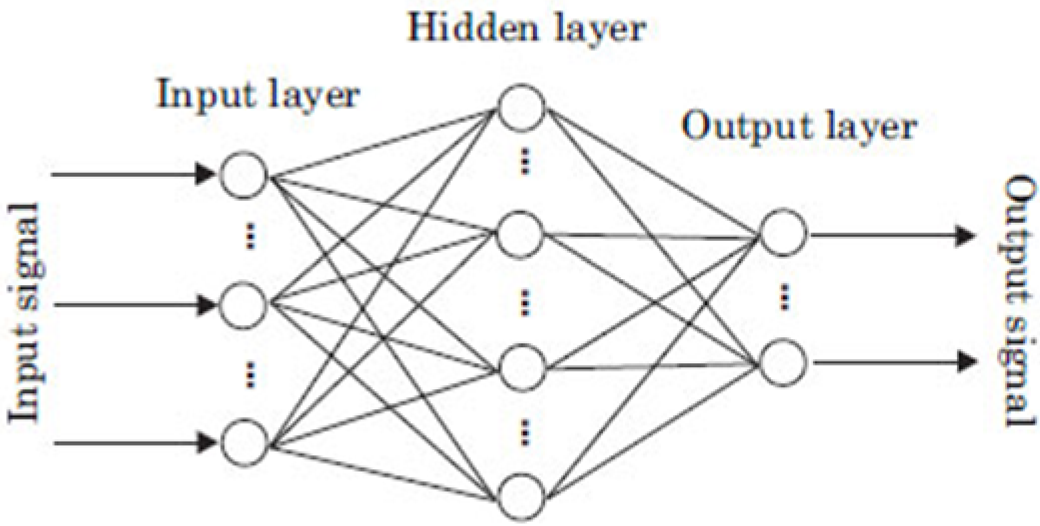

Fig 2 Structured chart of neural network

The architecture of the network was defined with an input layer composed of two neurons, one hidden and one output with a neuron have been trained, then, a multiplicity of neural networks whereas from time Once a different number of neurons of the hidden layer, all the possible functions of activation and various learning algorithms. Having trained 200 networks Neural is a better approximation is obtained with three neurons in the hidden layer, sigmoidal activation function or symmetric f (x) = tanh(x) and learning algorithm of [12]. The latter allows for obtain an absolute minimum as well as a rapid convergence. For correct operation of the network it was necessary to bring the values of CAT and Traffic in a range between 0 and 1 in accordance with the form of the function tan-sigmoid. Furthermore, in consideration of the size of the database, in order to improve the results, was made the following additional steps: in particular, after This has allowed present the total multiplicity and variety of cases in the training phase, avoiding the danger of subjecting the samples to the network completely outside the range considered in the test phase, otherwise the network would not be able to absolutely interpret.

2. METHODOLOGY

Sigmoidal function is the most used as an activating function. The knowledge of the decay curves of the functional parameters of the paving road (lift, regularity and roughness) is of paramount importance in the process of planning of maintenance. The definition of optimal strategies of intervention, in fact, as their main objective the safety of circulation, taking into account the cost constraints, is based on the identification of thresholds intervention of the indicators of the state of these features, which are essential for prioritize interventions.

$$G(x) = \sum_{j=1}^{N} \alpha_j \sigma(y_j^{\mathrm{T}} x + \theta_j) \tag{1}$$

$$\int_{I_n} \sigma(y^{\mathrm{T}} x + \theta)\, d\mu(x) = 0 \tag{2}$$

Let a be any continuous discriminatory function. Then finite sums of the form

$$\sigma(t) \to \begin{cases} 1 & \text{as } t \to +\infty, \\ 0 & \text{as } t \to -\infty. \end{cases} \tag{3}$$

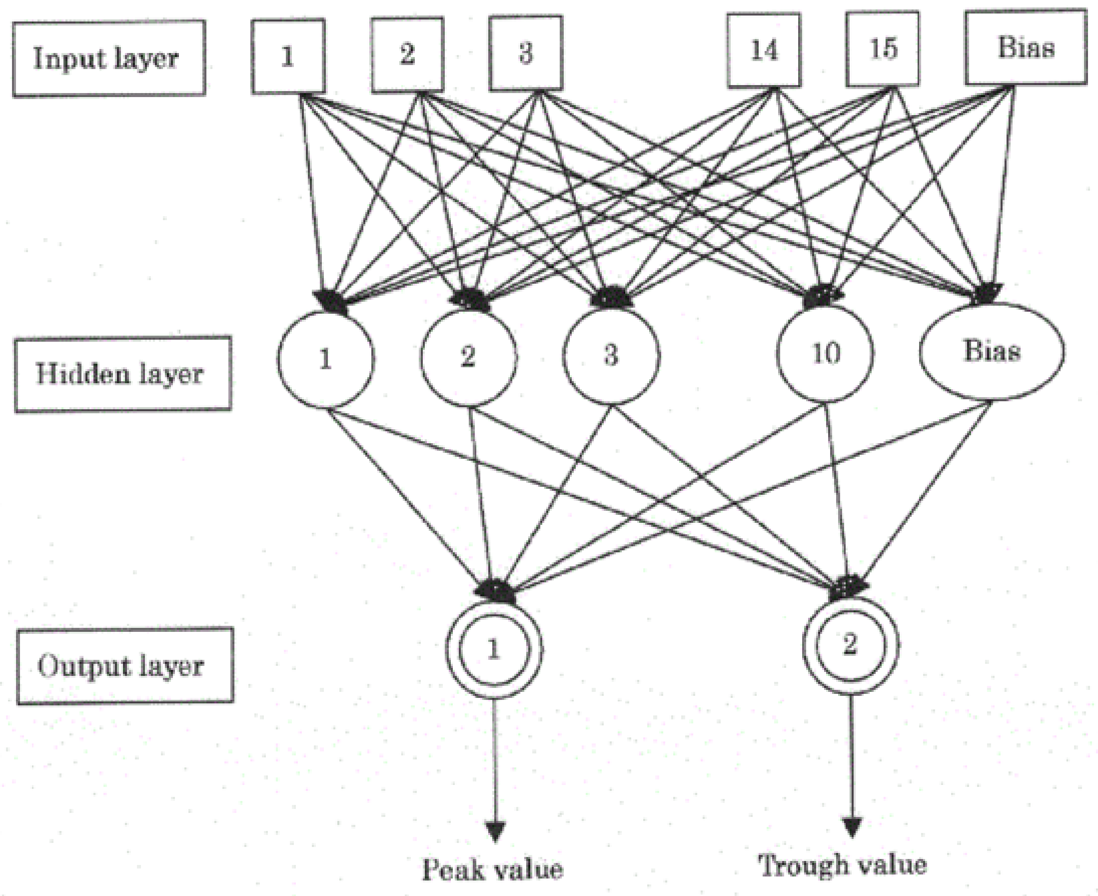

Fig 3 Structure of Three Layer Artificial Neural Network

The study and application of predictive models can, in this context, provide a valid contribution by virtue of the limited resources available to the managing bodies In particular, the techniques of artificial intelligence, already widely used with success in various fields of engineering including that road, can be appropriate for the purposes outlined above.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

This paper describes the first results of a search as having objective study of a neural network model for the prediction of the values of the coefficient of adhesion transverse of the floor of the Sigmoidal. The first phase of the research showed a good representation of the model and, previously, helped to identify the optimal architecture of the network. The 'experimental work is still in progress since the ultimate goal of the research consists in the definition of a network model that can simulate the decay temporal characteristics of grip on the section in question.

3. LITERATURE SURVEY

The artificial neural network (ANN) are suitable for this kind of problems. They have been researched and applied in real systems [1] [3]. Genetic algorithms were presented in several references [3] [5]. In the short period of their developments, AG showed their superior capabilities and have been successfully applied in many fields. An MLP network consists of an input layer of neurons source, one or more hidden layers and an Release layer. The number of neurons in layer input and output based on the number of input variables and desired number of classes respectively.

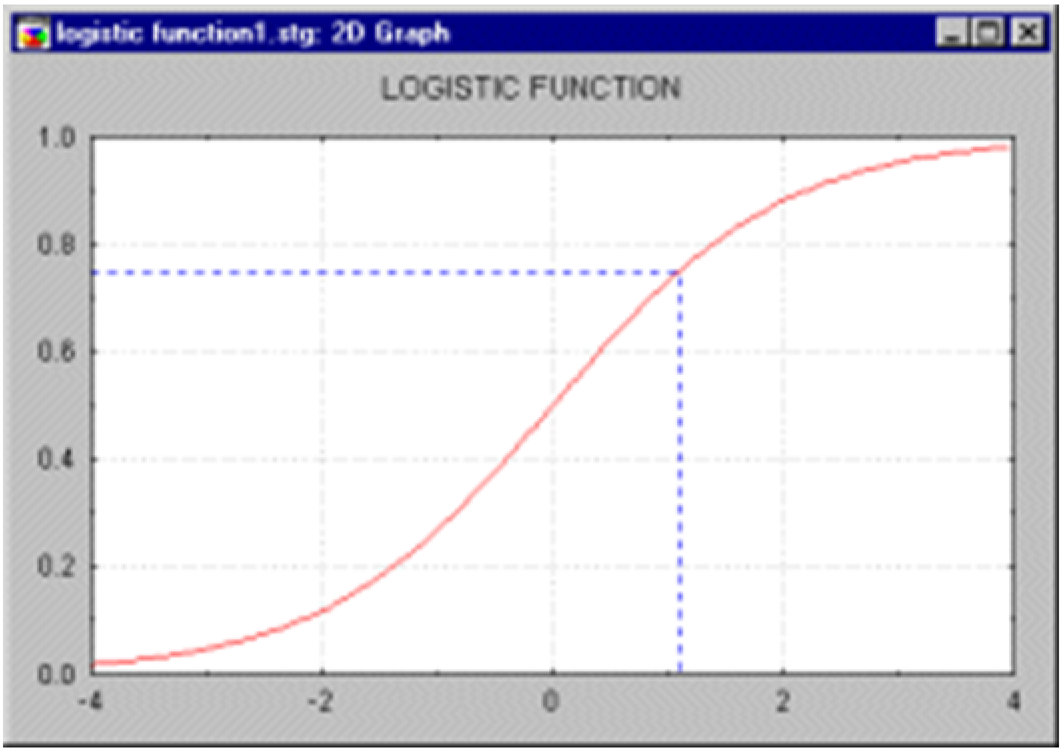

Fig 4 Neural Network Example

The number of hidden layers and the number of neurons in each layer hidden affect the generalizability of the network. In this paper, following the idea of using first-order time derivatives [21], a general RNN model with implicit dynamics is developed and analyzed for solving the problem of time-varying matrix inversion. Neural dynamics are elegantly introduced by defining the matrix-valued error-monitoring function rather than the usual scalar-valued cost function such that the computation error can be made decreasing to zero globally and asymptotically. As noted, nonlinearity and errors always exist. Even if a linear activation function is used, the nonlinear phenomenon may appear in its hardware implementation. For superior convergence and better robustness, different kinds of activation functions (linear, sigmoid, power functions, and/or their variants, e.g., power-sigmoid function) are investigated. Theoretical and simulation results both demonstrate the efficacy of the proposed neural approach. To the best of our knowledge, there is little work dealing with such a problem in the literature at present stage, except some preliminary results presented in [21].

4. Proposed method

Instead of the standard sigmoid function, ABFNN uses a variable sigmoid function defined as:

$$O_f = \frac{a + tanh(x)}{1 + a} \tag{5}$$

This rule can be explained in these terms: increases the weight that connects two neurons in such a way proportional to the product of output supplied by them for a given input. It is not a rule universally valid and is applicable only to particular types of neural networks, such as the one we are talking about in this chapter. There are different types of learning rules intended purposes specific, such as the delta rule (from which comes backpropagation of 'error which will be discussed depth), or the rule of Neural Network: I want to emphasize that the learning rule is the critical point of each neural network to Beyond the architecture on which it is applied.

$$\hat{\sigma}^2 = \frac{n}{n-d} \cdot \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{6}$$

$$= \frac{n}{n - \frac{n}{k}} \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{7}$$

$$= \frac{k}{k-1} \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{8}$$

In the previous chapter we have analyzed the operation of a neural network structured as associative memory. Recall that an associative memory realized with neural technique must submit properties. Soon we will deal with neural networks that are not used as associative memories but are able to perform more complex functions, such as the recognition of all forms and the extrapolation of correlations between data sets seemingly random. In making this passage from the memoirs associative networks omit the multilayer perceptron, a type two-layer neural network that has certainly a historical importance as the parent of the current backpropagation networks and that it is worth mention. The type of neural networks that we discuss is unidirectional in the sense that signals propagate only from input to output without feedback loops that are present associative memory in the BAM view in chapter previous (remember that the network reached stability as minimum energy when the oscillations due to feedback then we understand that the input layer is a layer decision because it has no changeable weights in the learning phase on its inputs. Each neuron has a specific transfer function as we had already mentioned in speaking of associative memories such neurons have a transfer function of the step. In error_back_propagation a network where we want to be possibility of working with real values

$$y = sigmoid(\sum_{i=0}^{f} w_i x_i) = \frac{1}{1+e^{-\sum_{i=0}^{f} w_i x_i}} \tag{9}$$

$$y^t = sigmoid(\sum_{i=1}^{f} w_i x_i^t + w_0) \tag{10}$$

$$H_h^t = sigmoid(\sum_{i=0}^{f} w_{hi} x_i^t + w_{h0}) \tag{11}$$

$$y^t = sigmoid(\sum_{h=0}^{m} T_h H_h^t + H_0) \tag{12}$$

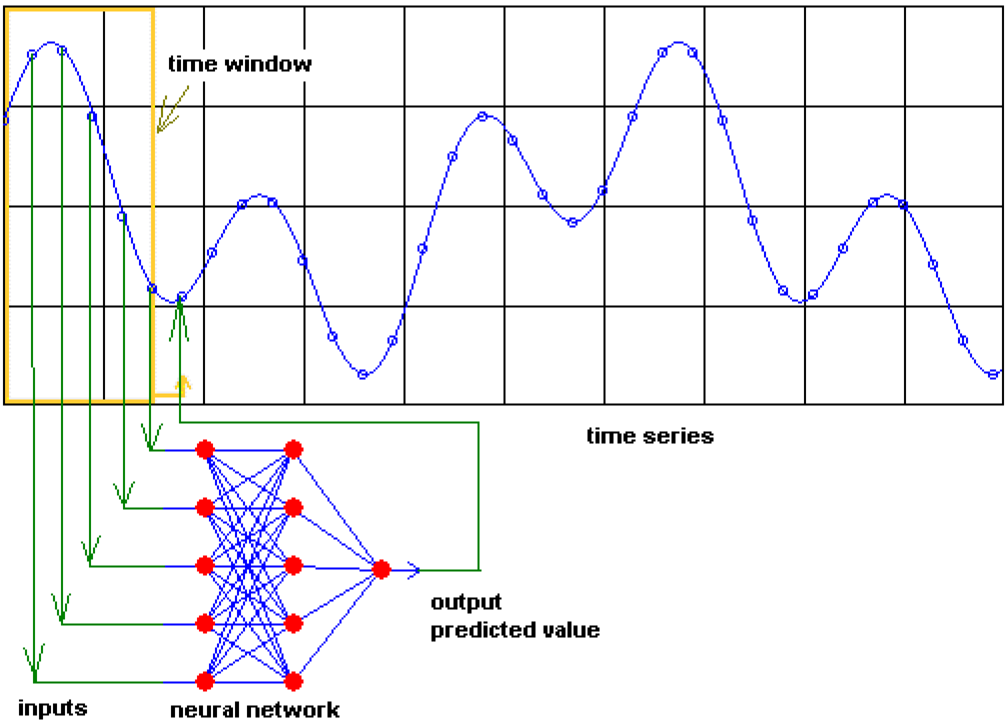

Fig 5 various types of neural networks can be used for prediction

Training a neural network model essentially means selecting one model from the set of allowed models (or, In the sigmoid is centered on zero, but in many applications it is quite appropriate that the center of the sigmoid of each neuron is "custom" from the same neuron to ensure greater flexibility of calculation. This can be achieved by editing the last formula in the following way:

$$f(x_1,...,x_n) = \frac{\sum_{k=1}^{m} b^k [\prod_{i=1}^{n} \mu_{A_i^k}(x_i)]}{\sum_{k=1}^{m} [\prod_{i=1}^{n} \mu_{A_i^k}(x_i)]} \tag{13}$$

$$E^p = \frac{1}{2}[f(x_1^p,...,x_n^p) - y^p]^2 \tag{14}$$

$$b^k(t+1) = b^k(t) - \theta \left.\frac{\partial E^P}{\partial b^k}\right|_t \tag{15}$$

$$\sigma^k(t+1) = \sigma^k(t) - \theta \left.\frac{\partial E^P}{\partial \sigma^k}\right|_t \tag{16}$$

$$a^k(t+1) = a^k(t) - \theta \left.\frac{\partial E^P}{\partial a^k}\right|_t \tag{17}$$

$$\eta^k(t+1) = \eta^k(t) - \theta \left.\frac{\partial E^P}{\partial \eta^k}\right|_t \tag{18}$$

Where S (k) is the point in which is centered the sigmoid of neuron. So that this threshold is personalized is necessary that it be learned (i.e is changed during the learning phase) exactly as the weights of the connections between the neurons of the different layers. With a little trick we can consider this as an additional input threshold constant at a value of 1 which is connected to neuron k with a weight of "learn" our network is transformed therefore into that of calculate:

The follow formula represents the activation of the neural network:

$$f(x) = \sigma(W_o \square \sigma(W_H \times X^T)) \tag{19}$$

5. Experimental Result

Experiments have shown effectiveness proposed in completely automatic method in formation documents and categorization that is based in the applied clustering algorithm for full texts. Software implementation of the method designed for digital libraries as an element of their search engines. Such an element capable of be as independent search mechanism and serve as a means to improve the quality of other search engines, for example, search by keyword.

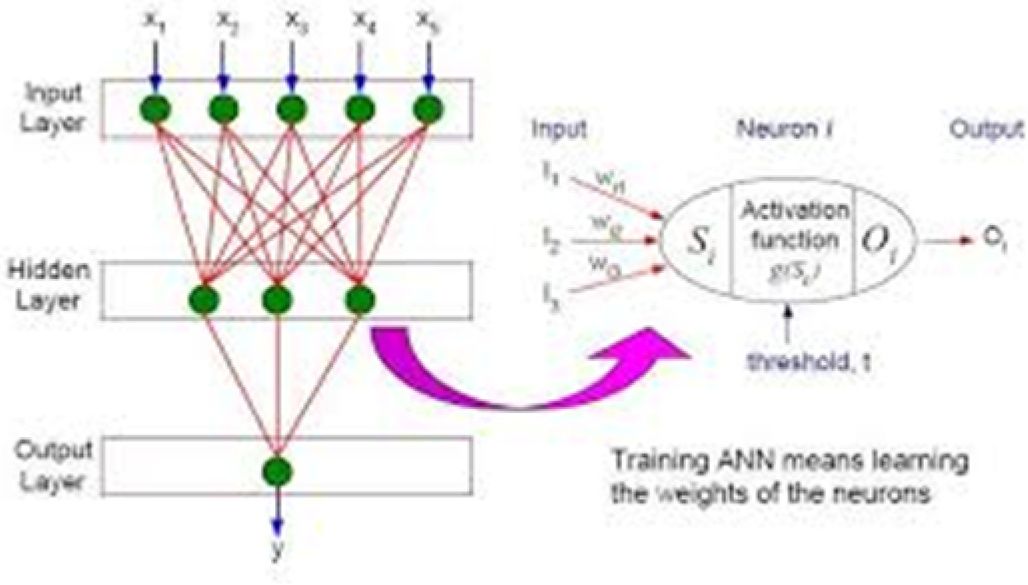

Fig 6 Sigmoidal Activating process

In this method, the obtained experimental results are evaluated through evaluation metrics namely, sensitivity, specificity and accuracy. In order to find these metrics, we first compute some of the terms like, True positive, True negative, False negative and False positive based.

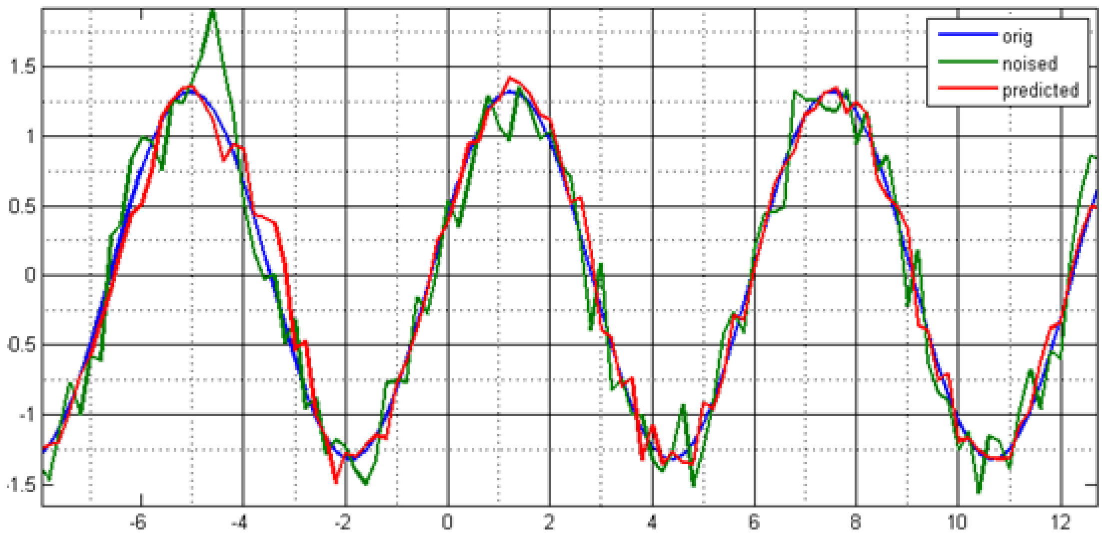

Fig 7 A screenshot of the forecasting results using MATLAB.

It also proposed method In turn, the sigmoidal function is one category of functions used as the activation function in FF neural networks solved using back prop.

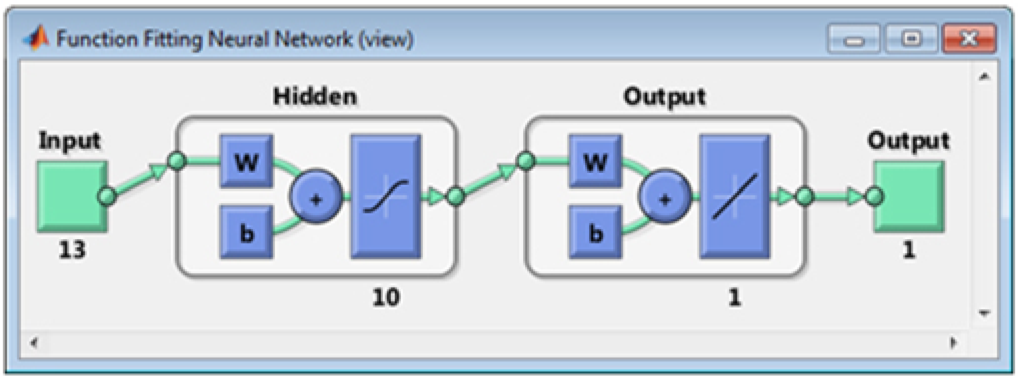

Fig 8 sigmoidal function fitting neural network

During training or prediction, the weighted sum of the inputs (for a given layer, one layer at a time) is passed in as an argument to the activation function which returns the output for that layer. Another group of functions apparently used as the activation function is piecewise linear function.

6. DISCUSSION AND CONCLUSION

This paper has presented the design and implementation of a neuron that will be used in any neural network, the activation function that designed inside the neuron is a sigmoid function. Of course, the extrapolation is more difficult and imprecise that interpolation, however, and both give better results the more complete the set of uniformly distributed examples. We could teach a neural network of this type in Do the sums between two input values by providing in phase learning a series of sums "pre-packaged" with the result adjusted within the range as widely as possible: the network will be able to do Also sums of values different from those examples train a neural network to do a sum is obviously useless if not for study or experimental as it is useful to study phenomena of which is not known the mathematical correlation between input and output (or is extremely complex).

The current methodology is based on Sigmoid neural network has been proposed, in which the continuous input space is localized into some regions by using RBF (Gaussian) units where the location on the input space is represented by only one parameter. It can be said that this network has both advantages of RBF-based network and sigmoid-based multi-layer neural network

7. References

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