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Full Length Research Paper

Application of ultrasonic waves coupled with functional link neural network for estimation of carrageenan concentration

Duduku Krishnaiah*, D.M. Reddy Prasad, Awang Bono, P.M. Pandiyan and Rosalam Sarbatly

School of Engineering and Information Technology, University Malaysia Sabah, 88999, Kota Kinabalu, Sabah, Malaysia.

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In this paper, a simple functional link neural network (FLNN) model is developed for the quantification of polysaccharides using ultrasonic waves. Every material has its own intensity to absorb the sound waves. The sound absorption capability of Carrageenan is based on its concentration in the solution. The sound pressure leave obtained from the one third octave band frequency spectrum is given as input to the FLNN and the carrageenan concentration is estimated as output. Two simple modifications in the architectures of FLNN are newly proposed and its performances are compared with the conventional FLNN method. In the first architecture, a hidden layer is newly introduced in a FLNN and trained by Error Back Propagation (EBP) procedure. In the second architecture, the Functional Link concept is extended to the neuron in the hidden layer and the network is trained by EBP procedure. The proposed procedure has minimized the training time as well as the number of failures.

Key words: Ultra Sonic Waves, Carrageenan Concentration, Frequency Spectrum, Functional Link Neural Networks.

INTRODUCTION

Carrageenans are water-soluble natural polymers, which occur in certain species of seaweeds. They are sulfated natural biopolymers made up of galactose units. It consists of a main chain of D-galactose residues linked alternately α - (1 → 3) and β - (1 → 4). The differences between the fractions are the number and the position of the sulfate groups. This is due to the possible presence of a 3.6 anhydro-bridge on the galactose linked through the 1 - and 4 –positions (Janaswamy and Chandra-sekaran 2001). The quantification of carrageenan (Mat-thew and Bernard, 1999) can be done from various methods such as colorimetric, spectroscopy and chroma-tography. The colorimetric analysis (Soedjak, 1994) and chromatographic methods (Quemener and Marot, **1999**; Chopin and Whalen, 1993; Turquois, 1996) require the sample preparation and depolymerization. The aim of this work is that ultrasonic waves are generated at one third octave frequency and a simple FLNN (Ganapati and Taposhi, 1992) is proposed for estimation of carrageenan concentration. Further, two simple modifications in the architectures of FLNN are also proposed.

Analysis of materials using sonic waves

Sonic waves propagate through most materials, allowing analysis of a wide variety of samples including optically nontransparent materials (Breda, 2003). They probe the elastic (rather than electric and magnetic) characteristics of materials, which are extremely sensitive to intermo-lecular interactions. Compression in the sonic wave changes the distances between the molecules of the sample, which responds by intermolecular repulsions (Lorimer and Mason, 1995).

Sound in water propagates much faster (five times) than in air because of the differences in the elasticity's of these mediums (Alrutz and Schroeder, 1983). The high sensitivity of the ultrasonic parameters to intermolecular

*Corresponding author. E-mail: krishna@ums.edu.my. Tel: +60-88-320000 x 3059. Fax: +60-88-320348.

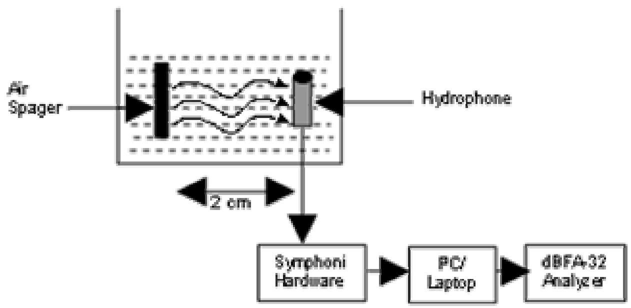

Figure 1. Experimental setup.

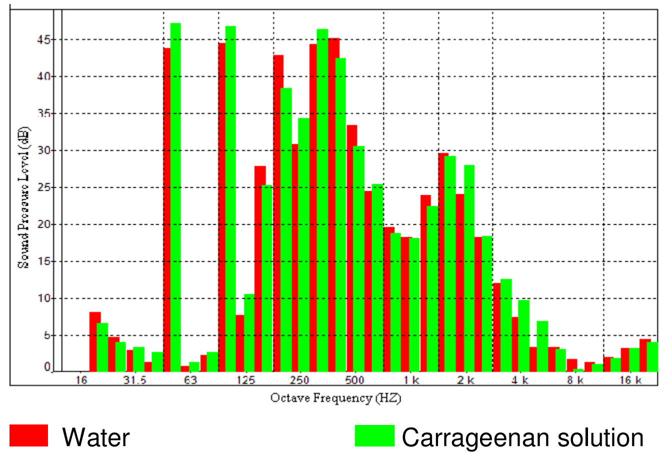

Figure 2. Typical one third octave frequency spectrum at 4 cm for different concentration levels.

interactions permits the ultrasonic analysis of a broad range of molecular processes (Milia, 1993; Vitaly, 2001). It is relatively easy to generate and change the wave-length of high-frequency ultrasonic wave's absorb on subdivision surfaces. This allows the construction of robust and multipurpose instruments that perform a multi-tude of analytical functions for fast, nondestructive analy-sis (Vitaly et al., 2001 - 2002).

The online estimation of carrageenan by using underwater acoustic techniques and artificial intelligence can be immensely useful in the quality control of food and processes industries (Malika et al., 2003).

MATERIALS AND METHODS

Carrageenan extracted from the *Euchema spinosum* (Sabah seaweed) Seaweed by the "Borneo Marine Research Institute, University of Malaysia Sabah" is used in this experiment. The Hydrophone with the following operating specifications is used to measure the frequency spectrum of sound level in the carrageenan solution. Specifications; Operating depth: 700 m, Survival depth: 1000 m, Receiving Sensitivity: -211 dB ± 3 dB, Transmitting sen-sitivity: 132 dB ± 3 dB.

The Experimental setup for the estimation of carrageenan using the air spager as an underwater sound generator and a wide band hydrophone transducer is the receiving sensor of the sound signals as shown in Figure 1. The source and the receiver can be moved on a straight line at constant depth for scanning the bottom profile.
A personal computer receives the sound signal from the hydrophone, and the signals are discretized. These signals are then analyzed using the decibel frequency analyzer (dBFA) software and the frequency spectrum of the signal is obtained. The above experiment is repeated for various distances between the air spager and the hydrophone and for various carrageenan concentration levels. The one third octave band frequency spec-trum at 4 cm for different concentration levels of carrageenan is shown in Figure 2. The sound pressure level at various octave frequencies (range 20 Hz to 20000 Hz) and the distance between the air spager and the hydrophone are then associated to the mass of the carrageenan.

Network architecture

Conventional FLNN method: Warren has proposed a Conven-tional FLNN model (Sarle, 1994) which consists of a single input layer, an enhanced functional link input layer and one output layer. The neurons in the input layer receive signals x_1, x_2 … x_n and the enhanced functional link layer neurons receives the input signal namely x_1^2, x_2^2 … x_n^2. Figure 3 depicts a conventional FLNN model. The output neurons are activated by bipolar sigmoidal activation function (Myungsook Klassen et al., 1990, 1991) as given in Equation (1).

$$f(x) = [2(1+\exp(-x/q)^{-1} - 1)] \quad (1)$$

Network training

A two layer FLNN with 32 input neurons and 64 functional link neurons in the input layer and 1 neuron in the output layer is considered. The 31 sound pressure levels corresponding to various octave band frequencies obtained from frequency analyzer, the functional composition of the 32 input neurons along with the distance between the air spager and the hydrophone are used as the input feature to the FLNN and associated to the concentration of carrageenan in the solution. The activation function used for the hidden and output neuron is a bipolar sigmoidal activation function as shown in Equation (1). The initial input features were normalized by using Equation (2).

$$x_n = \frac{1.8\left(x - x_{\min}\right)}{(x_{\max} - x_{\min})} - 0.1 \quad (2)$$

FLNN with hidden layer (method –I)

Without loss of generality and simplicity a FLNN (Yoh – Han Pao et al., 1992) having 'm' number of neurons in the hidden layer and one neuron in the output layer is considered. The network has (2n – 1) number of neurons in the input layer. The first 'n' neurons in the input layer receive input signals x_1, x_2 … x_n and the remaining (n – 1) neurons receive the functional composition of the input signal namely x_1x_2, x_2x_3 … $x_{n-1}x_n$. Figure 4 depicts the proposed method - I. The hidden and output neurons are activated by bipolar sigmoidal activation function (Klassen et al., 1990, 1991) as given in Equation 1.The Functional Link units for the input layer is the network is trained using EBP procedure. The training takes places in three stages namely the feed forward of the input training pattern, backpropagation of the associated error and weight generated and

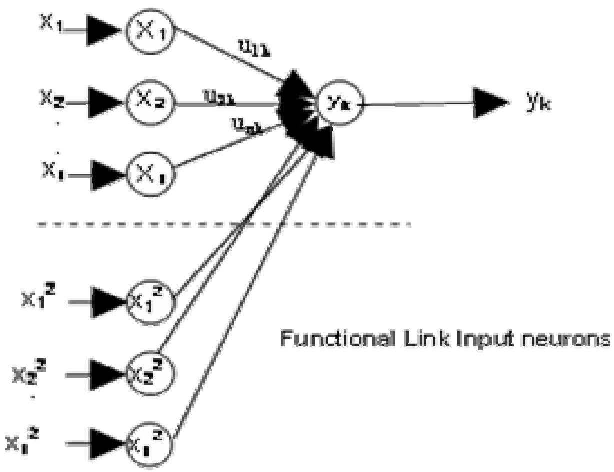

Figure 3. Basic functional link neural network.

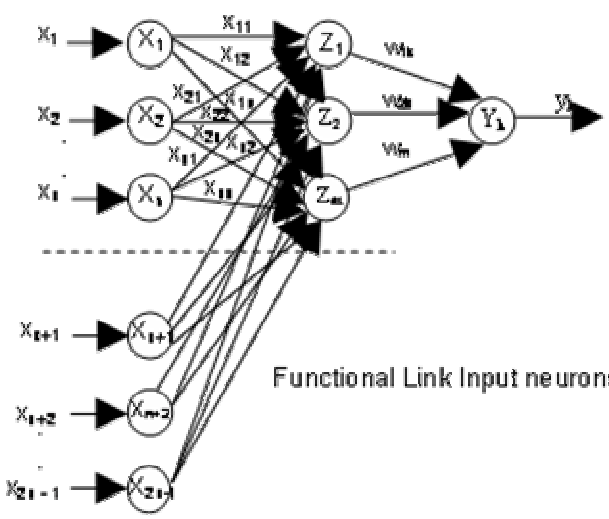

Figure 4. Proposed FLNN with hidden layer (method – I). Where x_{min} – minimum concentration value; x_{max} – maximum concentration value; x – actual value; x_n – total number of input samples.

if there are 'n' numbers of input neurons then (2n-1) neurons are in the functional link layer (Figure 4) adjustment. During feed forward, each input neuron receives an input signal and broadcasts it to each hidden neuron, which in turn computes the activation and passes it on to each out put unit. This again computes the activation to obtain the net output. During training, the net output is compared with the target value and the appropriate error is calculated. From the error, the error gradient at the hidden and the output neurons are calculated and the new weights are determined.

Network training

In this method has a simple three layer FLNN with 32 input neurons and 63 functional link neurons in the input layer, 20 neurons in the hidden layer and 1 neuron in the output layer is considered. The 31 sound pressure levels corresponding to various octave band frequencies obtained from frequency analyzer. The functional composition of the 32 input neurons (63 additional input features derived from the 32 original input features) along with the distance between the air spager and the hydrophone are used as the input feature to the FLNN and associated to the concentration of carrageenan in the solution. The following training algorithm is used to train the Proposed FLNN Method – I. The nomenclature is given in the Appendix.

Algorithm

Step 1: The weights are initialized randomly between - 0.5 and 0.5 and normalized.
Step 2: While the sum squared error is greater than the tolerance level, do steps 3 to 9.
Step 3: For each training pair (x: t), do steps 4 to 8.
Step 4: Generate the functional link input neurons of (n+1) to (2n – 1) units.

$$x_{n+i} = x_i\, x_{i+1} \qquad i = 1, 2, 3, \ldots, n-1$$

Step 5: Compute the output signal for the hidden units Z_j, j = 1, 2, 3,….. , m

$$z_{in\_j} = \sum_{i=1}^{2n-1} u_{ij} x_i$$

$$z_j = f\,(z_{in\_j})$$

Step 6: Compute the output signal for the output units Y_k, k = 1, 2, 3, ….., p

$$y_{in\_k} = \sum_{j=1}^{m} w_{jk} z_j$$

$$y_k = f\,(y_{in\_k})$$

Step 7: Compute δ_k, k = 1,2, ….., p

$$\delta_k = (t_k - y_k)\, f'(y_{in\_k}).$$

For (k = 1,2, …, p) and for (j = 0,1,2, …. , m),

Compute the change in weight Δw_{jk} and the new weight w_{jk} (new)

$$\Delta w_{jk} = \alpha\, \delta_k z_j + \eta\, \Delta w_{jk}(old)$$

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$$

Step 8: Compute δ_j (for j = 1, 2, 3,…,m.)

$$\delta_j = \left(\sum_{k=1}^{p} \delta_k w_{jk}\right) f\,(z_{in\_j})$$

For (j = 1,2,3,…,m.) and for (i =1,2,…,2n-1.)

Compute change in weight Δu_{ij}, and the new weight u_{ij}(new)

$$\Delta u_{ij} = \alpha \delta_j x_i + \eta\, \Delta u_{ij}(old)$$

$$u_{ij}(new) = u_{ij}(old) + \Delta u_{ij}$$

Step 9: Test for stopping condition

FLNN with extended functional link at the hidden layer (method – II)

Figure 5 depicts the proposed FLNN method - II. It consists of a three layer network with input, hidden and output layers. The hidden and output neurons are activated by bipolar sigmoidal activation function (Haykin, 1999; Chen et al., 1998) as given in Equation (1). The Functional Link units for the input and hidden layer are generated and if there are 'n' numbers of input neurons then (2n-1) neurons are in the functional link input layer. If there are 'm' numbers of hidden neurons, then (2m-1) neurons are in the functional link hidden layer as shown in Figure 5.

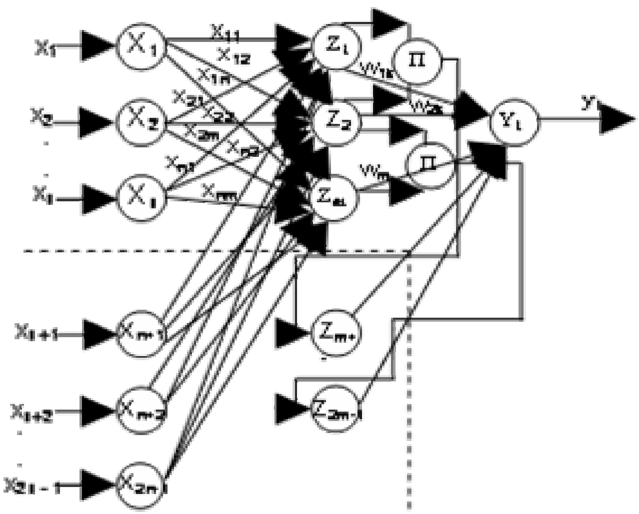

Figure 5. Proposed FLNN with extended Functional Link at the Hidden Layer (method – II).

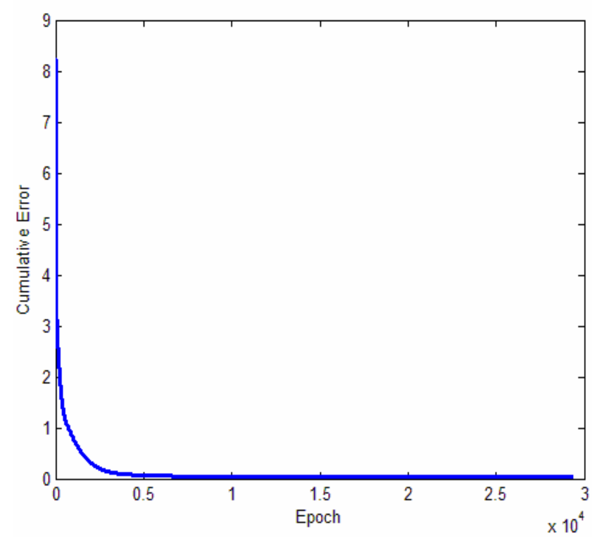

Figure 6. Cumulative Error versus Epoch.

Network training

The proposed FLNN method – II has three layer with 32 input neurons and 63 functional link neurons in the input layer, 20 hidden neurons and 39 functional link neurons in the hidden layer and 1 neuron in the output layer. The 31 sound pressure levels corresponding to various octave band frequencies are obtained from frequency analyzer. The functional composition of the 32 input neurons (63 additional input features derived from the 32 original input features) along with the distance between the air spager and the hydrophone are used as the input feature to the FLNN and associated to the concentration of carrageenan in the solution. Further, the functional composition of the signals obtained from the hidden neurons and fed to the 39 functional link hidden neurons (39 additional features are derived from the output of the 20 hidden neurons). The following algorithm is used to train the FLNN method-II.

Step 1: The weights are initialized randomly between - 0.5 and 0.5 and normalized.

Step 2: While the sum squared error is greater than the tolerance level, do steps 3 to 9.

Step 3: For each training pair (x: t), do steps 4 to 8.

Step 4: Generate the functional link input neurons of (n+1) to (2n – 1) units.

$$x_{n+i} = x_i x_{i+1} \qquad i = 1,2,3,\ldots,n-1$$

Step 5: Compute the output signal for the hidden units Z_j, j = 1, 2, 3,....., m.

$$z_{in\_j} = \sum_{i=1}^{2n-1} u_{ij} x_i$$

$z_j = f(z_{in\_j})$

Step 6: Generate the functional link input neurons of (m+1) to (2m – 1) units.

$$z_{m+j} = z_j z_{j+1} \qquad j = 1, 2, \ldots, m-1$$

Step 7: Compute the output signal for the output units Y_k, k = 1, 2, 3,..., p.

$$y_{in\_k} = \sum_{j=1}^{2m-1} w_{jk} z_j$$

$y_k = f(y_{in\_k})$

Step 7: Compute δ_k, k = 1,2, … , p.

$$\delta_k = (t_k - y_k) f'(y_{in\_k}).$$

For (k = 1,2, …,p) and for (j = 1,2, … , 2m-1),

Compute the change in weight Δw_{jk} and the new weight w_{jk} (new)

$$\Delta w_{jk} = \alpha \delta_k z_j + \eta \Delta w_{jk}(old)$$
$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$$

Step 8: Compute δ_j (for j = 1,2,3,…,2m-1.)

$$\delta_j = \left(\sum_{k=1}^{p} \delta_k w_{jk}\right) f'(z_{in\_j})$$

For (j = 1,2,3,…,2m-1.) and for (i =1,2,3,…,2n-1.)

Compute change in weight Δu_{ij}, and the new weight u_{ij} (new)

$$\Delta u_{ij} = \alpha \delta_j x_i + \eta \Delta u_{ij}(old)$$
$$u_{ij}(new) = u_{ij}(old) + \Delta u_{ij}$$

Step 9: Test for stopping condition

RESULTS AND DISCUSSION

All the three FLNN methods are trained with 90 samples. All the three FLNN methods are trained with 90 samples and tested with 110 samples. The learning rate and momentum factor is chosen as 0.01 and 0.45 respectively. The network is trained with training tolerance of 0.05 and testing tolerance of 0.05. The resulting cumulative error

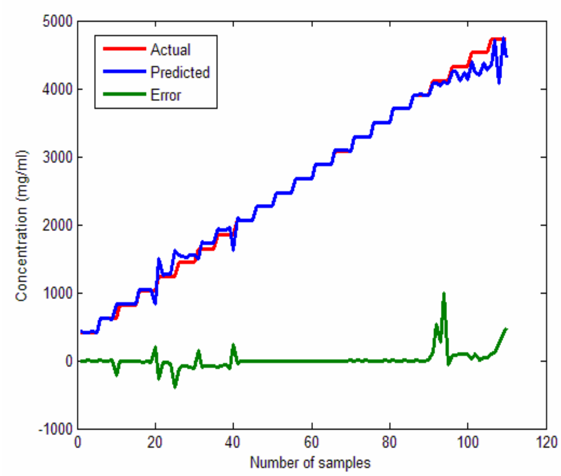

Figure 7. Actual and predicted concentration for samples.

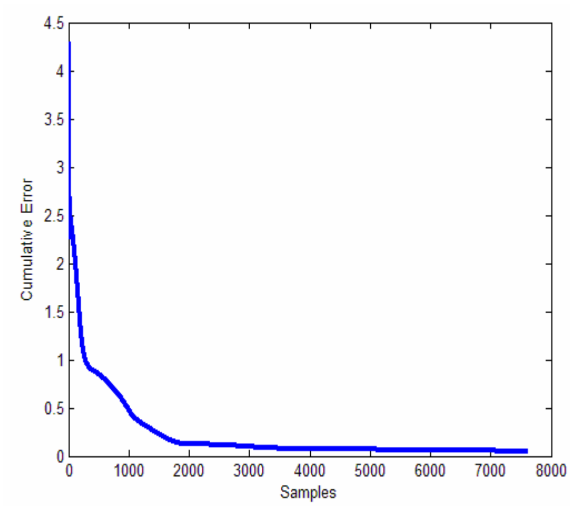

Figure 8. Cumulative Error versus Epoch – Proposed method – I.

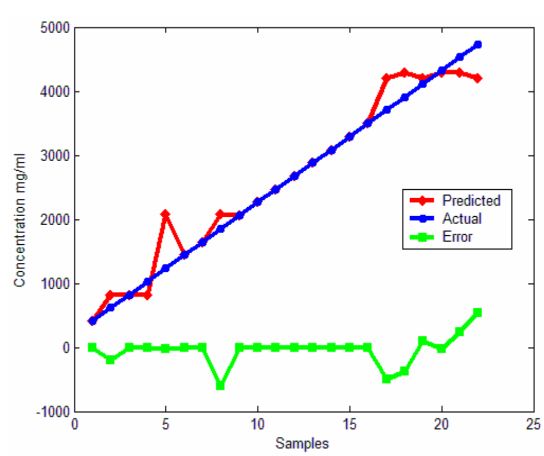

Figure 9. Actual and predicted concentration for samples – Proposed method – I.

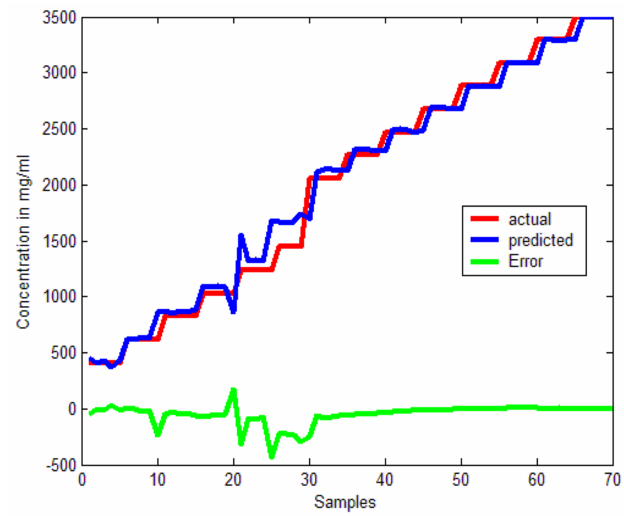

Figure 10. Cumulative Error versus Epoch – Proposed method – II.

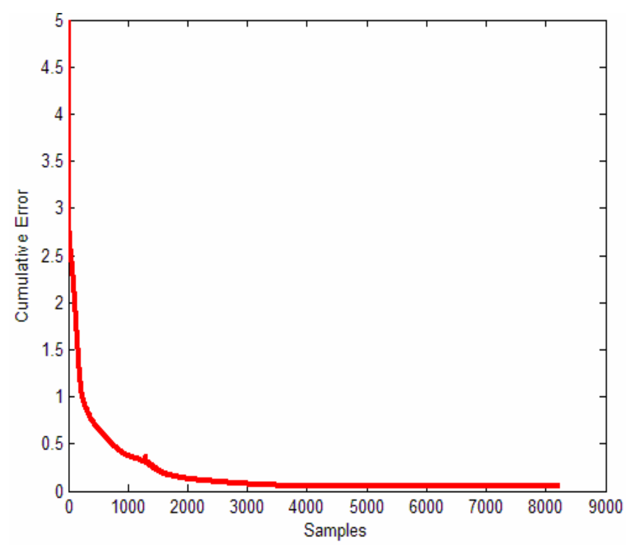

Figure 11: Actual and predicted concentration for samples – Proposed method – II.

versus epoch graph is shown in Figures 6, 8, 10 respectively. The actual value of the carrageenan concentration is compared with the predicted value and shown in Figures 7, 9, 11 respectively. The percentage of success rate obtained from the three methods is 85.6, 91.09 and 92.91% respectively. The network training parameters and the training time are shown in Table 1. From the Table 1, it is observed that the computational time for proposed methods is less when compared to the conventional FLNN method. Similarly the success rates for proposed methods are better than the conventional FLNN method. The overall results illustrates that the proposed FLNN-II method is an appropriate method to quantify the

Table 1. Network training phases.

Parameters	Functional Link Neural Network		
	Conventional	Method I	Method II
Number of input neurons	32	32	32
Number of FLNN input neurons	64	63	63
Number of hidden neurons	-	20	20
Number of FLNN hidden neurons	-	-	39
Number of output neurons	1	1	1
Training tolerance	0.05	0.05	0.05
Momentum factor	0.45	0.45	0.45
Learning rate	0.01	0.01	0.01
Number of training samples	90	90	90
Normalized mean square error	0.0345	0.0125	0.0025
Computational time	1200sec	73 sec	62 sec
Number of testing samples	110	110	110
Testing tolerance	0.05	0.05	0.05
Number of epochs	84056	12959	7892
Success rate	85.6%	91.09%	92.91%

carrageen in the process.

Conclusions

In this paper, simple procedures are presented to determine the carrageenan concentration based on ultrasonic technique. Further, simple neural network models trained using FLNN procedure is newly proposed to obtain the carrageenan concentration from the one third octave frequency spectrum. In the process, the carrageenan polymer exposes least duration to the ultrasonic waves. Hence, the depolymerization is negligible. The proposed method can be extended to determine the concentration level of the carrageenan in real time processing. This approach offers unprecedented tool in developing new carrageenan gel-based products.

NOMENCLATURE

n: Number of input neurons.
m: Number of hidden neurons.
p: Number of output neurons.
x: Input training vector: $x = (x_1,x_2,x_3,...,x_n)$
Z_j: Hidden unit j.
Y_k: Output neuron k.
t: Output target vector: $t = (t_1,t_2,t_3,...,t_p)$
u_{ij}: Connection weights from the i^{th} input neuron to the j^{th} hidden neuron.
w_{jk}: Connection weight from the j^{th} hidden neuron to the k^{th} output neuron.
u_{ik}: Connection weights from the i^{th} input neuron to the k^{th} output neuron.
w_{ik}: Connection weight from the i^{th} enhanced FLNN input neuron to the k^{th} output neuron.
z_{inj} : Net input to the j^{th} hidden neuron.
z_j : Output of j^{th} hidden neuron.
y_{ink} : Net input to the k^{th} output neuron.
y_k : Output of k^{th} output neuron.
δ_j: Portion of error correction factor for $u_{ij.}$
δ_k: Portion of error correction factor for $w_{jk.}$
α: Learning rate.
η: Momentum factor

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