Quality Evaluation of E-commerce Sites Based on Adaptive Neural Fuzzy Inference System

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Abstract. This paper describes a combined approach to the intelligent evaluation problem of E-commerce sites. The methodology of adaptive neural networks with fuzzy inference was used. A model of a neural network was proposed, in the frame of which expert fuzzy reasoning and rigorous mathematical methods were jointly used. The intelligent system with fuzzy inference was realized based on the model in Matlab software environment. It shows that the system is an effective tool for the quality analysis process modelling of the given type of sites. It also shows that the convenient and powerful tool is much better than the traditional artificial neural network for the simulation of sites evaluation.

Keywords: Neural network, quality evaluation, Adaptive Neural Fuzzy Inference System (ANFIS), fuzzy logic, E-commerce website.

1 Introduction

In the rapid development of global networks gained wide popularity with businesses of electronic commerce (also called "e-commerce" or "eCommerce"). This term covers a wide range of activities of modern enterprises. It includes the entire Internet - the process for the development, marketing, sale, delivery, maintenance, payment for goods and services.

The key to e-commerce companies are problems of understanding customer inquiries and the development of tools for the implementation of feedback. Companies is usually presented poorly online with sites, which are difficult for the reaction. This significantly weakens the position of the company as a whole. Consequently, it is very important that businesses have the opportunity to assess the quality of their business proposals and understand how customers perceive them in the context of the industry [1,2].

Therefore, it plays an important role that e-commerce companies assess their sites for successful operation. Ratings are a kind of feedback mechanism that allows refining the strategy and methods of control. Website is a software product that can be

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considered as a system with a sufficiently complex structure and function. Its importance as a basic element of e-commerce is impossible to assess from the perspective of only one criterion. Therefore, the problem of assessing sites refers to the classification of multi-criteria optimization, which takes source data typically used subjective information from experts [2,3].

At present, two main approaches to solving the problem of evaluation of e-commerce sites: quantitative when building a numerical score, and qualitative when the resulting estimate is described by some kind of linguistic expression "as good (or bad)". Because of the weak formalization problem, all algorithms developed in the framework of these approaches are heuristic. They are based on knowledge and experience of the researcher and are a set of systematic steps in some way without the relationship of factors affecting the final decision [4,5]. In this paper, we are focusing on the assessing problem, for solving which we built an adaptive evaluation system to assess the E-commerce website, on the base of previous assessments projects from experts.

Therefore, we propose a combined approach for solving the problem of estimating the quality of e-commerce sites. In this approach, expert information and rigorous mathematical methods are effectively used. As a basic tool offers the possibility to use an adaptive neural fuzzy inference system (ANFIS), which belongs to a class of hybrid intelligent systems. A model of adaptive neural network was implemented intelligent fuzzy inference in the Matlab programming environment. It shows that the system is a convenient and powerful tool for the simulation of assessment sites, and it uses the "if-then" type rules that are easy to understand and interpret.

2 Modeling Based on Adaptive Neural Network Fuzzy Inference

2.1 Description of the Problem

For the above purpose, at first, we constructed the knowledge base from these projects; then we designed and realized the evaluation ANFIS; at last, we trained and tested the ANFIS. Each of previous E-commerce website assessment projects can be expressed as follows:

$$\begin{aligned} &P =< S, FEM >, \\ &S = \{EM^{C_i}\}, \quad for\ i = 1 \ldots n \end{aligned} \tag{1}$$

where S is the set of evaluation marks of all criteria, *FEM* is the final evaluation mark, EM^{C_i} is evaluation mark i_{th} criterion C_i, and n is the total amount of criteria. Moreover, the EWAS can be descripted as:

$$\begin{aligned} &O =< PS^{Tr}, PS^{Ts}, S, R >, \\ &PS^{Tr} = \{P^i\}, \\ &PS^{Ts} = \{P^{m-i}\}, \quad for\ i = 1 \ldots m \end{aligned} \tag{2}$$

where PS^{Tr} is training set from part of all projects, PS^{Ts} is testing set from the rest part of all projects, S is set of evaluation marks of all criteria, and R is final evaluation mark from our ANFIS.

2.2 ANFIS Method

Analysis of existing literature [6,7,8,9] shows that ANFIS has good opportunities for learning, prediction and classification. The architecture of these networks allows adaptively based on numerical or expertise data to create a knowledge base (in the form of a set of fuzzy rules) for the system output.

ANFIS is a multilayer unidirectional neural learning network, which uses fuzzy reasoning. Figure 1. shows a typical ANFIS architecture with two entrances, four rules and one output. Each input network mapped two membership functions (MF).

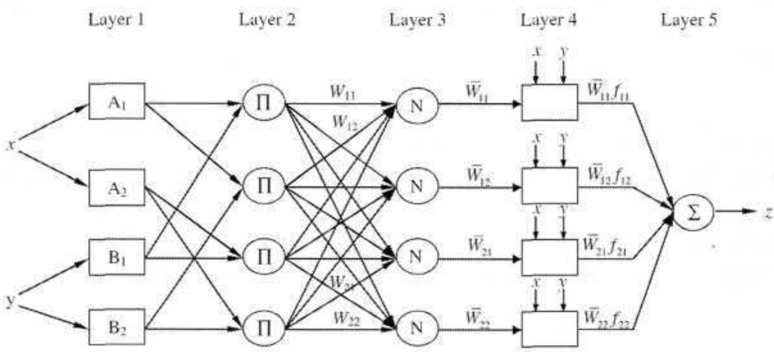

Fig. 1. ANFIS architecture with two inputs and four rules

In this model, the first-order rules are used if-then type that are given by:

Rule 1: *If x is* A_1 *and y is* B_1 *then* $f_{11} = p_{11}x + q_{11}y + r_{11}$
Rule 2: *If x is* A_1 *and y is* B_2 *then* $f_{12} = p_{12}x + q_{12}y + r_{12}$
Rule 3: *If x is* A_2 *and y is* B_1 *then* $f_{11} = p_{21}x + q_{21}y + r_{21}$
Rule 4: *If x is* A_2 *and y is* B_2 *then* $f_{12} = p_{22}x + q_{22}y + r_{22}$

A_1, A_2, B_1 and B_2 are membership functions of inputs x and y, respectively, p_{ij}, q_{ij} and r_{ij} $(i, j = 1,2)$ are the output parameters.

Reduced network architecture consists of five layers. In order to continue to use this type of architecture, each layer are described in details.

Layer 1: The input nodes. All nodes are adaptive layer. They generate membership grades to which they belongs to each of the appropriate fuzzy sets by the following formulas:

$$O^1_{A_i} = \mu_{A_i}(x) \quad i = 1, 2,$$

$$O^1_{B_j} = \mu_{B_j}(y) \quad j = 1, 2, \tag{3}$$

where x and y where x and y are crisp inputs, and A_i and B_j are fuzzy sets such as low, medium, high characterized by appropriate MFs, which could be triangular, trapezoidal, Gaussian functions or other shapes. In this study, the generalized bell-shaped MFs defined below are utilized

$$\mu_{A_i}(x) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^{2b_i}}, \quad i = 1, 2,$$

$$\mu_{B_j}(y) = \frac{1}{1 + \left(\frac{y - c_j}{a_j}\right)^{2b_j}}, \quad j = 1, 2, \tag{4}$$

where $\{a_i, b_i, c_i\}$ and $\{a_j, b_j, c_j\}$ are the parameters of the MFs, governing the bell-shaped functions. Parameters in this layer are referred to as premise parameters.

Layer 2: The nodes in this layer are fixed nodes labelled, indicating that they perform as a simple multiplier. The outputs of this layer are represented as

$$O^2_{ij} = W_{ij} = \mu_{A_i}(x)\mu_{B_j}(y), \quad i, j = 1, 2, \tag{5}$$

which represents the firing strength of each rule. The firing strength means the degree to which the antecedent part of the rule is satisfied.

Layer 3: The nodes in this layer are also fixed nodes labelled N, indicating that they play a normalization role in the network. The outputs of this layer can be represented as

$$O^3_{ij} = \overline{W}_{ij} = \frac{W_{ij}}{W_{11} + W_{12} + W_{21} + W_{22}}, \quad i, j = 1, 2, \tag{6}$$

which are called normalized firing strengths.

Layer 4: Each node in this layer is an adaptive node, whose output is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by

$$O^4_{ij} = \overline{W}_{ij} f_{ij} = \overline{W}_{ij} \left(p_{ij} x + q_{ij} y + r_{ij}\right), \quad i, j = 1, 2, \tag{7}$$

Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labelled Σ, which computes the overall output as the summation of all incoming signals, i.e.

Parameters in this layer are referred to as consequent parameters.

$$
\begin{aligned}
z = O_1^5 &= \sum_{i=1}^{2}\sum_{j=1}^{2}\overline{W}_{ij} f_{ij} = \sum_{i=1}^{2}\sum_{j=1}^{2}\overline{W}_{ij}\left(p_{ij}x + q_{ij}y + r_{ij}\right) \\
&= \sum_{i=1}^{2}\sum_{j=1}^{2}\left[(\overline{W}_{ij}x)p_{ij} + (\overline{W}_{ij}y)q_{ij} + (\overline{W}_{ij})r_{ij}\right]
\end{aligned}
\tag{8}
$$

which is a linear combination of the consequent parameters when the values of the premise parameters are fixed.

It can be observed that the ANFIS architecture has two adaptive layers: Layers 1 and 4. Layer 1 has modifiable parameters $\{a_i, b_i, c_i\}$ and $\{a_j, b_j, c_j\}$ related to the input MFs. Layer 4 has modifiable parameters $\{p_{ij}, q_{ij}, r_{ij}\}$ pertaining to the first-order polynomial. The task of the learning algorithm for this ANFIS architecture is to tune all the modifiable parameters to make the ANFIS output match the training data. Learning or adjusting these modifiable parameters is a two-step process, which is known as the hybrid learning algorithm. In the forward pass of the hybrid learning algorithm, the premise parameters are hold fixed, node outputs go forward until Layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the consequent parameters are held fixed, the error signal propagate backward and the premise parameters are updated by the gradient descent method. The detailed algorithm and mathematical background of the hybrid-learning algorithm can be found in [9].

3 E-commerce Site Evaluation Using AHCHB

This section presents the development of an ANFIS for E-commerce websites assessment and tests its performance.

3.1 Data Description

The dataset used for developing an ANFIS was provided by the Heilongjiang Institute of Information. The dataset contains 507 E-commerce website assessment (EWA) projects and is randomly split into two sample sets: training dataset with 390 projects and testing dataset with 117 projects. Both the training and testing cover all levels and types of E-commerce website assessment.

Inputs to the ANFIS are the usability (U), reliability (R) and design (d) from the 507 E-commerce website assessment projects, which all range from 0 to 4 with 0 representing very bad, 1 bad, 2 normal, 3 good and 4 very good. Output to the ANFIS is the assessment scores (ASs) of the 507 assessment projects, which range from 5 to 99, as shown in Fig. 2.

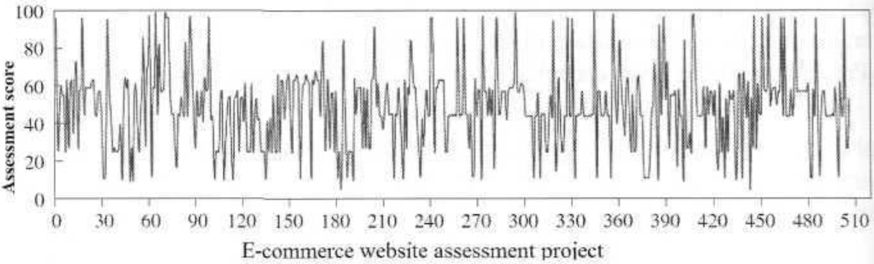

Fig. 2. E-commerce website assessment scores of 506 assessment projects

3.2 Development of the ANFIS

With the training dataset, we choose two generalized bell-shaped MFs for each of the three inputs to build the ANFIS, which leads to 27 if–then rules containing 104 parameters to be learned. Note that it is inappropriate to choose four or more MFs for each input; because the parameters needing to be learned in that case will be greater than the number of training samples. Fig. 3 shows the structure of the ANFIS that is to be built for E-commerce website assessment in this study. The model structure is implemented using the fuzzy logic toolbox of MATLAB software package [10].

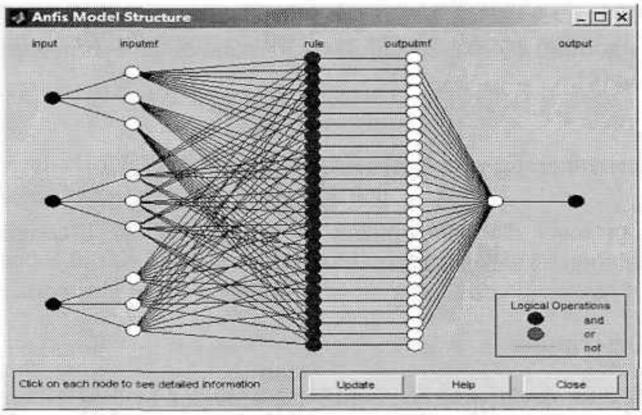

Fig. 3. Model structure of the ANFIS for E-commerce website assessment

The trained if–then rules are presented in Fig. 4, which can be used for prediction. For example, if we change the values of the four inputs from 1.5 to 3, then we immediately get the new output value of the ANFIS as 75.7. This is illustrated in Fig. 5.

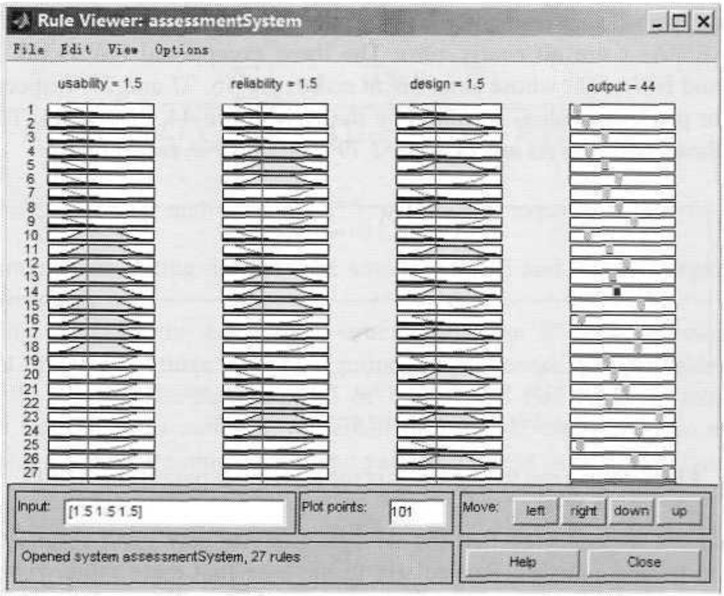

Fig. 4. "If–then" rules after training

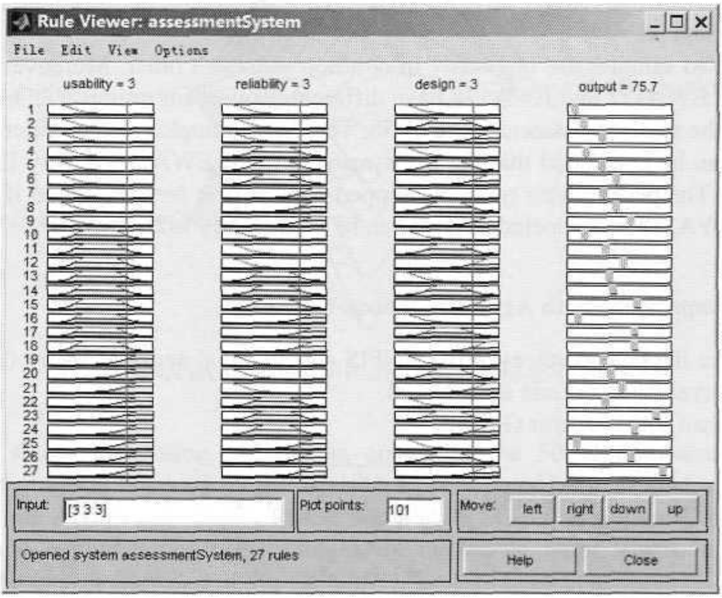

Fig. 5. "If–then" rules for prediction by changing the values of inputs

The trained ANFIS is validated by the testing dataset. Fig. 6 shows the testing errors for the testing dataset. For convenience, the fitting errors for the training dataset are also shown in Fig. 8, from which it can be observed that except for three

E-commerce website assessments (EWAs), the fitting and testing errors for all the other 504 EWAs s are all nearly zero. The three exceptional EWAs are EWA178, EWA407 and EWA446, whose assessment scores are 56, 77 and 77, respectively, but the fitted or predicted values for them by the ANFIS are 44, 83 and 83. The relative errors for these three EWAs are 21.43%, 7.79% and 7.79%, respectively.

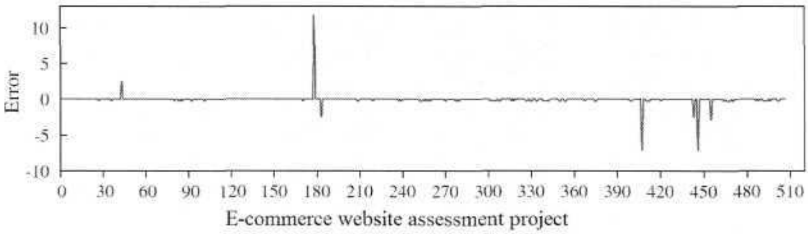

Fig. 6. Fitting and testing errors of the assessment projects by ANFIS

It should not be expected that the ANFIS produce very good results for all the training and testing samples. Particularly in the case that there might be conflicting data in the training or testing dataset.

Looking into the training dataset, we find that both EWA170 and EWA178 have the same assessment ratings: 2, 2, 3 for U, R, D, respectively, but different assessment scores: 44 and 56.

These two samples are obviously in conflict with each other. Moreover, it is also found that EWA177 and EWA178 have different assessment ratings: (2, 3, 1) and (2, 1, 1), but the same assessment score of 56. These two samples also conflict with each other. It can be concluded that the assessment score of EWA178 is very likely to be an outlier. The performance of the developed ANFIS is in fact very good if the fitting error of EWA178 is not included. This can be seen clearly from Fig. 8.

3.3 Comparisons with Artificial Neural Network

To compare the performances of the ANFIS and artificial neural network (ANN), the following evaluation criteria are adopted.

Root mean squared error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2}, \tag{9}$$

where A_t and F_t are actual (desired) and fitted (or predicted) values, respectively, and N is the number of training or testing samples.

Mean absolute percentage error (MAPE):

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \tag{10}$$

Correlation coefficient (R):

$$R = \frac{\sum_{t=1}^{N}(A_t - \overline{A})(F_t - \overline{F})}{\sqrt{\sum_{t=1}^{n}(A_t - \overline{A})^2 \cdot \sum_{t=1}^{n}(F_t - \overline{F})^2}} \tag{11}$$

where $\overline{A} = \frac{1}{N}\sum_{t=1}^{N} A_t$ and $\overline{F} = \frac{1}{N}\sum_{t=1}^{N} F_t$ are the average values of A_t and F_t over the training or testing dataset. The smaller RMSE and MAPE, larger R means better performance.

According to [11], the best ANN structure for the 507 E-commerce website assessment projects is a three layer back propagation network with 10 hidden neurons, as shown in Fig. 7. The performances of the ANFIS and ANN in modelling E-commerce website assessment are presented in Table 1, where the two models are trained using the same training dataset and validated by the same testing dataset.

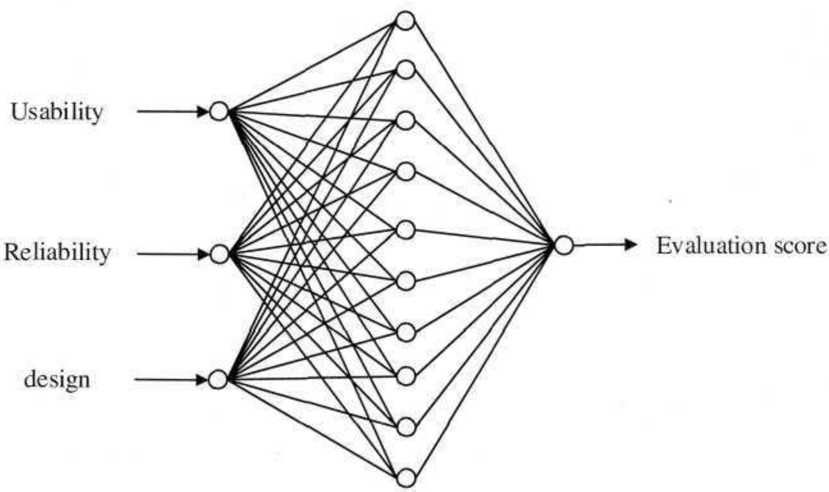

Fig. 7. ANN architecture for E-commerce website assessment

Fig. 8 shows the fitting and testing errors for the 507 E-commerce website assessment projects obtained by the ANN. It is very clear from Table 1 and Figs. 6 and 8 that the ANFIS has smaller RMSE and MAPE as well as bigger R for both the training and testing datasets than the ANN model. In other words, the ANFIS achieves better performances than the ANN model. Therefore, ANFIS is a good choice for modelling E-commerce website assessment.

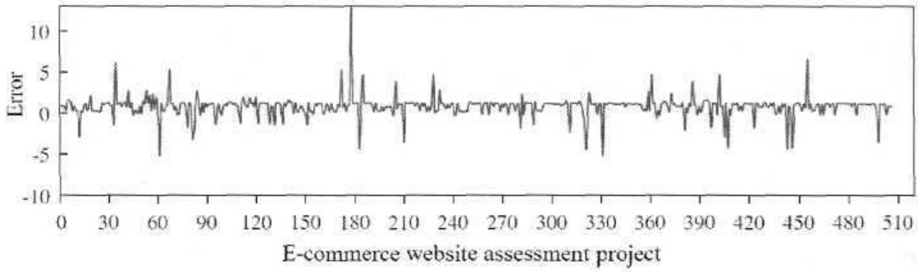

Fig. 8. Fitting and testing errors of the assessment projects by ANN

Table 1. Performances of ANFIS and ANN in modelling E-commerce website assessment

Model	Training dataset			Testing dataset		
	RMSE	MAPE(%)	R	RMSE	MAPE(%)	R
ANFIS	0.57	0.36	0.9994	0.98	0.59	0.9992
ANN	1.64	3.19	0.9963	1.58	3.63	0.9961

Moreover, ANN is a black box in nature and its relationships between inputs and outputs are not easy to be interpreted, while ANFIS is transparent and its if–then rules are very easy to understand and interpret. However, the drawback of ANFIS is its limitation to the number of outputs. It can only model a single output.

4 Conclusion

Evaluation of E-commerce sites is an urgent problem for the majority of e-business enterprises. Within the effective use expert information and rigorous mathematical methods, "if-then" type rules are easily understand and interpreted. An adaptive neural fuzzy inference system was described. After building, training and testing, the proposed ANFIS can evaluate E-commerce site by experts' expressions. It is shows that the convenient and powerful tool is much better than the ANN for the simulation of sites evaluation.

Thus, the use of mathematical models and methods significantly reduces the amount of resources and time, and are necessary to obtain sites assessment results in unconventional decision-making.

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