A NEW TIME SERIES PREDICTION METHOD BASED ON INTUITIONISTIC FUZZY C MEANS AND SIGMA PI NEURAL NETWORK

Ozge Cagcag Yolcu – Eren Bas – Erol Egrioglu

Abstract

Most of the fuzzy-based prediction methods have been not originally designed for prediction problem since they ignore the dependency throughout time series observations. In addition to this, fuzzy time series methods consider dependency structure of time series. Moreover, while they consider the memberships, they do not regard the non-memberships in the prediction process. In this study, a new time series prediction method which also takes into account the non-membership and hesitation values is proposed. In the proposed method, the membership, the non-membership and the hesitation values are obtained from intuitionistic fuzzy C-means. Non-linear relationships between inputs and outputs are determined by two separate Sigma-Pi neural networks (SPNNs). The membership and the non-membership values are separately used as inputs in two separate SPNNs, and crisp values are utilized as targets and outputs in both SPNNs. The outputs obtained from SPNNs are converted into final output i.e. final prediction of whole method via an approach based on hesitation margin. The optimal weights of both SPNNs are obtained by utilizing modified particle swarm optimization. To demonstrate the prediction performance of the proposed method, various real-life time series data sets have been analysed and the obtained results prove the outstanding prediction performance of the proposed method.

Key words: intuitionistic fuzzy C means, sigma pi neural network, time series prediction

JEL Code: C22, C45, C53

Introduction

The primary aim of the current time series analysis methods is to get an accurate picture of case and behaviour of related time series in the future. For this purpose, there are various studies produced in the literature based on different approaches. These methods can be evaluated under three basic titles as; statistical-based methods grounded on probability theory, fuzzy-based methods grounded on fuzzy sets and fuzzy arithmetic, and finally computational-methods used various artificial neural networks (ANNs).

Statistical-based methods have to satisfy some assumptions such as model assumption, normal distribution and the number of observation due to the probability theory on which they are based. Fuzzy and computational-based methods do not have such strict assumptions, unlike statistical-based methods. In respect to this, fuzzy and computational-based methods are evaluated as non-probabilistic time series prediction methods. In time series prediction literature, although probabilistic prediction methods have been widely used, they can fail to predict some of time series which are including complex relations. To outface of this deficiency of probabilistic prediction methods some fuzzy-based methods such as adaptive network fuzzy inference system (ANFIS), fuzzy regression (FR) and fuzzy function (FF) approaches have been brought into play in recent years. However, it is known that none of these fuzzy-based methods have been natively designed as a prediction tool since they ignore the dependency structure of time series observations. To get better prediction performance, a method which considers the dependency structure can be utilized.

In the various engineering problems, while some fuzzy inference systems (FISs) (Mamdani, 1974; Takagi and Sugeno, 1985 and Jang, 1993) use rule bases, FF approach use fuzzy regression functions (Turksen, 2008). Although they do not consider time dependency of time series observations, these methods have been also used in time series prediction problems in the recent literature. Moreover, various fuzzy time series (FTS) methods (Song and Chissom, 1993; Chen, 1996) based on fuzzy set theory have been successfully used in time series prediction since early nineties. In recent years, different FTS prediction methods based on fuzzy C-means clustering technique have been proposed (Tak et al., 2018). Furthermore, a network structures called as fuzzy time series network has been proposed for time series prediction (Bas et al., 2015).

In recent studies, to determine relationships between inputs and outputs of the systems, the fuzzy-based methods take in consideration the membership values. In addition to this, in this study a new time series prediction method used the non-membership values and hesitation margin as well as membership values is proposed. In the proposed method, for each time series observation, the membership, the non-membership and the hesitation values are obtained from intuitionistic fuzzy C-means (IFCM). Non-linear relationships between inputs and outputs of the proposed method are determined by two separate SPNNs. The membership and the non-membership values are separately used as inputs in separate SPNNs, and crisp values are utilized as targets and outputs in both SPNNs. The outputs obtained from each

SPNN are converted into final output i.e. final prediction of whole method via an approach based on hesitation margin. The optimal weights of both SPNNs are obtained by utilizing modified particle swarm optimization (MPSO).

The rest of the paper is organised as follow. Chapter one represents IFCM and SPNN in different sub-chapter. In the second chapter, the proposed time series prediction method is introduced by also giving a training algorithm step-by-step. The third chapter include some real-life time series analysis results. In the final chapter, the obtained results are discussed.

1 Preliminary

1.1 Intuitionistic Fuzzy C-Means

Intutionistic fuzzy sets (Atanassov, 1986) take into consideration non-membership $v(x)$ function too, different from fuzzy set that considers only membership function $\mu(x), x \in X$. For an intuitionistic fuzzy set A, $\mu_A(x) \to [0,1]$ and $v_A(x) \to [0,1]$ are the membership and non-membership degrees of an element x in the set A with the condition; $0 \leq \mu_A(x) + v_A(x) \leq 1$. Atanassov also indicated a hesitation degree, $\pi_A(x)$, it is given as $\pi_A(x) = 1 - \mu_A(x) - v_A(x)$. Where it is obvious that $0 \leq \pi_A(x) \leq 1$.

1.2 Sigma-Pi Neural Network

After SPNN has been firstly introduced (Shin and Ghosh, 1991), Sigma-Pi-Sigma neural network, composed of different orders of memory-based SPNN, has been given (Li, 2003). Additive and multiplicative neuron models are synchronically operated in SPNN. SPNN structure consists of input, hidden and output layers. Moreover, the hidden layer of SPNN causes to get a data driven model and also it ensures to having advantage of using high order structure.

1.3 Modified Particle Swarm Optimization

PSO is an evolutionary computation technique and it can be regarded as a population based optimization tool (Kennedy and R. Eberhart, 1995). The particle swarm concept is inspired social behaviour of bird flocking or fish schooling. The characteristic attribute of this algorithm is that it simultaneously examines different points in different regions of the solution space to obtain the global optimum solution. The MPSO algorithm has time varying inertia weight (Shi and Eberhart, 1999) and time varying acceleration coefficient (Ma et al., 2006).

2 The Proposed Method

This study presents a new time series prediction method which uses the non-membership and the membership values as inputs and uses crisp values as target values of two separate SPNNs that determines the non-linear relations between inputs and outputs. In the proposed method, IFCM is taken advantage of in obtaining the non-membership and membership, MPSO is utilized to specify the optimal weights of SPNNs. The proposed method can be given step-by-step by an algorithm. The training algorithm of each SPNN can be given step-by-step in algorithm. The algorithm given as below represents only one of SPNNs, and same procedure is realized for another.

***Step 1** The parameters are determined*

pn	: Particle number of swarm
c_1	: Cognitive coefficient
c_2	: Social coefficient
w	: Inertia weight
(c_{1i}, c_{1f})	: The intervals which includes possible values of c_1.
(c_{2i}, c_{2f})	: The intervals which includes possible values of c_2.
(w_1, w_2)	: The intervals which includes possible values of w.
$maxitr$	: Maximum iteration number
p	: Model order for membership and non-membership values part
K	: Order of SPNN
$ntest$	: Length of test set
c	: Number of fuzzy clusters
n	: Number of observations

***Step 2** Apply IFCM clustering algorithm*

For training data, membership values, non-membership values and hesitation degrees are specified by IFCM. Let $L_l, (l = 1,2,\ldots,c)$ represent the cluster. The membership values and the non-membership values can be stored U_1 and U_2 matrices, respectively.

$$U_1 = [u_{lt}] \ , l = 1,2,\ldots,c \, ; t = 1,2,\ldots,n - ntest \quad (1)$$

$$U_2 = [v_{lit}] \ , l = 1,2,\ldots,c \, ; t = 1,2,\ldots,n - ntest \quad (2)$$

where the elements of $U_1$and U_2 matrix are membership $\left(\mu_{L_l}(y_t)\right)$ and non-membership $\left(v_{L_l}(y_t)\right)$ values of time series observations to L_l fuzzy set.

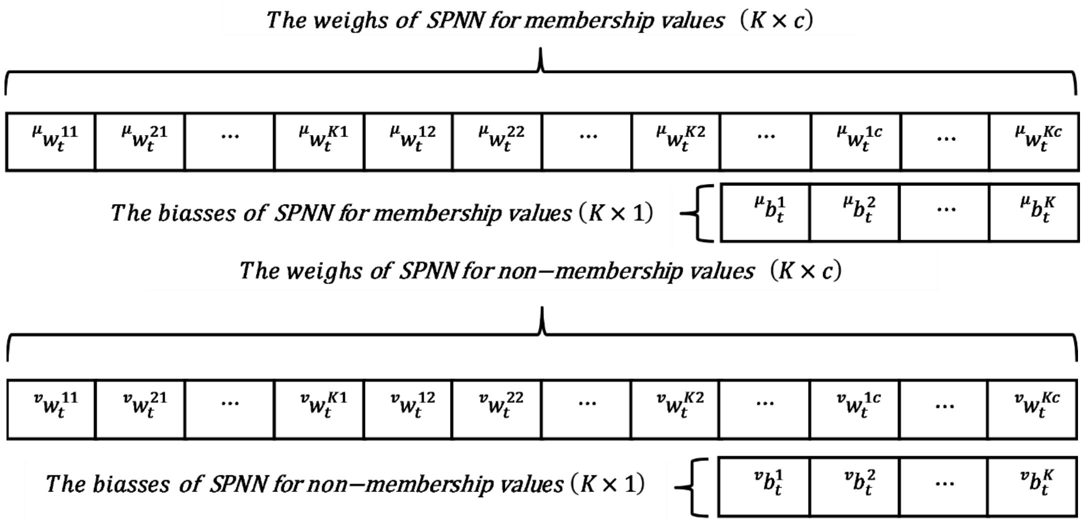
Step 3 *Constituted the inputs (M) and targets (T) of each SP-NN*

While the inputs of each SP-NNs represented by U_{1p}, and U_{2p} vectors, the targets of both SPNNs are represented by same vector; $T = [y_t]$, $(t = q + 1, \dots, n - ntest)$. Where U_{1p}, and U_{2p}, are composed of the merged membership and non-membership values by using minimum $t - norm$ according to model order p. The number of elements of U_{1p} and U_{2p} is equal the number of fuzzy sets (c), the each elements of U_{1p} and U_{2p} are merged membership and non-membership values for a fuzzy set L_l, respectively.

Step 4 *Generate initial positions and velocities of particles*

The number of inputs for each SP-NN is c. The number of positions for a particle of is $d = cK + K$ and positions of a particle are weights and biases of both SPNNs. The structure of a particle of MPSO is given in Fig. 1.

Fig. 1: The elements of a particle



Source: Own research

The Positions and the velocities of particles are randomly generated from $\text{Uniform}(-1,1)$ distribution and they stored in P and V matrices:

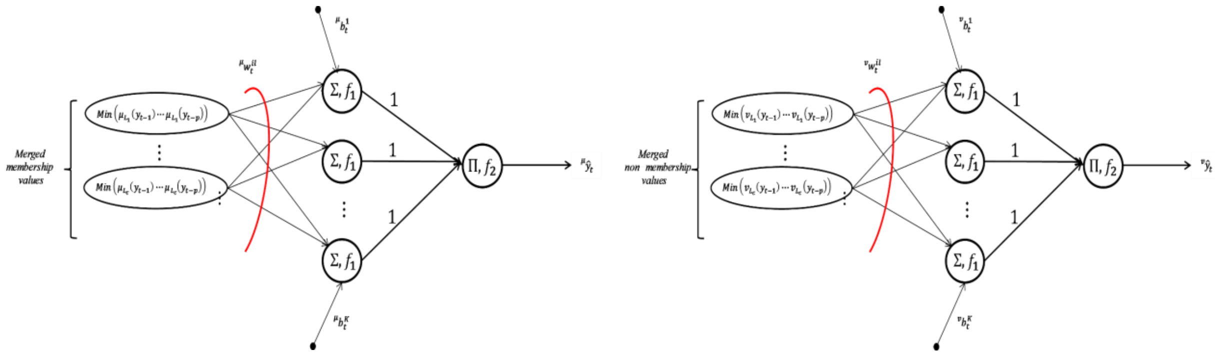
$$P = [p_{rs}]; r = 1,2.,,,.pn; s = 1,2, \dots, d \tag{3}$$

$$V = [v_{rs}]; r = 1,2.,,,.pn; s = 1,2, \dots, d \tag{4}$$

***Step 5** Calculate the outputs of SP-NN*

According to positions values of particles, each SPNNs are performed and the outputs are obtained for each particle. SPNNs with K order and c inputs are given in Fig. 2.

Fig. 2: The graphical presentations of both SPNNs



Source: Own research

Linear combinations of inputs are obtained by using ${}^{\mu}w_t^{il}$, $(i = 1,2,\cdots,K\,; l = 1,2,\cdots,c)$ and ${}^{v}w_t^{il}$ weights, ${}^{\mu}b_t^{i}$ and ${}^{v}b_t^{i}$ biases. o_i is output.

for hidden layer unit i and it is calculated by using following formula.

$$ {}_{h}^{\mu}o_t^{i} = f_1\left(\sum_{l=1}^{c} {}^{\mu}w_t^{il} min\left(\mu_{L_l}(y_{t-k})\right)\right), k = 1,2,\dots,p\,;,\ t = p+1,\dots,n-ntest \qquad (5) $$

$$ {}_{h}^{v}o_t^{i} = f_1\left(\sum_{l=1}^{c} {}^{v}w_t^{il} min\left(v_{L_l}(y_{t-k})\right)\right), k = 1,2,\dots,p\,;,\ t = q+1,\dots,n-ntest \qquad (6) $$

In Eq. (7), $f_1(x) = x$ function is a linear activation function. The outputs of networks are calculated by using Eq. (8). In Eq. (8), f_2 function is logistic activation function.

$$ {}^{\mu}o_{SPNNt} = {}^{\mu}\hat{y}_t = f_2\left(\prod_{i=1}^{K} {}_{h}^{\mu}o_t^{i}\right) = \frac{1}{1+\exp\left(-\prod_{j=1}^{K} {}_{h}^{\mu}o_t^{i}\right)} \qquad (7) $$

$$ {}^{v}o_{SPNNt} = {}^{v}\hat{y}_t = f_2\left(\prod_{i=1}^{K} {}_{h}^{v}o_t^{i}\right) = \frac{1}{1+\exp\left(-\prod_{j=1}^{K} {}_{h}^{v}o_t^{i}\right)} \qquad (8) $$

Final predict is calculated as in Eq. (9).

$$ \hat{Y}_t = {}^{\mu}\hat{y}_t\ (1-\pi) + {}^{v}\hat{y}_t\ \mu \qquad (9) $$

***Step 5** Calculate the fitness function values*

For each particle, fitness function is root of mean square error (RMSE) for training targets and its formula is given in Eq. (10).

$$RMSE = \sqrt{\sum_{t=q+1}^{n-ntest}(Target_t - Output_t)^2} \tag{10}$$

Step 6 *Determine* $Pbest$ *and* $gbest$

According to RMSE values $Pbest$ and $gbest$ are created as in Eqs. (11) and (12).

$$Pbest = [Pb_{r,s}];\ r = 1,2.,,,.pn;\ s = 1,2,\ldots,d \tag{11}$$

$$gbest = [Pg_s];\ s = 1,2,\ldots,d \tag{12}$$

Step 7 *Update the parameters of MPSO*

Cognitive (c_1), social (c_2) coefficients and w are updated by using the below equations.

$$c_1 = (c_{1f} - c_{1i})\frac{maxt-k}{maxitr} + c_{1i} \tag{13}$$

$$c_2 = (c_{2f} - c_{2i})\frac{maxt-k}{maxitr} + c_{2i} \tag{14}$$

$$w = (w_2 - w_1)\frac{maxt-k}{maxt} + w_1 \tag{15}$$

Step 8 *Update the positions and the velocities*

Velocities and positions are updated by using formula given in Eq. (16) and (17).

$$v_{rs}^{itr+1} = w.v_{rs}^{itr} + c_1.rand_1^{itr}.(Pbest_{rs}^{itr} - P_{rs}^{itr}) + c_2.rand_2^{itr}.(gbest_s^{itr} - P_{rs}^{itr}) \tag{16}$$

$$p_{r,s}^{itr+1} = p_{r,s}^{itr} + v_{r,s}^{itr+1} \tag{17}$$

Step 9 *Check the stopping criteria*

If the number of repetition reach maximum iteration number $(maxitr)$ then stop the process, or else repeat from Steps 5 to Step 9 until a predetermined maximum iteration number $(maxitr)$ is reached. When $maxt$ is reached the optimum values of weights and biases are specified. And then the training of SP-NNs is completed.

2 Implementations

To display the prediction performance of the proposed method, the daily Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) in 2000, 2001, 2002, 2003 and 2004 TAIEX have been analysed. In the application process, available data are divided into two parts as training set and test set. The last two months are taken as test set for TAIEX data sets. The properties of the time series are given in Table 1.

Tab. 1: The Properties of the Time Series

Series	TAIEX2000	TAIEX2001	TAIEX2002	TAIEX2003	TAIEX2004
# Observation	271	244	248	24	250
The size of test set	47	43	43	43	45

Source: Own research

In the implementations, model order (p) is taken between 2 and 5, and the number of fuzzy sets (c) is changed from 3 to 7. To compare the predction performance of the proposed method, TAIEX data are analyzed by some different current methods. The obtained results are given in Tab. 2 in respect to RMSE values.

Tab. 2: RMSE values for TAIEX data test sets

Methods	TAIEX					RMSE's	
	2000	**2001**	**2002**	**2003**	**2004**	**Average**	**Median**
(Song and Chissom, 1993)	293	116	76	77	82	129	82
(Chen, 1996)	225	116	76	77	82	115	82
(Bas et al., 2015)	140	120	77	60	59	91	77
(Tak et al., 2018)	128	**106**	65	52	54	81	65
ANFIS	137	115	66	57	61	87	66
MANFIS	124	112	63	52	54	81	63
The Proposed Method	**122**	112	**59**	**48**	**52**	**79**	**59**

Source: Tak et al., 2018; own research

When taking into consideration Tab. 2, the proposed prediction method has the superior prediction performance for all TAIEX time series. Moreover, in terms of both average and median statistics of RMSE, the proposed method is the best. The model order (p), and the order of SPNN (K), for the best cases of TAIEX data sets, are given in Tab. 3.

Tab. 3: The best parameter values

TAIEX2000	TAIEX2001	TAIEX2002	TAIEX2003	TAIEX2004
p/K	p/K	p/K	p/K	p/K
3/2	4/3	3/3	4/2	3/2

Source: Own research

Conclusion

Getting an accurate picture of case and behaviour of the related systems is a major challenge in many areas. One of them is time series problem. There are a large of studies in the time series literature which are based different kinds of base. Especially, statistical, fuzzy and computational-based prediction methods compete against each other with regards to performance of them. In this study a new competitive prediction method is introduced. The proposed method can be evaluated as based on intuitionistic fuzzy sets. The proposed method takes advantage of the information of non-membership values and hesitation margin as well as membership values. Moreover, Non-linear relationships between inputs and outputs of the proposed method are specified by two separate SPNNs, the training of which is carried out by MPSO. In consequence of the implementations, it is observed that the proposed method has outstanding prediction performance for TAIEX data sets. In future studies, to more improve the performance, it can be used more information in the analysis process by given the crisp time series observations as inputs of the analysis process.

References

Atanassov, K.T., 1986. Intuitionistic fuzzy sets. Fuzzy Sets Syst. 20, 87–96.

Bas, E., Egrioglu, E., Aladag, C.H., Yolcu, U., 2015. Fuzzy-time-series network used to forecast linear and nonlinear time series. Appl. Intell. 43, 343-355.

Chaira, T., 2011. A novel intuitionistic fuzzy C means clustering algorithm and its application to medical images. Appl. Soft Comput. 11, 1711–1717.

Chen, S.-M., 1996. Forecasting enrollments based on fuzzy time series. Fuzzy sets Syst. 81, 311–319.

Jang, J.S.R., 1993. ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Trans. Syst. Man Cybern. 23, 665–685.

Kennedy J., Eberhart R 1995. Particle swarm optimization, In Proceedings of IEEE International Conference on Neural Networks, Piscataway, NJ, USA, IEEE Press., 1942–1948.

Li, C.-K., 2003. A Sigma-Pi-Sigma Neural Network (SPSNN). Neural Process. Lett. 17, 1–19.

Ma Y., Jiang C., Hou Z., Wang C. 2006. The formulation of the optimal strategies for the electricity producers based on the particle swarm optimization algorithm, IEEE Trans Power Syst., 21(4), 1663–71

Mamdani, E.H., 1974. Application of fuzzy algorithms for control of simple dynamic plant. Proc. Inst. Electr. Eng. 121, 1585.

Shi Y., Eberhart R.C. 1999. Empirical study of particle swarm optimization. Proc IEEE Int Congr Evol Comput. 3:101–6.

Shin, Y., Ghosh, J., 1991. The pi-sigma network: an efficient higher-order neural network for\npattern classification and function approximation. IJCNN-91-Seattle Int. Jt. Conf. Neural Networks, 13–18.

Song, Q., Chissom, B.S., 1993. Forecasting enrollments with fuzzy time series - Part I. Fuzzy Sets Syst. 54, 1–9.

Tak, N., Evren, A.A., Tez, M., Egrioglu, E., 2018. Recurrent type-1 fuzzy functions approach for time series forecasting. Appl. Intell. 48, 68–77.

Takagi, T., Sugeno, M., 1985. Fuzzy Identification of Systems and Its Applications to Modeling and Control. IEEE Trans. Syst. Man Cybern. SMC-15, 116–132.

Turksen, I.B., 2008. Fuzzy functions with LSE. Appl. Soft Comput. J. 8, 1178–1188.

Contact

Ozge Cagcag Yolcu
Giresun University
Giresun University, Faculty of Engineering, Campus of Gure, 28200, Giresun / TURKEY
ozgecagcag@yahoo.com

Eren Bas
Giresun University
Giresun University, Faculty of Arts and Sciences, Campus of Gure, 28200, Giresun / TURKEY
eren.bas@giresun.edu.tr

Erol Egrioglu
Giresun University
Giresun University, Faculty of Arts and Sciences, Campus of Gure, 28200, Giresun / TURKEY
erol.egrioglu@giresun.edu.tr