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Predicting Usability of Library Websites: Artificial Neural Network and Fuzzy Inference System Approach

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Abstract: Authors report soft computing approach for predicting usability of library websites using Artificial Neural Network (ANN) and Fuzzy Inference System (FIS). Proposed model is the fusion of these two computing paradigms to create a successful synergic effect. The website usability dataset is derived from doctoral thesis on Usability Evaluation of Library Websites [1]. Usability index (UI) determinants such as visibility, SR_world, user control, consistency, error, recognition, flexibility, aesthetic, recovery, documentation, effectiveness, efficiency, memorability, learnability, satisfaction and motivation are considered here for computing. The reported investigations depicts optimum ANN architecture achieved by tuning the parameters viz. network type, training function, transfer function and number of neurons in hidden neurons. ANN architecture, thus derived entails hidden layer with nonlinear sigmoid activation function and Levenberg-Marquardt back propagation method for training the model. Moreover the performance of the model is evaluated with reference to Pearson Correlation Coefficient (r), Mean Squared Error (MSE), and Gradient (g). Validation of the model has portrayed reasonably good prediction accuracy.

Keywords: usability index, artificial neural network, fuzzy logic, UI determinants, website usability

I. INTRODUCTION

An arithmetical or statistical technique does not inevitably offer the most ideal approach to assess website execution since the parameters which determine UI are actually fuzzy concepts. The most suitable methods for taking care of such uncertain information is to utilize fuzzy reasoning which replicates the method of human-thinking [5]. Literatures in soft computing reveals that soft computing is more powerful in providing practicable solutions to the problems that deal with uncertainties. Fuzzy reasoning handles uncertainty in a natural way by facilitating a human oriented knowledge representation and ANN is capable to capture the non-linear relationship than statistical methods which makes the network to provide higher forecast accuracy.

Amanatiadis et al have approximated the associations between user satisfaction and its determinants using ANN with the perceptions of a broad review on user fulfillment as for site characteristics [2]. Nagpal et al have identified the important parameters that affect the usability of an educational websites and then designed a model for ease of use evaluation utilizing the Adaptive Neuro Fuzzy reasoning [3]. Rekik et al have presented a quality evaluation procedure and model that measure the performance of sites [4]. Their model demonstrates an extensive and normal way of reasoning in light of different criteria basic decision making process. Yet another paper by Mirdehghani et al presents an automatic system for web pages aesthetic evaluation based on the image processing techniques and ANN [6]. Nikov et al have reported design of web site usability evaluation system using neuro-fuzzy approach [7].

Thus the literature review indicates a crystal-clear possibility to exploit soft computing approach for websites' usability index modeling. This has in fact served as motivation for us to develop the conception of computing and modeling of UI using FIS and ANN in the present investigations. Quantifying performance dimensions is a challenging task since the judgment may include approximated information and linguistic phrasing. The proposed model encompassed with fuzzy rating for converting numerical values of UI determinants into linguistic grades. FIS is employed here to compute Usability Index, the target column of dataset. Thus derived dataset is exploited to train ANN to get optimized network architecture.

II. FIS FOR USABILITY INDEX COMPUTATION

The website usability dataset is derived from doctoral thesis on Usability Evaluation of Library Websites [1]. Dataset consists of UI determinants such as visibility, SR_world, user control, consistency, error, recognition, flexibility, aesthetic, recovery, documentation, effectiveness, efficiency, memorability, learnability, satisfaction and motivation. Figure 1 depicts architecture of FIS employed in the present investigation to compute target column of this dataset. Scores of these input parameters are converted as fuzzy inputs by applying fuzzification. Fuzzifying of these parameters involved passing the binary value to each membership function (MF) attached [9]. A membership function is a curve that characterizes how each point in the info space is mapped to a membership value in the range of 0 and 1. Table 1 explains linguistic terms, their crisp value and corresponding Gaussian MF parameters for inputs. The parameters represent the standard deviation and center for the Gaussian curve.

Set of rules defined to relate input parameters to UI. These rules are depending on linguistic terms instead of mathematical expressions. We have formulated four such rules as shown in figure 2. The assurance of membership function and generation of fuzzy rules depends much on human experience. Fuzzy reasoning applied to compute UI, output parameter. Deffuzzification is employed to convert fuzzy output to crisp value which denotes usability index of website.

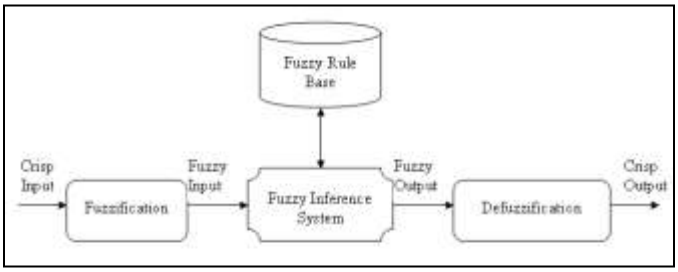

Figure 1. Fuzzy inference system architecture of UI

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If all inputs are 'low' then UI is 'low'
    Else If all inputs are 'average' then UI is 'average'
        Else If all inputs are 'good' then UI is 'good'
            Else UI is 'excellent'
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Figure 2. Pseudocode for Rulebase

Table 1. Linguistic terms and corresponding parameters

Linguistic term	Crisp Range	Gaussian MF Parameters
Excellent	[4-5]	[0.5864, 5]
Good	[3-4]	[0.5864, 3.668]
Average	[2-3]	[0.5864, 2.332]
Low	[1-2]	[0.5864, 1]

III. ANN Modeling: Computational Details

ANN is a computational model in light of the structure and elements of biological neural system. It is a framework of interconnected neurons, which trade data between each other. The connections have values denote numeric weights that can be tuned in the light of experience making networks capable of learning. A schematic diagram of ANN model designed in the present investigation is shown in figure 3. ANN framework consists of nonlinear sigmoid activation function and linear activation function for hidden layer and the output layer respectively. The ANN is trained by Levenberg-Marquardt feed-forward method. This framework consists of one hidden layer and one output layer with multiple neurons to perform intelligent computation. Equation (1) shows the input function 'η' and equation (2) presents the hidden layer's nonlinear sigmoid activation functions.

$$\eta = \sum_{i=1}^{n} W_i X_i + b \qquad (1)$$

$$S(\eta) = \frac{1}{1+e^{-\eta}} \qquad (2)$$

Where, Xi is input of ANN, Wi is a input weight, and b is a bias of ANN.

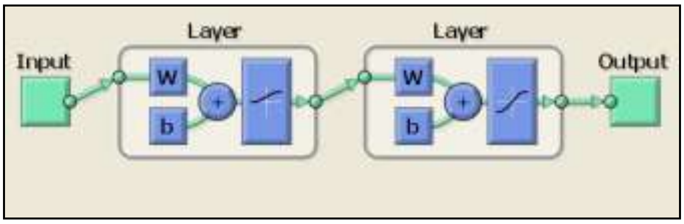

Figure 3. Schematic representation of ANN model [8]

The present investigation of website usability index modeling is recreated in MATLAB platform. The model is considered as a Multi-Input Single-Output (MISO) setup. The experiment is tuned with set of network properties such as the network type, training function, transfer function and number of neurons in hidden neurons [10]. Table 2 gives the details of network properties for present modelling. The cross-validation method is used for administrating network learning. This splits the data sets into three types namely training, validation and testing by adopting random sampling method.

Table 2: Network properties for UI Modeling

Network Properties	ANN Model for Protein Expression
Network Type	Feed Forward Back Propagation
Learning Function	Gradient descent with momentum weight and bias learning
Training Function	Levenberg Marquardt
Transfer Function	Log-sigmoid transfer
Performance Function	MSE, correlation coefficient and gradient
Data division	Random

IV. Results and Discussion

We explored ANN modeling with different network architectures. This section explains predicting UI for library website. MATLAB is used to analyze model structure, neuron number of concealed layer, and training function [8].

We have demonstrated ANN modeling with network types such as Cascade Forward Back Propagation and Feed Forward Back Propagation per variation in the number of neurons in the hidden layer and whereas maximum epochs 100 kept as

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constant to get the optimized ANN structure. We set maximum 100 epochs at the preceding end of the training procedure. Details of the experiment conducted for these two networks are summarized in table 3(a) and (b). The figure 4(a) and 4(b) represent MSE of the model for Feed Forward Back Propagation with hidden neurons equal to 10 and Cascade Forward Back Propagation with hidden neurons equal to 15 respectively. The results clearly indicate that the correlation coefficient for training, validation and testing data is higher only at the lesser number of neurons in hidden layer and correlation coefficients tends to decrease as the hidden neurons increases. The gradients are the individual error for each of the weights in the neural network. Minimum the value of gradient coefficient better will be training and testing of networks. The results also indicate that the MSE between target output and output produced by ANN decreases at lesser number of neurons in hidden layer and MSE is tending to raise with the increase in hidden neurons.

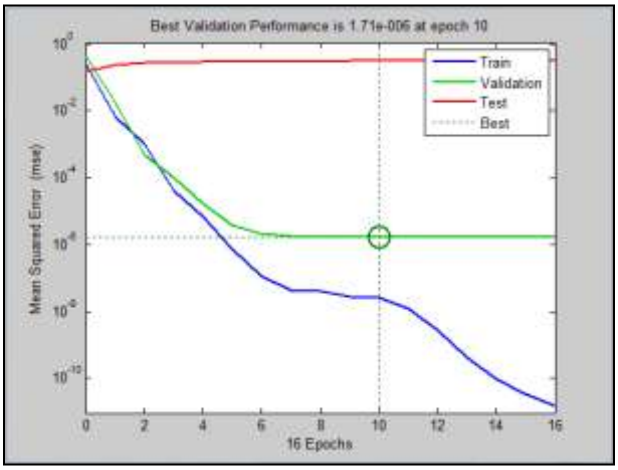

Figure 4(a). Mean square error of the model for Feed Forward Back Propagation with hidden neurons equal to 10

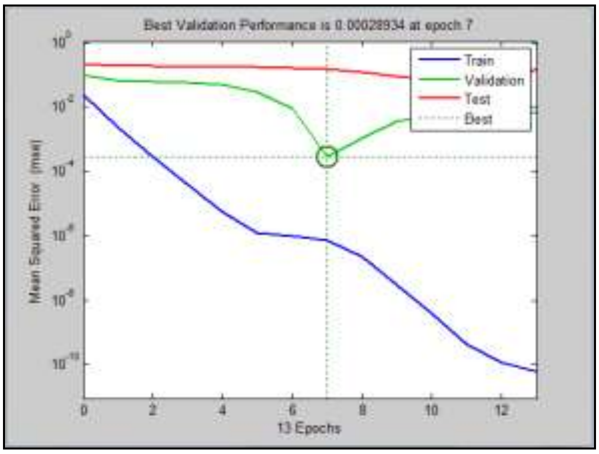

Figure 4(b). Mean square error of the model for Cascade Forward Back Propagation with hidden neurons equal to 15

Thus derived optimized ANN structure for the UI modelling has nonlinear sigmoid activation function for hidden layer, Levenberg-Marquardt back propagation method for training the model and 5 neurons in the hidden layer. Figure 5(a-c) depicts the performance of ANN modelling. Fig. 5(a) portrays the MSE between three splits of data, fig. 5(b) reveals gradient, mu, validation fail plot for the present model. In this case, MSE is found to be 7.0377e-010 at epoch 6 while the coefficient r is 1, Gradient is 1.2759e-007 and Mu is 1e-008. Fig. 5(b) shows variation in gradient coefficient with respect to a number of epochs. The final value of gradient coefficient at epoch number 6 is 1.2759e-007 which is approximately tending to zero. The gradient attains the minimal range at epoch 6 which also leads to linear training graph indicating that there is no further training.

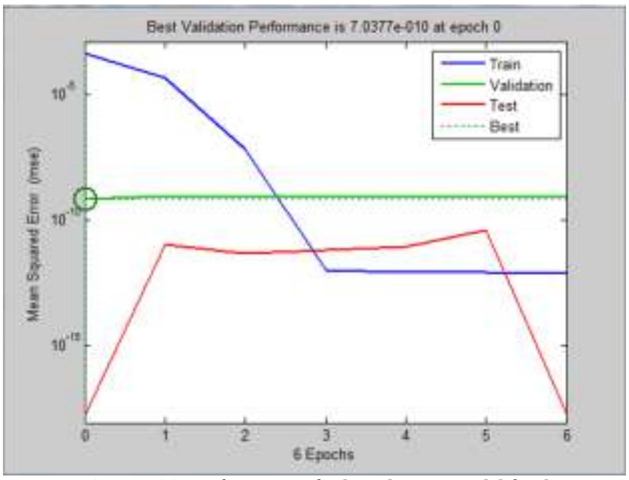

Figure 5(a). Performance of selected ANN Model for data

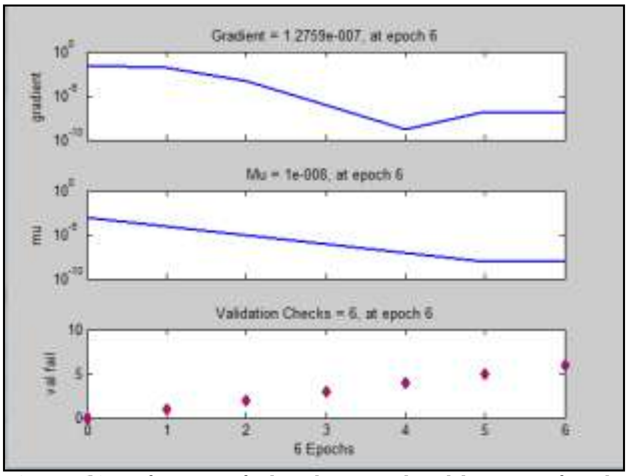

Figure 5(b). Performance of selected optimized model in terms of Gradient, Mu,Validation fail parameters

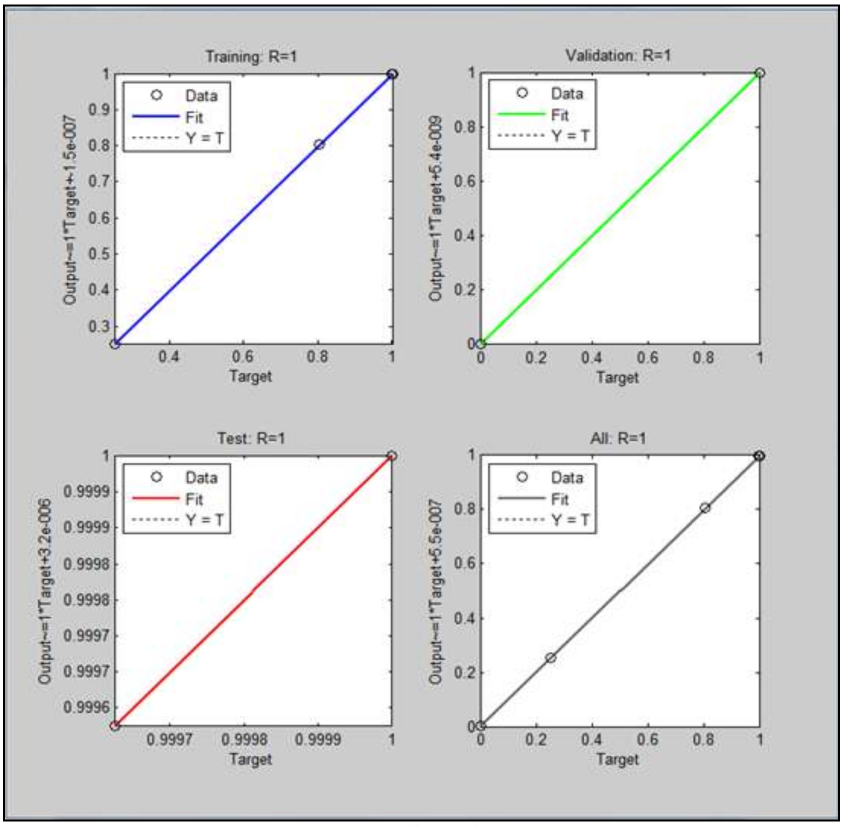

Figure 5(c). Correlation coefficient for selected ANN model

Table 3(a): Performance evaluation for accuracy of Feed Forward Back Propagation Configuration

No. of hidden neurons	Max. Epoch reached at	Mean Square Error	Gradient	Pearson Correlation Coefficient		
				Training	Validation	Testing
5	6	7.0377e-010	1.2759e-007	1	1	1
10	16	1.71e-006	2.2405e-006	1	0.71163	0.74934
15	11	0.00013185	0.00037021	1	1	0.970402
20	40	2.81e-008	9.3353e-011	1	0.24994	0.96552
30	Max	2.0076e-015	3.5399e-008	1	0	0.3267
40	6	0.0216	2.603e-006	0.97261	0.99984	0.25064

Table 3(b): Performance evaluation for accuracy of Cascade Forward Back Propagation Configuration

No. of hidden neurons	Max. Epoch reached at	Mean Square Error	Gradient	Pearson Correlation Coefficient		
				Training	Validation	Testing
5	15	9.8608e-033	2.488e-011	0.11724	0	0
10	40	1.2826e-012	1.3322e-011	1	1	0
15	13	0.00028934	3.7068e-006	1	1	0.22798
20	Max	1.2893e-008	1.6312e-009	1	0	1
30	6	0.19472	0.00042845	0.99992	0.24807	0.3114
40	Max	5.6593e-005	4.5716e-008	1	0.99987	0.24602

V. Conclusion

Soft computing approach for predicting usability index of library websites using FIS and ANN is presented in this paper. The reported investigation dealt with fuzzy rating for converting numerical values of UI determinants into linguistic grades. FIS is employed here to compute Usability Index, the target column of dataset. This dataset is exploited to train ANN to get optimized network architecture. ANN architecture, thus derived entails nonlinear sigmoid activation function for hidden layer and Levenberg-Marquardt back propagation method for training the model can be used for computing usability index of websites efficiently with very less error. Result concludes that ANN prediction is a suitable approach since the resulting analysis is much more accurate and precise. The lower number of hidden neurons signifies the less memory requirement for prediction of different composition.

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