Chapter 1
Introduction

Based on the evolution of a variable or a set of variables given in a time series, to predict future values of this variable we should seek the dynamic laws governing the real state of the system over time. This preliminary step is the prediction modeling process. In short, time series analysis aims at drawing conclusions about a complex system using past data.

The time series analysis consists of a description of the movements that compose it, then building models using these movements to explain the structure and predict the evolution of a variable over time [1, 2]. The main and fundamental procedure for the analysis of a time series is described below:

1. Collecting data of the time series, and trying to ensure that these data are reliable.
2. Representing the time series qualitatively by noting the presence of long-term trends, cyclical variations and seasonal variations.
3. Plot a graph or trend line and obtain the appropriate trend values using the least squares method.
4. When seasonal variations are present, obtained these and adjust the data to these seasonal variations (i.e. data seasonally).
5. Adjust the seasonally trend.
6. Represent the cyclical variations obtained in step 5.
7. Combining the results of steps 1–6 and any other useful information to make a prediction (if desired) and if possible discuss the sources of error and their magnitude.

In general the above ideas can help in solving the important problem of prediction in time series. Along with common sense, experience, skill and judgment of the researchers, such mathematical analysis can, however, be of value for predicting the short, medium and long term.

This book focuses on the construction of ensembles for the Interval Type-2 Fuzzy Neural Networks (IT2FNN) architectures and the optimization of the fuzzy integrators for time series prediction with Bio-inspired algorithms. Interval type-2

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and type-1 fuzzy systems are used to integrate the output (forecast) of each Ensemble of IT2FNN models are used. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used for the optimization of the parameters values of fuzzy integrators. The Mackey-Glass, Mexican Stock Exchange (BMV) , Dow Jones and NASDAQ time series are used to test of performance of the proposed method. Prediction errors are evaluated by the following metrics: Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE).

As related work we can mention: Type-1 Fuzzy Neural Network (T1FNN) [3–7] and the IT2FNN [8–11], also the type-1 [12–15] and type-2 [16, 17] fuzzy evolutionary systems are typical hybrid systems in soft computing. These systems combine T1FLS generalized reasoning methods [18–22] and IT2FLS [23–25] with NN learning capabilities [26–28] and evolutionary algorithms [4, 29–33] respectively.

References

1. Brocklebank, J.C., Dickey, D.A.: SAS for Forecasting Series, pp. 6–140. SAS Institute Inc., Cary, NC, USA (2003)
2. Brockwell, P.D., Davis, R.A.: Introduction to Time Series and Forecasting, pp. 1–219. Springer, New York (2002)
3. Horikowa, S., Furuhashi T., Uchikawa, Y.: On fuzzy modeling using fuzzy neural networks with the backpropagation algorithm. IEEE Trans. Neural Netw. 3 (1992)
4. Melin, P., Soto, J., Castillo, O., Soria, J.: A new approach for time series prediction using ensembles of ANFIS models. Experts Syst. Appl. **39**(3), 3494–3506 (2012)
5. Jang, J.S.R.: ANFIS: Adaptive-network-based fuzzy inference systems. IEEE Trans. Syst. Man Cybern. **23**, 665–685 (1992)
6. Jang, J.S.R., Sun, C.T., Mizutani, E.: Neuro-fuzzy and Soft Computing. Prentice-Hall, New York (1997)
7. Lin, Y.C., Lee, C.H.: System identification and adaptive filter using a novel fuzzy neuro system. Int. J. Comput. Cogn. **5**(1), 2 (2007)
8. Hagras, H.: Comments on dynamical optimal training for interval type-2 fuzzy neural network (T2FNN). IEEE Trans. Syst. Man Cybern. Part B **36**(5), 1206–1209 (2006)
9. Wang, C.H., Cheng, C.S., Lee, T.T.: Dynamical optimal training for interval type-2 fuzzy neural network (T2FNN). IEEE Trans. Syst. Man Cybern. Part B: Cybern. **34**(3), 1462–1477 (2004)
10. Lee, C.H., Lin, Y.C.: Type-2 fuzzy neuro system via input-to-state-stability approach. In: Liu, D., Fei, S., Hou, Z., Zhang, H., Sun, C. (eds.) International Symposium on Neural Networks, vol. 4492, pp. 317–327. Springer, Heidelberg, LNCS (2007)
11. Lee, C.H., Hong, J.L., Lin, Y.C., Lai, W.Y.: Type-2 fuzzy neural network systems and learning. Int. J. Comput. Cogn. **1**(4), 79–90 (2003)
12. Ascia, G., Catania, V., Panno, D.: An integrated fuzzy-GA approach for buffer management. IEEE Trans. Fuzzy Syst. **14**(4), 528–541 (2006)
13. Pedrycz, W.: Fuzzy Evolutionary Computation. Kluwer Academic Publishers, Dordrecht (1997)
14. Chiou, Y.C., Lan, L.W.: Genetic fuzzy logic controller: an iterative evolution algorithm with new encoding method. Fuzzy Sets Syst. **152**(3), 617–635 (2005)

15. Ishibuchi, H., Nozaki, K., Yamamoto, N., Tanaka, H.: Selecting fuzzy if-then rules for classification problems using genetic algorithms. IEEE Trans. Fuzzy Syst. **3**, 260–270 (1995)
16. Gaxiola, F., Melin, P., Valdez, F., Castillo, O.: Optimization of type-2 fuzzy weight for neural network using genetic algorithm and particle swarm optimization. In: World Congress on Nature and Biologically Inspired Computing (NaBIC), pp. 22–28 (2013)
17. Wu, D., Wan-Tan, W.: Genetic learning and performance evaluation of interval type-2 fuzzy logic controllers. Eng. Appl. Artif. Intell. **19**(8), 829–841 (2006)
18. Mamdani, E.H., Assilian, S.: An experiment in linguistic synthesis with a fuzzy logic controller. Int. J. Man-Mach. Stud. **7**, 1–13 (1975)
19. Zadeh, L.A.: Fuzzy logic, neural networks and soft computing. Commun. ACM **37**(3), 77–84 (1994)
20. Pedrycz, W.: Fuzzy Modelling: Paradigms and Practice. Kluwer Academic Press, Dordrecht (1996)
21. Takagi, T., Sugeno, M.: Derivation of fuzzy control rules from human operation control actions. In: Proceedings of the IFAC Symposium on Fuzzy Information, Knowledge Representation and Decision Analysis, pp. 55–60 (1983)
22. Takagi, T., Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control. IEEE Trans. Syst. Man Cybern. **15**, 116–132 (1985)
23. Karnik, N.N., Mendel, J.M.: Applications of type-2 fuzzy logic systems to forecasting of time-series. Inf. Sci. **120**, 89–111 (1999)
24. Wu, D., Mendel, J.M.: A vector similarity measure for interval type-2 fuzzy sets and type-1 fuzzy sets. Inf. Sci. **178**, 381–402 (2008)
25. Mendel, J.M.: Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions. Prentice-Hall, NJ (2001)
26. Hagan, M.T., Demuth, H.B., Beale, M.H.: Neural Network Design. PWS Publishing, Boston, MA (1996)
27. Russell, S., Norvig, P.: Artificial Intelligence: A Modern Approach. Prentice-Hall, NJ (2003)
28. Haykin, S.: Adaptive Filter Theory. Prentice Hall, Englewood Cliffs. ISBN 0-13-048434-2 (2002)
29. Pulido, M., Melin, P., Castillo, O.: Particle swarm optimization of ensemble neural networks with fuzzy aggregation for time series prediction of the Mexican Stock Exchange. Inf. Sci. **280**, 188–204 (2014)
30. Soto, J., Melin, P., Castillo, O.: Time series prediction using ensembles of ANFIS models with genetic optimization of interval type-2 and type-1 fuzzy integrators. Int. J. Hybrid Intel. Syst. **11**(3), 211–226 (2014)
31. Bonissone, P.P., Subbu, R., Eklund, N., Kiehl, T.R.: Evolutionary algorithms + domain knowledge = real-world evolutionary computation. IEEE Trans. Evol. Comput. **10**(3), 256–280 (2006)
32. Engelbrech, P.: Fundamentals of Computational of Swarm Intelligence: Basic Particle Swarm Optimization, pp. 93–129. Wiley, New York (2005)
33. Deb, K.: A population-based algorithm-generator for real-parameter optimization. Springer, Heidelberg (2005)