Application of Evolving Fuzzy Systems to Construct Real Estate Prediction Models

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Abstract. Four variants of the *eTS* algorithms (evolving Takagi-Sugeno fuzzy systems) were implemented and examined in respect of their usefulness for the intelligent system of real estate market. The *eTS* algorithms were compared as regards their predictive accuracy with the *Flexfis* algorithm and ensembles employing general linear models (*Glm*) devoted to predict from a data stream of real estate sales transactions. The experiments were conducted in Matlab environment using real-world data taken from a dynamically changing real property market. The analysis of the results was performed using statistical methodology including nonparametric tests followed by post-hoc procedures designed especially for multiple $N \times N$ comparisons. The models produced by two versions of *Simple_eTS* and *Flexfis* algorithms and as well as ensembles composed of *Glm* models revealed statistically similar performance.

Keywords: Evolving fuzzy systems · *eTS* · *Flexfis* · General linear models · Ensemble models · Data stream · Property valuation

1 Introduction

For several years we have been exploring techniques for constructing an intelligent model of real estate market to assist with of property valuation. It is devoted to a broad spectrum of users involved in the real property management ranging from individual citizens and real estate appraisers to banks, insurance companies, and local self-governments. The architecture of the system to be exploited on a cloud computing platform is outlined in Figure 1. Various public registers and cadastral systems establish a manifold data source for the system. The essential part of the system are property valuation models including models built in accordance with the professional standards as well as automated data-driven models constructed with machine learning algorithms.

M. Núñez et al. (Eds.): ICCCI 2015, Part II, LNCS 9330, pp. 606–616, 2015.
DOI: 10.1007/978-3-319-24306-1_59

Two classes of computer systems including Automated Valuation Models (AVM) and Computer Assisted Mass Appraisal (CAMA) are intensively developed to fulfil the needs of numerous users interested in the premises values. These systems combine models generated using statistical multiple regression [1], neural networks [2], rough set theory [3], and hybrid approaches [4]. The requirement for informative and interpretable models gave rise to fuzzy and neuro-fuzzy systems [5], [6] as alternative solutions. Incremental online techniques are especially suitable for this purpose because each day dozens of the records of real estate sales-purchase transactions income to cadastral information centres to be registered. The stream of transactional data reflect also the changes of real estate market over time. This motivated us to employ evolving fuzzy systems to process streams of data utilizing their ability to learn, update, expand their memory on-line on demand.

For almost a decade we have been working out and exploring techniques for constructing data driven regression models to assist with property valuation based on genetic fuzzy systems [7], [8]. We devised also ensemble models built employing different resampling techniques including bagging together with evolutionary fuzzy systems, decision trees, and neural networks [9], bagging comprising linear regression, artificial neural networks, decision trees, and support vector machines [10], bagging encompassing16 various fuzzy algorithms implemented in KEEL [11] as well as subagging, repeated holdout, and repeated cross validation using genetic fuzzy systems [12]. A relatively good performance provided evolving fuzzy systems applied to a data stream formed from cadastral data [13], [14]. We have also studied the application of ensembles of genetic fuzzy systems and neural networks to predict from a data stream of real estate sales transactions [15], [16].

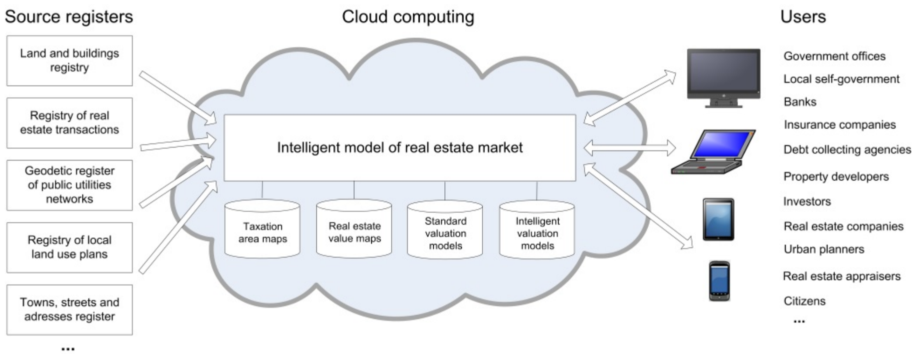

Fig. 1. General schema of the intelligent system of real estate market

The goal of the study reported in the paper was to implement four variants of the *eTS* evolving fuzzy systems devised by Angelov and Filev [17], [18] with modifications proposed by Victor and Dourado [19], [20] and examine from the point of view of their usefulness for the intelligent system of real estate market. The eTS algorithms were compared in respect of predictive accuracy with the *Flexfis* algorithm based on evolving fuzzy systems for incremental learning from data streams worked out by

Lughofer et al. [21], [22] and ensembles employing general linear models devoted to predict from a data stream of real estate sales transactions [23], [24]. The experiments were conducted in Matlab environment using using real-world data taken from a dynamically changing real property market.

2 Implemented Evolving Fuzzy Algorithms

For the purpose of the study reported in this paper we implemented four versions of the evolving Takagi-Sugeno system, proposed by Angelov and Filev in [17] (*eTS* algorithm) and [18] (*simple_eTS* algorithm), incorporating modifications based on ideas introduced by Victor and Dourado in [19], [20]. In the eTS model, its rule-base and parameters continuously evolve by adding new rules with more summarization power, and/or modifying existing rules and parameters. The core of the systems is keeping up to date Takagi-Sugeno consequent parameters and scatter antecedents derived from a fuzzy clustering process. The flow of the *simple_eTS* algorithm [18] can be outlined as follows:

1. Read input vector x_k
2. Predict output y'_k
3. Read output y_k
4. Compute scatter S_k for a new data point ($z_k = [x_k\ y_k]$)
5. Update centres of existing clusters by S_k
6. Compare S_k with potentials of existing clusters to check if the new data point ($z_k = [x_k\ y_k]$) is enough important to modify or upgrade an existing cluster center. Depending on the result of this comparison:
   a) MODIFY – the new data point replaces existing cluster
   b) UPGRADE – the new data point creates new cluster
   c) DO NOTHING – the new data is non-relevant
7. Compute new parameters of the model
8. k += 1; GOTO 1.

Steps 4 and 6 influence the decision whether new incoming data are enough important to be considered for evolving rules. Original decision in [18] about using a new data is based on the criterion if a new scatter is the smallest or the biggest of all scatters according to Formula 1. This is a very intuitive approach to consider a new data sample only if it represents some valuable data.

$$S_k(z(k)) < minS_k(z^i) \vee S_k(z(k)) > maxS_k(z^i), i \in (1, R) \tag{1}$$

In this paper we used approach proposed in [19] which introduced threshold ε in between which new data will be relevant (2). In consequence the new significant data can be detected earlier and in consequence the clusters can evolve faster. As proven in

[19] and [20] using threshold provides lower performance measures RMSE (*root mean square error*) and NDEI (*non-dimensional error index*) compared to the original *eTS* [17] without threshold (3).

$$S_k(z(k)) > maxS_k(z^i) \vee 0.5\varepsilon < S_k(z(k)) < 0.675\varepsilon, i \in (1, R) \tag{2}$$

$$(z(k)) > maxS_k(z^i) \tag{3}$$

Second modification changes the way how scatter value is computed (4). Scatter is an average distance from a data sample to all other samples [18]. The base *eTS* algorithm uses potentials instead of the scatter. The potential is a monotonic function inversely proportional to the distance which enables recursive calculation what is important for online implementation of the learning algorithm (6) [17].

$$S_k(z(k)) = \frac{1}{(k-1)(n+m)}\left((k-1)\sum_{j=1}^{n+m} z_j^2(k) - 2\sum_{j=0}^{n+m} z_j(k)\beta_j(k) + \gamma(k)\right) \tag{4}$$

where

$$\beta_j(k) = \sum_{l=1}^{k-1} z_j(l); \gamma(k) = \sum_{l=1}^{k-1}\sum_{j=1}^{n+m} z_j^2(l) \tag{5}$$

$$P_k(z_k) = \left(1 + \frac{1}{k-1}\sum_{l=1}^{k-1}\sum_{j=1}^{n+1}\left(d_{lk}^j\right)^2\right)^{-1} \tag{6}$$

where

$$d_{lk}^j = z_l^i - z_k^j \tag{7}$$

The goal of this modification is to examine if simpler scatter function, in terms of computational complexity, will give better or equal results compared to the version of the algorithm using the potential (6). In evaluation experiments we used four versions of the eTS algorithm denoted as follows:

- *evTS-1* – modified *simple_eTS* algorithm using condition (2) and the scatter function (4);
- *evTS-2* – original *simple_eTS* algorithm using condition (1) and the scatter function (4);
- *evTS-3* – modified *eTS* algorithm using condition (1) and the potential (6);
- *evTS-4* – original *eTS* algorithm using condition (2) and the potential (6).

3 Evolving Fuzzy System *Flexfis*

The *Flexfis* algorithm, short for FLEXible Fuzzy Inference Systems, incrementally evolves clusters associated with rules and performs a recursive adaptation of consequent parameters by employing local learning approach. The *Flexfis* method, was first proposed in [21] and significantly extended in [22]. It was devised for incremental learning of Takagi-Sugeno fuzzy systems from data streams in a sample-wise single-pass manner. This signifies that always only one sample is loaded into the *Flexfis* learning engine where the model is updated and immediately discarded, afterwards. In consequence the method needs low resources both with respect to computational complexity and with respect to virtual memory and therefore is feasible for on-line modelling applications. In this sort of applications models should be kept-up-to-date as early as possible in order adapt to new operating conditions, systems states etc. and to prevent extrapolation situations when performing predictions on new samples. The basic steps in *Flexfis* technique can be outlined as follows [25]:

1. Rule evolution and updating of antecedent parameters in the cluster space with the help of an incremental evolving clustering variant.
2. Recursive adaptation of consequent parameters exploiting the local learning approach (parameters are updated for each rule separately).
3. Balancing out a non-optimal situation by adding a correction vector to the vector of consequent parameters.
4. In the extended version: Detecting redundant rules with the help of specific overlap measures (two variants: one-dimensional intersection points of fuzzy sets and inclusion metric) and performing on-line rule merging/pruning after each incremental update cycle.

The detailed description of *Flexfis* can be found in [22], [25].

4 Ensemble Approach to Predict from a Data Stream

For comparative experiments we employed our method to predict from a data stream of real estate sales transactions based on ensembles of regression models [15]. The method was worked out as the result of exploring the intermediate solution between evolving fuzzy systems and evolutionary fuzzy systems built over stationary datasets.

Our approach consists in the utilization of aged models to compose ensembles and correction of the output provided by component models by means of trend functions reflecting the changes of prices in the market over time. The idea of our method is illustrated in Figure 2.

The data stream is segmented into data chunks according to the periods of a constant length t_c. Each time interval determines the shift of a sliding time window which encompasses training data to create regression (*RM)* models. The length of the sliding window t_w is equal to the multiple of t_c so that $t_w = jt_c$, where j=1,2,3,... . The window determines the scope of training data to generate a model RM_i. from scratch. It is assumed that a model generated over a given training dataset is valid for the next interval which specifies a test dataset. Similarly, the interval t_t which delineates a test dataset is equal to the multiple of t_c so that $t_t=kt_c$, where k=1,2,3,.. . The sliding window is shifted step by step of a period t_s in the course of time, and likewise, the interval t_s is equal to the multiple of t_c so that $t_s=lt_c$, where l=1,2,3,… .

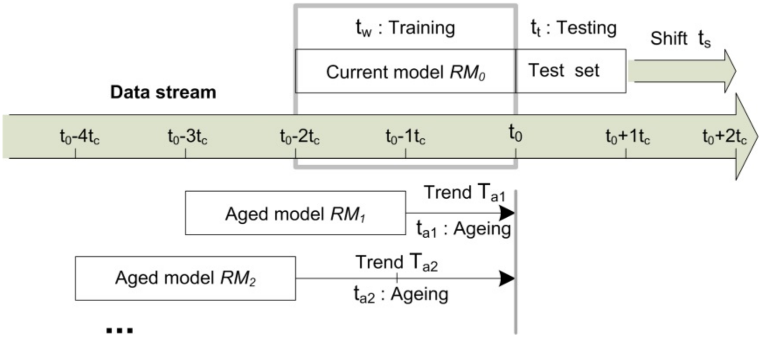

Fig. 2. Idea of an ensemble approach to predict from a data stream

We consider in Figure 2 a point of time t_0 at which the current model RM_0 was built over data that came in between time t_0–2t_c and t_0. The models created earlier, i.e. RM_1, RM_2, etc. aged gradually and in consequence their accuracy deteriorated. However, they are neither discarded nor restructured but utilized to compose an ensemble so that the current test dataset is applied to each component RM_i. However, in order to compensate ageing, their output produced for the current test dataset is updated using trend functions *T(t)*. As the functions to model the trends of price changes the polynomials of the degree from one to five can be employed. For the *Ens-glm* algorithm used in this paper the trends were determined over a time period: encompassing the length of a sliding window plus model ageing intervals, i.e. t_w plus, t_{ai} for a given aged model RM_i. The polynomial of the degree was used as trend function. The method for updating the prices of premises according to the trends of the value changes over time was based on the difference between a price and a trend value in a given time point [15].

5 Experimental Setup and Results

The goal of experiments was to examine the performance of four variants of the eTS algorithm: *evTS-1, evTS-2, evTS-3, evTS-4*. We compared also the results obtained with the outcome of the *Flexfis* algorithm and ensembles composed of general linear models models which output was updated using a second-degree polynomial trend function (*Ens-glm*). The latter two algorithms provided the best accuracy in our previous research [23]. All algorithms were implemented in Matlab environment.

Real-world dataset used in experiments was derived from an unrefined dataset containing above 100 000 records referring to residential premises transactions accomplished in one Polish big city with the population of 640 000 within 14 years from 1998 to 2011. First of all, transactional records referring to residential premises sold at market prices were selected. Then, the dataset was confined to sales transaction data of residential premises (apartments) where the land was leased on terms of perpetual usufruct. The other transactions of premises with the ownership of the land were omitted due to the conviction of professional appraisers stating that the land ownership and lease affect substantially the prices of apartments and therefore they should be used separately for sales comparison valuation methods. The final dataset counted 9795 samples. Due to the fact we possessed the exact date of each transaction we were able to order all instances in the dataset by time, so that it can be regarded as a data stream.

Four following attributes were pointed out as main price drivers by professional appraisers: usable area of a flat (*Area*), age of a building construction (*Age*), number of storeys in the building (Storeys), the distance of the building from the city centre (*Centre*), in turn, price of premises (*Price*) was the output variable.

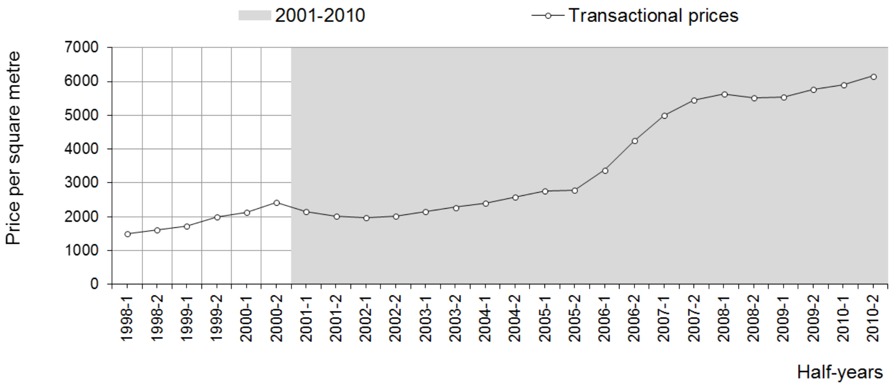

Fig. 3. Change trend of average transactional prices per square metre over time

The evaluating experiments were conducted for 108 points of time from 2002-01-01 to 2010-12-01. Single models were generated over chunks of a data stream delineated by a sliding window which was 12 months long. The window was shifted by one month. Each step, the test datasets were determined by the interval of 3 months, current for a given time point. 108 datasets, obtained in this way, ensured the variability of individual points of observation due to the dramatic rise of the prices of residential premises during the worldwide real estate bubble (see Figure 3). In the case of *evTS-1, evTS-2, evTS-3, evTS-4*, and *Fexfis* algorithms the accuracy of single models was determined the root mean square error (*RMSE*). In turn, for *Ens-glm* average value of *RMSE* provided by 24 component models was computed.

The analysis of the results was performed using statistical methodology including nonparametric tests followed by post-hoc procedures designed especially for multiple *N*×*N* comparisons [26], [27], [28]. The idea behind statistical methods applied to analyse the results of experiments was as follows. The commonly used paired tests i.e. parametric t-test and its nonparametric alternative Wilcoxon signed rank tests are not appropriate for multiple comparisons due to the so called family-wise error. The proposed routine starts with the nonparametric Friedman test, which detect the presence of differences among all algorithms compared. After the null-hypotheses have been rejected the post-hoc procedures should be applied in order to point out the particular pairs of algorithms which produce significant differences. For *N*×*N* comparisons nonparametric Nemenyi's, Holm's, Shaffer's, and Bergamnn-Hommel's procedures are recommended.

6 Statistical Analysis of Experimental Results

The goal of the statistical analysis was to compare the accuracy of the predictive models generated by *evTS-1*, *evTS-2, evTS-3, evTS-4, Flexfis* and ensembles composed of *Glm* models which output was updated using trend functions *T2* for *Age Trends.* Nonparametric tests of statistical significance adequate for multiple comparisons were conducted for all years together. Within this period 108 values of *RMSE,* constituted the points of observation.

Average rank positions of RMSE produced by the models constructed over merged regions which were determined by the Friedman test are shown in Table 1, where the lower rank value the better model. However, please note, it does not mean that each model placed in the lower position significantly outperforms the ones ranked higher on the list.

Table 1. Average rank positions of model performance in terms of *RMSE*

1st	2nd	3rd	4th	5th	6th
Flexfis (2.71)	evTS-2 (2.87)	Ens-glm (3.17)	evTS-1 (3.26)	evTS-3 (4.13)	evTS-4 (4.87)

Table 2. Adjusted p-values for *N*×*N* comparisons in terms of *RMSE*

Alg vs Alg	**pWilcox**	**pNeme**	**pHolm**	**pShaf**	**pBerg**
evTS-4 vs Flexfis	*0.000000*	*4.15E-16*	*4.15E-16*	*4.15E-16*	*4.15E-16*
evTS-2 vs evTS-4	*0.000000*	*6.89E-14*	*6.43E-14*	*4.59E-14*	*4.59E-14*
evTS-4 vs Ens-glm	*0.000000*	*3.74E-10*	*3.24E-10*	*2.49E-10*	*1.74E-10*
evTS-1 vs evTS-4	*0.000000*	*4.18E-09*	*3.35E-09*	*2.79E-09*	*1.95E-09*
evTS-3 vs Flexfis	*0.000000*	*4.37E-07*	*3.21E-07*	*2.92E-07*	*2.92E-07*
evTS-2 vs evTS-3	*0.000000*	*1.25E-05*	*8.30E-06*	*8.30E-06*	*4.98E-06*
evTS-3 vs Ens-glm	*0.000000*	*0.002506*	*0.001503*	*0.001169*	*6.68E-04*
evTS-1 vs evTS-3	*0.000000*	*0.010087*	*0.005380*	*0.004707*	*0.002690*
evTS-3 vs evTS-4	*0.000000*	0.054289	*0.025335*	*0.025335*	*0.025335*
evTS-1 vs Flexfis	0.067267	0.478323	0.191329	0.191329	0.191329
Ens-glm vs Flexfis	0.151434	1.000000	0.373654	0.298923	0.224193
evTS-1 vs evTS-2	0.067267	1.000000	0.506522	0.506522	0.379891
evTS-2 vs Ens-glm	0.288900	1.000000	0.733480	0.733480	0.379891
evTS-2 vs Flexfis	0.254190	1.000000	1.000000	1.000000	1.000000
evTS-1 vs Ens-glm	0.084960	1.000000	1.000000	1.000000	1.000000

The post-hoc procedures for *N*×*N* comparisons should be applied to point out the pairs of models between which statistically significant differences occur. Adjusted p-values for Nemenyi's, Holm's, Shaffer's, and Bergmann-Hommel's post-hoc procedures for *N*×*N* comparisons for all possible pairs of machine learning algorithms are shown in Table 2. For illustration the p-values of the paired Wilcoxon test are also given. The significance level considered for the null hypothesis rejection was 0.05. The p-values indicating the statistically significant differences between given pairs of algorithms are marked with italics.

Following main observations can be done: there are not significant differences among *evTS-1, evTS-2, Flexfis*, and *Ens-glm* models. In turn, *evTS-3* and *evTS-4* models reveal significantly worse performance than any of first four models in the ranking. This means that the simpler scatter function incorporated into the *simple_eTS* algorithm (4) provides better performance compared to the version of the algorithm using the potential (6). Moreover, employing modified conditions to modify and upgrade the fuzzy rules (2) does not result in significantly bigger accuracy of the *eTS* models.

7 Conclusions and Future Work

In this paper we examined the application of incremental data-driven fuzzy modelling techniques for the purpose to estimate the future prices of residential premises based on the past sales-purchase transactions.

Following main conclusions can be drawn from our study. The simpler scatter function incorporated into the *simple_eTS* algorithm provides better performance compared to the original version of the *eTS* algorithm using the potential. Moreover, there were not significant differences in accuracy between algorithms using original conditions to modify and upgrade the fuzzy rules and the ones with conditions employing threshold values. Finally, the models produced by two versions of *Simple_eTS* and *Flexfis* algorithms and as well as ensembles composed of *Glm* models revealed statistically similar performance.

We can conclude that evolving fuzzy modelling methods constitute a reliable and powerful alternative for valuation of residential premises and can be successfully utilized in the AVM systems to support appraisers' work.

Acknowledgments. Many thanks also to Edwin Lughofer for granting us his FLEXFIS algorithm code, thereby allowing us to conduct the experiments.

References

1. Nguyen, N.: Cripps. A.: Predicting housing value: A comparison of multiple regression analysis and artificial neural networks. Journal of Real Estate Research **22**(3), 313 (2001)
2. Selim, H.: Determinants of house prices in Turkey: Hedonic regression versus artificial neural network. Expert Systems with Applications **36**, 2843–2852 (2009)
3. D'Amato, M.: Comparing Rough Set Theory with Multiple Regression Analysis as Automated Valuation Methodologies. Int. Real Estate Review **10**(2), 42–65 (2007)
4. Kontrimas, V., Verikas, A.: The mass appraisal of the real estate by computational intelligence. Applied Soft Computing **11**(1), 443–448 (2011)
5. González, M.A.S., Formoso, C.T.: Mass appraisal with genetic fuzzy rule-based systems. Property Management **24**(1), 20–30 (2006)

6. Guan, J., Zurada, J., Levitan, A.S.: An Adaptive Neuro-Fuzzy Inference System Based Approach to Real Estate Property Assessment. Journal of Real Estate Research **30**(4), 395–421 (2008)
7. Król, D., Lasota, T., Nalepa, W., Trawiński, B.: Fuzzy system model to assist with real estate appraisals. In: Okuno, H.G., Ali, M. (eds.) IEA/AIE 2007. LNCS (LNAI), vol. 4570, pp. 260–269. Springer, Heidelberg (2007)
8. Król, D., Lasota, T., Trawiński, B., Trawiński, K.: Comparison of mamdani and TSK fuzzy models for real estate appraisal. In: Apolloni, B., Howlett, R.J., Jain, L. (eds.) KES 2007, Part III. LNCS (LNAI), vol. 4694, pp. 1008–1015. Springer, Heidelberg (2007)
9. Lasota, T., Telec, Z., Trawiński, B., Trawiński, K.: Exploration of bagging ensembles comprising genetic fuzzy models to assist with real estate appraisals. In: Corchado, E., Yin, H. (eds.) IDEAL 2009. LNCS, vol. 5788, pp. 554–561. Springer, Heidelberg (2009)
10. Lasota, T., Telec, Z., Trawiński, B., Trawiński, K.: A multi-agent system to assist with real estate appraisals using bagging ensembles. In: Nguyen, N.T., Kowalczyk, R., Chen, S.-M. (eds.) ICCCI 2009. LNCS, vol. 5796, pp. 813–824. Springer, Heidelberg (2009)
11. Krzystanek, M., Lasota, T., Telec, Z., Trawiński, B.: Analysis of bagging ensembles of fuzzy models for premises valuation. In: Nguyen, N.T., Le, M.T., Świątek, J. (eds.) Intelligent Information and Database Systems. LNCS, vol. 5991, pp. 330–339. Springer, Heidelberg (2010)
12. Lasota, T., Telec, Z., Trawiński, G., Trawiński, B.: Empirical comparison of resampling methods using genetic fuzzy systems for a regression problem. In: Yin, H., Wang, W., Rayward-Smith, V. (eds.) IDEAL 2011. LNCS, vol. 6936, pp. 17–24. Springer, Heidelberg (2011)
13. Lasota, T., Telec, Z., Trawiński, B., Trawiński, K.: Investigation of the eTS Evolving Fuzzy Systems Applied to Real Estate Appraisal. Journal of Multiple-Valued Logic and Soft Computing **17**(2–3), 229–253 (2011)
14. Lughofer, E., Trawiński, B., Trawiński, K., Kempa, O., Lasota, T.: On Employing Fuzzy Modeling Algorithms for the Valuation of Residential Premises. Information Sciences **181**, 5123–5142 (2011)
15. Trawiński, B.: Evolutionary Fuzzy System Ensemble Approach to Model Real Estate Market based on Data Stream Exploration. Journal of Universal Computer Science **19**(4), 539–562 (2013)
16. Telec, Z., Trawiński, B., Lasota, T., Trawiński, G.: Evaluation of neural network ensemble approach to predict from a data stream. In: Hwang, D., Jung, J.J., Nguyen, N.-T. (eds.) ICCCI 2014. LNCS, vol. 8733, pp. 472–482. Springer, Heidelberg (2014)
17. Angelov, P., Filev, D.: An approach to online identification of Takagi-Sugeno fuzzy models. IEEE Trans. on Systems, Man and Cybernetics, part B **34**(1), 484–498 (2004)
18. Angelov, P., Filev, D.: Simpl_eTS: a simplified method for learning evolving Takagi-Sugeno fuzzy models. In: The 2005 IEEE International Conference on Fuzzy Systems FUZZ-IEEE, Reno, Las Vegas, USA, 22–25 May 2005, pp. 1068–1073 (2005)
19. Victor, J., Dourado, A.: Evolving Takagi-Sugeno Fuzzy Models. Technical Report, CISUC (2003). http://cisuc.dei.uc.pt/acg/view_pub.php?id_p=760
20. Angelov, P., Victor, J., Dourado, A., Filev, D.: On-line evolution of Takagi-Sugeno fuzzy models. In: Proceedings of the 2nd IFAC Workshop on Advanced Fuzzy/Neural Control (AFNC 2004), Oulu, Finland (2004)
21. Lughofer, E., Klement, E.P.: FLEXFIS: a variant for incremental learning of Takagi-Sugeno fuzzy systems. In: Proc. of FUZZ-IEEE 2005, Reno, USA, pp. 915–920 (2005)
22. Lughofer, E.: FLEXFIS: A robust incremental learning approach for evolving TS fuzzy models. IEEE Transactions on Fuzzy Systems **16**(6), 1393–1410 (2008)

23. Telec, Z., Trawiński, B., Lasota, T., Trawiński, K.: Comparison of evolving fuzzy systems with an ensemble approach to predict from a data stream. In: Bădică, C., Nguyen, N.T., Brezovan, M. (eds.) ICCCI 2013. LNCS, vol. 8083, pp. 377–387. Springer, Heidelberg (2013)
24. Telec, Z., Trawiński, B., Lasota, T., Trawiński, G.: Evaluation of neural network ensemble approach to predict from a data stream. In: Hwang, D., Jung, J.J., Nguyen, N.-T. (eds.) ICCCI 2014. LNCS, vol. 8733, pp. 472–482. Springer, Heidelberg (2014)
25. Lughofer, E.: Evolving Fuzzy Systems – Methodologies, Advanced Concepts and Applications. Studies in Fuzziness and Soft Computing, vol. 266. Springer Verlag, Heidelberg (2011)
26. Demšar, J.: Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research **7**, 1–30 (2006)
27. García, S., Herrera, F.: An Extension on "Statistical Comparisons of Classifiers over Multiple Data Sets" for all Pairwise Comparisons. Journal of Machine Learning Research **9**, 2677–2694 (2008)
28. Trawiński, B., Smętek, M., Telec, Z., Lasota, T.: Nonparametric Statistical Analysis for Multiple Comparison of Machine Learning Regression Algorithms. International Journal of Applied Mathematics and Computer Science **22**(4), 867–881 (2012)