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An Approach of Artificial Neural Networks Modeling Based on Fuzzy Regression for Forecasting Purposes

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ABSTRACT

In this paper, a new approach of modeling for Artificial Neural Networks (ANNs) models based on the concepts of fuzzy regression is proposed. For this purpose, we reformulated ANN model as a fuzzy nonlinear regression model while it has advantages of both fuzzy regression and ANN models. Hence, it can be applied to uncertain, ambiguous, or complex environments due to its flexibility for forecasting purposes.

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1. INTRODUCTION

In today's world, quantitative methods are essential for forecast purposes in markets that lead to improved decisions and investments. Artificial Neural Networks (ANNs) are one of the well-known and widely used quantitative methods in forecasting.

In the related literature, some efforts have been focused on modeling the fuzzy regression data using ANN approach. For this purpose, Fuzzy Neural Networks (FNNs) have been developed and often integrated into other techniques as a suitable alternative for fuzzy regression approaches. However, they lack the advantages of regression models. The neural models are simulation-based models and this leads to some shortcomings. For example, the weight of each input is not identified in a neural model, as well they can only be used for prediction instead of forecasting. To name a few, Lin et al. [1] integrated the high accuracy and robustness of Support Vector Regression (SVR) and the efficient human-like reasoning of FNN in handling uncertainty information. Similarly, Juang and Hsieh [2] proposed a new recurrent model, known as the locally recurrent FNN with SVR. Expanding simple FNNs to the non-symmetric FNNs [3]; the Fuzzy Radial Basis Function Networks (FRBFN) [4]; and the Fuzzy based General Regression Neural Network (FGRNN) for speed control of induction motor [5] can be found in the related recent publications.

Recently, a new hybrid artificial neural networks and fuzzy regression model for time series forecasting have been proposed [6]. The authors reformulated an ANN model as a time series model to be utilized under incomplete data conditions and where little historical data are available.

To add up, the ANNs are, in fact, examples of a flexible regression approach but they are basically different from the standard methods considering some aspects such as: 1) no prior assumption of the model form is required in the model building process, 2) they provide good solutions to model complex non-linear relationships much better than the parametric models, and 3) they have high robustness when the agenda of the appraisal is widened to include aspects such as outliers, non-linearity, and other kinds of dependence between data. However, the ANNs are not capable of handling the problems defined in uncertain situations and they are

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identified as black box techniques. Uncertain conditions often are available through rapid development of new technologies, imprecise and inadequate data, and lack of ensuring in adequacy of defined independent variables. Hence, we usually have to forecast future situation in uncertain and ambiguous conditions. The fuzzy regression models are suitable models for these cases. However, they cannot map the function with nonlinear behavior.

In the light of above mentioned reservations, we propose a reformulated ANN model as a fuzzy nonlinear regression model capable of dealing with uncertain situations and nonlinear functions. This proposed model has advantages of both fuzzy regression and ANNs models while their mentioned deficiencies have been decreased. The unique nature of this model lies in the integration of the Artificial Neural Network (ANN) and Fuzzy Linear Regression (FLR). Hence, it can be applied to uncertain, ambiguous, or complex environments due to its flexibility.

The remainder of this paper is organized as follows. Section 2 introduces the proposed modeling approach. Conclusions and final remarks are presented in section 3. In the following subsections, the techniques embedded in the proposed approach are explained.

1. 1. Fuzzy Regression Models In general, a single regression model is used for fitting a data set. However, the data set may contain more than one regression model, say *c* regression. Hathaway and Bezdek combined c-regression model (switching regression) with the fuzzy c-mean (FCM) algorithm and called it fuzzy c-regression. In this paper, we deal with a fuzzy c-regression model. Therefore, Let x_{mn} and y_m be the *n*th independent variable and the dependent variable, respectively, in the *m*th observation, β_i be the parameter associated with the *i*th independent variable (*i*=1,2,..,n), and ε_m be the error term associated with the *m*th observation. The classical regression model can be stated as follows:

$$y_m = \beta_0 + \beta_1 x_{m1} + ... + \beta_n x_{mn} + \varepsilon_m \quad m = 1,2,...,k \tag{1}$$

The regression parameter β_i must usually be estimated from sample data. If β_i be estimated under uncertainty in adequacy of indicator variables or sample data, then it falls into the category of fuzzy regression analysis as follows:

$$\tilde{Y} = \tilde{\beta}_0 + \tilde{\beta}_1 X_1 + \tilde{\beta}_2 X_2 + ... + \tilde{\beta}_n X_n = \sum_{i=0}^{n} \tilde{\beta}_i X_i = X'\tilde{\beta} \tag{2}$$

where $\tilde{Y}$ is the fuzzy output, $X' = [X_1, X_2, ..., X_n]^T$ is the real-valued input vector, and $\tilde{\beta} = \{\tilde{\beta}_0, \tilde{\beta}_1, ..., \tilde{\beta}_n\}$ is a set of fuzzy numbers which we want to find, according to some criteria of goodness of fit. In the form of triangular fuzzy numbers, $\tilde{\beta}_i$ are used:

$$\mu_{\tilde{\beta}_i} = \begin{cases} 1 - \dfrac{|\alpha_i - \beta_i|}{c_i} & \text{if } \alpha_i - c_i \le \beta_i \le \alpha_i + c_i \\ 0 & \text{Otherwise;} \end{cases} \tag{3}$$

where $\mu_{\tilde{\beta}_i}$ is the membership function of $\tilde{\beta}_i$, α_i is the center of fuzzy number, and c_i is the width or spread around the center of fuzzy number. According to the extension principle, the membership function of fuzzy numbers can be indicated using pyramidal fuzzy parameter $\tilde{\beta}_i$ as follows [6]:

$$\mu_{\tilde{Y}} = \begin{cases} 1 - \dfrac{|y_m - X_m.\alpha|}{c'|X_m|} & \text{for } X_m \ne 0 \\ 1 & \text{for } X_m = 0; Y_m = 0 \\ 0 & \text{for } X_m = 0; Y_m \ne 0 \end{cases} \tag{4}$$

In general, there are two approaches in fuzzy regression analysis: linear programming method and fuzzy least squares method. The first method is based on minimizing fuzziness as an optimal criterion. The second method used least-square of errors as a fitting criterion. The advantage of first approach is its simplicity in programming and computation, while the degree of fuzziness between the observed and predicted values is minimized using fuzzy least squares method.

In this paper, the problem of finding $\tilde{\beta}_i$ was formulated according to the literature [7] as a linear programming problem:

$$\text{Minimize} \quad S = \sum_{m=1}^{k} c'|X_m|$$

$$\text{Subject to} \begin{cases} X'_m \cdot \alpha + (1-h)c'|X_m| \ge y_m \\ X'_m \cdot \alpha - (1-h)c'|X_m| \le y_m \\ c \ge 0 \end{cases} \tag{5}$$

where the objective function is minimizing total vagueness (S), which is defined as sum of individual spreads of the fuzzy parameters of the model, *k* is the number of observations, and *h* is the threshold of membership function of $\tilde{Y}$.

1. 2. Neural Network Models Neural Network (NN) models are a class of flexible non-linear models that can find patterns adaptively from the data. Indeed, through processing the experimental data, these systems transfer the knowledge or rules hidden in data to the network's structure. They can predict a phenomenon's future by taking into account its history accordingly.

The architecture of neural network (NN) models usually consists of three parts: an input layer, hidden layer and an output layer. The information contained in the input layer is mapped to the output layer through the hidden layers. Each neuron can receive its input only from the lower layer and send its output to the neurons only on the higher layer.

Figure 1 illustrates the network architecture of NN models consisting of one hidden layer with *S* neurons along with input and output layers with *R* and one neuron, respectively. Here the input vector *p* with *R* input elements is represented by the solid dark vertical bar at the left. Thus, these inputs post multiply *S*-row, *R*-column matrix W. One as a constant value enters the neuron as an input and is multiplied by a vector bias *b* with *S* row and single column. The net input to the transfer function *f* is *n*, the sum of the bias *b* and the product *W*p. This summation is passed to the transfer function *f* to get the neuron's output, which in this case is an *S* length vector.

The relationship between the output y_m and the inputs $x_{m1}, x_{m2}, \ldots x_{mn}$ has the following mathematical representation:

$$y_m = f(w_0 + \sum_{q=1}^{Q} w_q . g(w_{0,q} + \sum_{i=1}^{n} w_{i,q} . x_{mi}) + \varepsilon_m = f(w_0 + \sum_{q=1}^{Q} w_q . X_{mq}) = f(\sum_{q=0}^{Q} w_q . X_{mq}) \tag{6}$$

where $w_{i,q} (i = 1,2,\ldots, n; q = 1,2,3.,\ldots, Q)$ and $w_q (q = 0,1,2,\ldots, Q)$ are model parameters often called connection weights; n is the number of input nodes; $X_{mq} = g(w_{0,q} + \sum_{i=1}^{n} w_{i,q} . x_{mi})$; Q is the number of hidden nodes and *f* and *g* are transfer function that are often used as a logistic function. Thus, the neural network is equivalent to a nonlinear multiple regression model. In practice, a network consisting of one hidden layer that has a small number of hidden nodes often works well in out-of-sample forecasting. This may be due to the over-fitting effect typically found in the neural network modeling process.

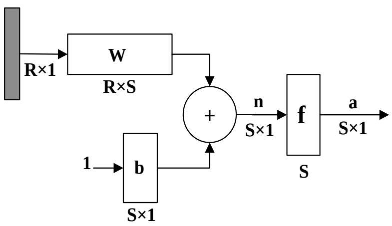

Figure 1. The network architecture of NN models consisting of one hidden layer with *S* neurons along with input and output layers with *R* and one neuron

An over-fitted model has a good fit to the sample used in model building process but has poor ability of generalization for data out of the sample [6]. In order to improve the performance of artificial neural networks, some data mining approaches are often applied in network training process, namely, Dynamic, Multiple, Prune, Exhaustive prune data-mining methods, as well as Networks with Radial Basis Function (RBFN) [8].

2. METHOD: MODEL FORMULATION

In this section, we explain the steps of reformulating an ANN model as a fuzzy nonlinear regression model capable of dealing with uncertain situations and nonlinear functions. This proposed model has advantages of both fuzzy regression and ANNs models while their mentioned deficiencies are decreased.

The steps are summarized as follows:

Step 1. Replace crisp parameters $w_{i,q} (i = 0,1,2,\ldots, n; q = 1,2,3.,\ldots, Q)$ and $w_q (q = 0,1,2,\ldots, Q)$ with fuzzy parameters in the form of triangular fuzzy numbers $\tilde{w}_{i,q} (i = 0,1,2,\ldots, n; q = 1,2,3.,\ldots, Q)$ and $\tilde{w}_q (q = 0,1,2,\ldots, Q)$ according to Equation (2).

$$\tilde{y}_m = f(\tilde{w}_0 + \sum_{q=1}^{Q} \tilde{w}_q . g(\tilde{w}_{0,q} + \sum_{i=1}^{n} \tilde{w}_{i,q} . x_{mi}) + \varepsilon_m = f(\tilde{w}_0 + \sum_{q=1}^{Q} \tilde{w}_q . \tilde{X}_{mq}) = f(\sum_{q=0}^{Q} \tilde{w}_q . \tilde{X}_{mq}) \tag{7}$$

Step 2. Determine membership function of fuzzy parameters $\tilde{w}_{i,q} = (a_{iq}, b_{iq}, c_{iq})$ and $\tilde{w}_q = (d_q, e_q, f_q)$ in the form of triangular fuzzy numbers as shown in Equations.(8) and (9), respectively:

$$\mu_{\tilde{w}_{i,q}} = \begin{cases} \dfrac{(w_{iq} - a_{iq})}{(b_{iq} - a_{iq})} & \text{If } a_{iq} \le w_{i,q} \le b_{iq} \\ \dfrac{(w_{iq} - c_{iq})}{(b_{iq} - c_{iq})} & \text{If } b_{iq} \le w_{i,q} \le c_{iq} \\ 0 & \text{Otherwise} \end{cases} \tag{8}$$

$$\mu_{w_q} = \begin{cases} \dfrac{(w_q - d_q)}{(e_q - d_q)} & \text{If } d_q \le w_q \le e_q \\ \dfrac{(w_q - f_q)}{(e_q - f_q)} & \text{If } e_q \le w_q \le f_q \\ 0 & \text{Otherwise} \end{cases} \tag{9}$$

Step 3. Calculate membership function of $\tilde{X}_{mq}$ in terms of $\mu_{\tilde{w}_{i,q}} (i = 0,1,2,\ldots, n)$; $(q = 0,1,2,\ldots, Q)$ and

$\mu_{\tilde{w}_q}(q=0,1,2,....,Q)$ through applying the extension principle [9] given as Equation (5):

$$\mu_{\tilde{X}_{mq}}=\begin{cases}\dfrac{X_{mq}-\sum_{i=0}^{n}a_{iq}\cdot x_i}{\sum_{i=0}^{n}b_{iq}\cdot x_i-\sum_{i=0}^{n}a_{iq}\cdot x_i} & If\sum_{i=0}^{n}a_{iq}\cdot x_i\le X_{mq}\le\sum_{i=0}^{n}b_{iq}\cdot x_i\\ \dfrac{X_{mq}-\sum_{i=0}^{n}c_{iq}\cdot x_i}{\sum_{i=0}^{n}b_{iq}\cdot x_i-\sum_{i=0}^{n}c_{iq}x_i} & If\sum_{i=0}^{n}b_{iq}\cdot x_i\le X_{mq}\le\sum_{i=0}^{n}c_{iq}\cdot x_i\\ 0 & \text{Otherwise}\end{cases}\tag{10}$$

It should be noted that transfer functions (f and g) are assumed for example, Tan-Sigmoid Transfer Function (tansig) and Saturated Linear Transfer Function (satlins); however, any function can be considered in this formulation. The connected weights between input and hidden layer are considered to be of a crisp form for simplicity.

Step 4. Similar to Step 3, membership function of $\tilde{y}_m$ is given as Equation (11) and is modified considering Equation (4) as Equation (12):

$$\mu_{\tilde{y}_m}=\begin{cases}\dfrac{y_m-\sum_{q=0}^{Q}d_q\cdot X_{mq}}{\sum_{q=0}^{Q}e_q\cdot X_{mq}-\sum_{q=0}^{Q}d_q\cdot X_{mq}} & If\sum_{q=0}^{Q}d_q\cdot X_{mq}\le y_m\le\sum_{q=0}^{Q}e_q\cdot X_{mq}\\ \dfrac{y_m-\sum_{q=0}^{Q}f_q\cdot X_{mq}}{\sum_{q=0}^{Q}e_q\cdot X_{mq}-\sum_{q=0}^{Q}f_q\cdot X_{mq}} & If\sum_{q=0}^{Q}e_q\cdot X_{mq}\le y_m\le\sum_{q=0}^{Q}f_q\cdot X_{mq}\end{cases}\tag{11}$$

$$\mu_{\tilde{y}_m}=\begin{cases}1-\dfrac{\left|y_m-\sum_{q=0}^{Q}e_q\cdot X_{mq}\right|}{\sum_{q=0}^{Q}c_q\cdot\left|X_{mq}\right|} & for\ X_{mq}\neq 0\\ 0 & \text{Otherwise}\end{cases}\tag{12}$$

Step 5: Finally, use the criteria of minimizing total vagueness, S (the sum of individual spreads of the fuzzy parameters) according to Equation (5) to develop the linear programming problem:

$$\text{Minimize } S=\sum_{m=1}^{k}\sum_{q=0}^{Q}(e_q-d_q)^2\cdot\left|X_{mq}\right|$$

$$\text{s.t: }\begin{cases}\sum_{q=0}^{Q}e_q.X_{mq}+(1-h)(\sum_{q=0}^{Q}(e_q-d_q)\cdot\left|X_{mq}\right|)\ge y_m\\ \sum_{q=0}^{q}e_q.X_{mq}-(1-h)(\sum_{q=0}^{Q}(e_q-d_q)\cdot\left|X_{mq}\right|)\le y_m\end{cases}\tag{13}$$

The phases of solving this linear programming problem has been described elsewhere [7].

3. CONCLUSION AND FINAL REMARKS

In today's world, quantitative methods are essential for forecasting purposes in markets that lead to improved decisions and investments. Recently, Artificial Neural Networks (ANNs) have been extensively used in forecast and prediction fields. However, the ANNs are not capable of handling the problems defined in uncertain environments and they are identified as black box techniques. Nowadays, we usually have to forecast future situation in uncertain and ambiguous conditions. The fuzzy regression models are suitable models for these cases. However, they cannot map the function with nonlinear behavior. Hence, we reformulated ANN model as a fuzzy nonlinear regression model while it is capable of dealing with both uncertain situations and nonlinear functions. This novel modeling approach can be applied to uncertain, ambiguous, or complex environments due to its flexibility.

The superiority of the proposed approach over several approaches discussed in some of the previous studies can be addressed to its outstanding features. The proposed approach is applicable to complex, non-linear and ambiguous environments due to embedded ANN and fuzzy mechanisms. It is robust against inconsistency and noise in data as well as high dimensionality and co-linearity. Besides, it performs as a clear box model and provides higher generalization capability. Dealing with uncertain, limited and non-crisp data has caused this approach to have preference over conventional approach. Consequently, the proposed approach as a preferred approach can be a good alternative for forecasting purpose in most cases.

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چکیده

در این مقاله یک رویکرد جدید از مدلسازی شبکه عصبی مصنوعی بر اساس مفهوم فازی توسعه داده شده است. در این رویکرد یک مدل عصبی مصنوعی براساس مفاهیم رگرسیون فازی به گونه ای فرموله شده است تا دارای مزیت های یک مدل عصبی مصنوعی و یک مدل رگرسیون به صورت هSزمان باشد. بنابران مدل توسعه داده شده به خوبی در محبط مدلسازی غیر قطعی، مبهم و پیچیده به توجه به انعطاف آن قابل بکارگیری است.

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