An Attempt to Employ Genetic Fuzzy Systems to Predict from a Data Stream of Premises Transactions

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Abstract. An approach to apply ensembles of genetic fuzzy systems, built over the chunks of a data stream, to aid in residential premises valuation was proposed. The approach consists in incremental expanding an ensemble by systematically generated models in the course of time. The output of aged component models produced for current data is updated according to a trend function reflecting the changes of premises prices since the moment of individual model generation. An experimental evaluation of the proposed method using real-world data taken from a dynamically changing real estate market revealed its advantage in terms of predictive accuracy.

Keywords: genetic fuzzy systems, data stream, sliding windows, ensembles, predictive models, trend functions, property valuation.

1 Introduction

The area of data stream mining has attracted the attention of many researchers during the last fifteen years. Processing data streams represents a novel challenge because it requires taking into account memory limitations, short processing times, and single scans of arriving data. Many strategies and techniques for mining data streams have been devised. Gaber in his recent overview paper categorizes them into four main groups: two-phase techniques, Hoeffding bound-based, symbolic approximation-based, and granularity-based ones [11]. Much effort is devoted to the issue of concept drift which occurs when data distributions and definitions of target classes change over time [9], [22], [27], [29]. Among the instantly growing methods of handling concept drift in data streams Tsymbal distinguishes three basic approaches, namely instance selection, instance weighting, and ensemble learning [25], the latter has been systematically overviewed in [16],[23]. In adaptive ensembles, component models are generated from sequential blocks of training instances. When a new block arrives, models are examined and then discarded or modified based on the results of the

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evaluation. Several methods have been proposed for that, e.g. accuracy weighted ensembles [26] and accuracy updated ensembles [4].

One of the most developed recently learning technologies devoted to dynamic environments have been evolving fuzzy systems [20]. Data-driven fuzzy rule based systems (FRBS) are characterized by three important features. Firstly, they are able of approximating any real continuous function on a compact set with an arbitrary accuracy [6], [13]. Secondly, they have the capability of knowledge extraction and representation when modeling complex systems in a way that they could be understood by humans [1]. Thirdly, they can be permanently updated on demand based on new incoming samples as is the case for on-line measurements or data streams. The technologies provide such updates with high performance, both in computational times and predictive accuracy. The major representatives of evolving fuzzy approaches are FLEXFIS [21] and eTS [2] methods. The former incrementally evolves clusters (associated with rules) and performs a recursive adaptation of consequent parameters by using local learning approach. The latter is also an incremental evolving approach based on recursive potential estimation in order to extract the most dense regions in the feature space as cluster centers (rule representatives).

Ensemble models have been drawing the attention of machine learning community due to its ability to reduce bias and/or variance compared with their single model counterparts. The ensemble learning methods combine the output of machine learning algorithms to obtain better prediction accuracy in the case of regression problems or lower error rates in classification. The individual estimator must provide different patterns of generalization, thus the diversity plays a crucial role in the training process. To the most popular methods belong bagging [3], boosting [27], and stacking [28]. Bagging, which stands for bootstrap aggregating, devised by Breiman [3] is one of the most intuitive and simplest ensemble algorithms providing good performance. Diversity of learners is obtained by using bootstrapped replicas of the training data. That is, different training data subsets are randomly drawn with replacement from the original training set. So obtained training data subsets, called also bags, are used then to train different classification and regression models. Theoretical analyses and experimental results proved benefits of bagging, especially in terms of stability improvement and variance reduction of learners for both classification and regression problems [5], [10]. However, the aforementioned approaches are devoted to static environments, i.e. they assume that all training data are available before the learning phase is conducted. Once this phase is completed, the learning system is no more capable of updating the generated model. It means the system is not adaptive and the model cannot evolve over time.When processing a data stream using nonincremental method, we cannot apply any resampling technique as bootstrap, holdout or cross-valitation. Instead, we should try to select a chunk of data coming in within the shortest time period possible, and use it to train a model, and validate the model using the data coming in the next period.

The goal of the study presented in this paper was to make an attempt to apply a nonincremental genetic fuzzy systems to build reliable predictive models from a data stream. The approach was inspired by the observation of a real estate market of in one big Polish city in recent years when it experienced a violent growth of residential premises prices. Our method consists in the utilization of aged models to compose ensembles and correction of the output provided by component models was updated with trend functions reflecting the changes of prices in the market over time.

2 Motivation and GFS Ensemble Approach

Property and real estate appraisals play the crucial role in many areas of social life and economic activity as well as for private persons, especially for asset valuation, sales transactions, property taxation, insurance estimations, and economic and spatial planning. The values of properties change with market conditions in the course of time and must be periodically updated, and the value estimation is based on the current indicators of real estate market, first of all on recent real estate sales transactions. The accuracy of real estate valuation models depends on proper identifying the relevant attributes of properties and finding out the actual interrelationship between prices and attributes. In current sales comparison approaches for residential premises, it is necessary to have transaction prices of the properties sold whose attributes are similar to the one being appraised. If good comparable transactions are available, then it is possible to obtain reliable estimates for the prices of the residential premises.

The approach based on fuzzy logic is especially suitable for property valuation because professional appraisers are forced to use many, very often inconsistent and imprecise sources of information, and their familiarity with a real estate market and the land where properties are located is frequently incomplete. Moreover, they have to consider various rice drivers and complex interrelation among them. An appraiser should make on-site inspection to estimate qualitative attributes of a given property as well as its neighbourhood. They have also to assess such subjective factors as location attractiveness and current trend and vogue. So, their estimations are to a great extent subjective and are on uncertain knowledge, experience, and intuition rather than on objective data.

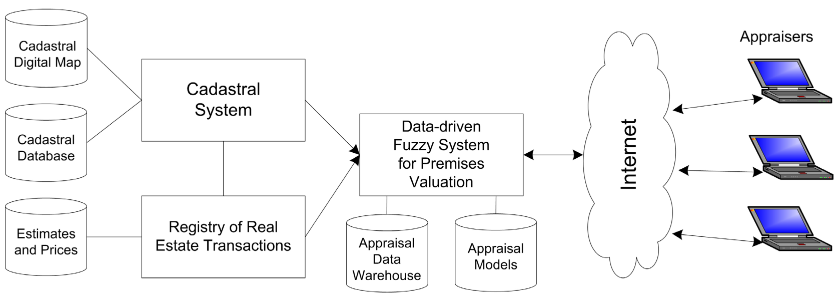

Fig. 1. Information systems to assist with real estate appraisals

So, the appraisers should be supported by automated valuation systems which incorporate data driven models for premises valuation developed employing sales comparison method. The data driven models, considered in the paper, were generated using real-world data on sales transactions taken from a cadastral system and a public registry of real estate transactions. The architecture of the proposed system is shown in Fig. 1. The appraiser accesses the system through the Internet and input the values of the attributes of the premises being evaluated into the system, which calculates the output using a given model. The final result as a suggested value of the property is sent back to the appraiser. We explore data-driven fuzzy rule-based systems (FRBS) as a specific data-driven model architecture used in the framework shown in Fig. 1, which were recognized to be able of approximating any real continuous function on a compact set with an arbitrary accuracy. Moreover, FRBSs allow for knowledge extraction and representation by modeling complex systems in a way understandable by humans. So, the interpretability of fuzzy systems is a characteristic that favors this type of models because it is often required to explain the behavior of a given real appraisal model.

So far, we have investigated several methods to construct regression models to assist with real estate appraisal based on fuzzy approach: i.e. genetic fuzzy systems as both single models [14] and ensembles built using various resampling techniques [12], [18], but in this case the whole datasets had to be available before the process of training models started. All property prices were updated to be uniform in a given point of time. An especially good performance revealed evolving fuzzy models applied to cadastral data [17], [19]. Evolving fuzzy systems are appropriate for modeling the dynamics of real estate market because they can be systematically updated on demand based on new incoming samples and the data of property sales ordered by the transaction date can be treated as a data stream. In this paper we present our first attempt to employ evolutionary fuzzy approach to explore data streams to model dynamic real estate market. The problem is not trivial because on the one hand a genetic fuzzy system needs a number of samples to be trained and on the other hand the time window to determine a chunk of training data should be as small as possible to retain the model accuracy at an acceptable level. The processing time in this case is not a very important issue because property valuation models need not to be updated and/or generated from scratch in an on-line mode.

Our approach is grounded on the observation of a real estate market in one big Polish city with the population of 640 000. The residential premises prices in Poland depend on the form of the ownership of the land on which buildings were erected. For historical reasons the majority of the land in Poland is council-owned or state-owned. The owners of flats lease the land on terms of the so-called perpetual usufruct, and consequently, most flat sales transactions refer to the perpetual usufruct of the land. The prices of flats with the land ownership differ from the ones of flats with the land lease. Moreover, the apartments built after 1996 attain higher prices due to new construction technologies, quality standards, and amenities provided by the developers. Furthermore, apartments constructed in this period were intended mainly for investments and trades which also led to the higher prices. To our study we selected sales transaction data of apartments built before 1997 and where the land was leased on terms of perpetual usufruct. Therefore the dynamics of real estate market concerns more the prices of residential premises rather than other basic attributes of properties such as usable area, number of rooms, floor, number of storeys in a building, etc.

Having a real-world dataset referring to residential premises transactions accomplished in the city, which after cleansing counted 5212 samples, we were able to determine the trend of price changes within 11 years from 1998 to 2008. It was modelled by the polynomial of degree three. The chart illustrating the change trend of average transactional prices per square metre is given in Fig. 2.

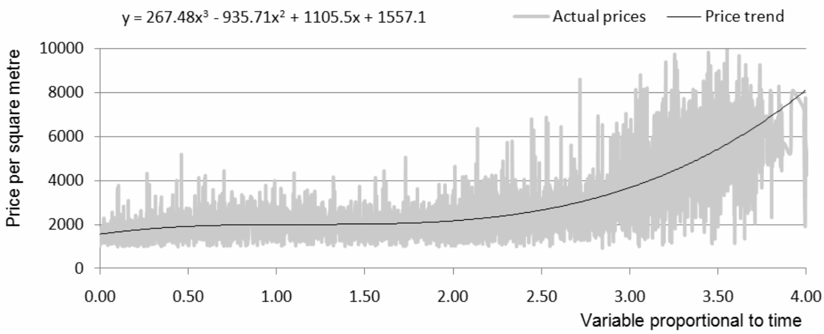

Fig. 2. Change trend of average transactional prices per square metre over time

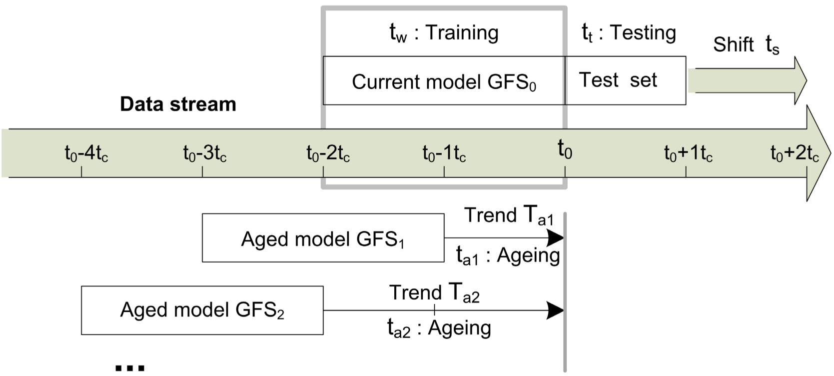

Fig. 3. GFS ensemble approach to predict from a data stream

The idea of the GFS ensemble approach to predict from a data stream is illustrated in Fig. 3. The data stream is partitioned into data chunks according to the periods of a constant length t_c. In the case of transactional data t_c can be equal to one, two, or more months. The sliding time window of the length 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 from scratch a property valuation model, in our case GFS. It is assumed that the models generated over a given training dataset is valid for the next interval which specifies the scope for 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,.. .

Let us consider a point of time t_0 at which the current model GFS_0 was generated from scratch over data that came in between time t_0-t_w and t_0. In the experiments reported in the next section as t_0 we took January 1, 2006, which corresponded the value of 2.92 on the x axis in the chart in Fig. 2. In this time the prices of residential premises were growing quickly due to the run on real estate. The models created earlier, i.e. GFS_1, GFS_2, etc. have aged gradually and in consequence their accuracy has deteriorated. They are neither discarded nor modified but utilized to compose an ensemble so that the current test dataset is applied to each component GFS_i. However, in order to compensate ageing, their output produced for the current test dataset is updated using trend functions determined over corresponding ageing intervals t_{ai} plus t_w. If all historical data would be saved and available the trend could be also modelled over data that came in from the beginning of a stream.

The idea of correcting the results produced by aged models is depicted in Fig. 4. For the time point t_{gi}=t_0-t_{ai} , when a given aged model GFS_i was generated, the value of a trend function $T(t_{gi})$, i.e. average price per square metre, is computed. The price of a given premises, i.e. an instance of a current test dataset, characterised by a feature vector **x**, is predicted by the model GFS_i. Next, the total price is divided by the premises usable area to obtain its price per square metre $P_i(\mathbf{x})$. Then, the deviation of the price from the trend value $\Delta P_i(\mathbf{x})=P_i(\mathbf{x})-T(t_{gi})$ is calculated. The corrected price per square metre of the premises $P_i'(\mathbf{x})$ is worked out by adding this deviation to the trend value in the time point t_0 using the formula $P_i'(\mathbf{x})=\Delta P_i(\mathbf{x})+T(t_0)$, where $T(t_0)$ is the value of a trend function in t_0. Finally, the corrected price per square metre $P'(\mathbf{x})$ is converted into the corrected total price of the premises by multiplying it by the premises usable area. Similar approach is utilized by professional appraisers.

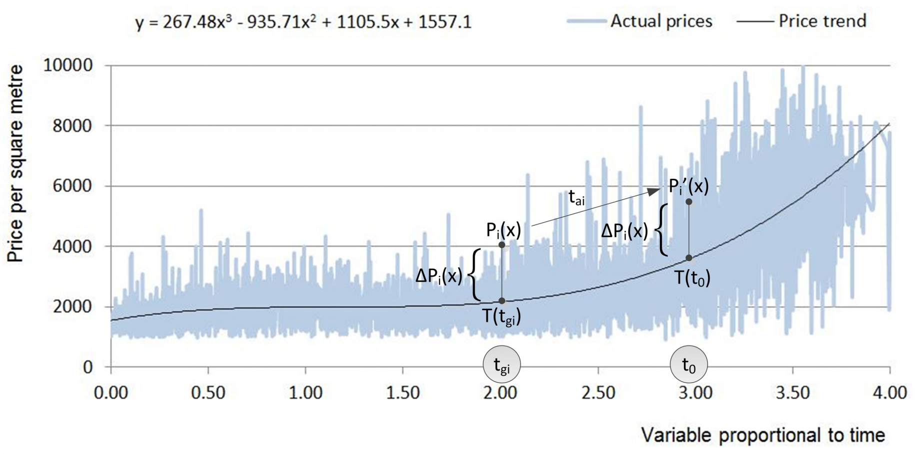

Fig. 4. The idea of correcting the output of aged models

The resulting output of the ensemble for a given instance of the test dataset is computed as the arithmetic mean of the results produced by the component models and corrected by corresponding trend functions. Moreover, weighting component models in an ensemble can be applied according to time past or estimated model accuracy. In the study we applied a simple method proposed in our work in 2006 [15], where the weights assigned to a component model are inversely proportional to its ageing time: $w_i=1-i/N$, where i is the index of a model, i=0,1,2,..,N-1, and N denotes the number of component models encompassed by the ensemble.

In this paper we present our first attempt to employ evolutionary fuzzy approach to explore data streams to model dynamic real estate market. The problem is not trivial because on the one hand a genetic fuzzy system needs a number of samples to be trained without overfitting and on the other hand the time window to determine a chunk of training data should be as small as possible to diminish the ageing impact and retain the model accuracy at an acceptable level. The processing time in this case is not a decisive factor because property valuation models need not to be updated and/or generated from scratch in an on-line mode. Thus, our approach, outlined above, raises a challenge to find the trade-off between the length of a sliding window delimiting the training dataset and the deteriorating impact of ageing models, overfitting, and computational efficiency. Moreover, the issue of how different trend functions modeled over different time intervals affect the accuracy of single and ensemble fuzzy models could be explored. In addition to this, different weighing techniques of component aged models in an ensemble could be investigated.

3 Experimental Setup and Results

The investigation was conducted with our experimental system implemented in Matlab environment using Fuzzy Logic, Global Optimization, Neural Network, and Statistics toolboxes. The system was designed to carry out research into machine learning algorithms using various resampling methods and constructing and evaluating ensemble models for regression problems.

Real-world dataset used in experiments was drawn from an unrefined dataset containing above 50 000 records referring to residential premises transactions accomplished in the Polish big city, mentioned in the previous section, within 11 years from 1998 to 2008. In this period most transactions were made with non-market prices when the council was selling flats to their current tenants on preferential terms. 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 apartments built before 1997 and where the land was leased on terms of perpetual usufruct.

The final dataset counted the 5213 samples. Five 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), number of rooms in the flat including a kitchen (*Rooms*), the distance of the building from the city centre (*Centre*), in turn, price of premises (*Price*) was the output variable.

The property valuation models were built by genetic fuzzy systems over chunks of data stream determined by the time span of 3, 6, 9, and 12 months, as described in the previous section. The parameters of the architecture of fuzzy systems as well as genetic algorithms are listed in Table 1. Similar designs are described in [7], [8], [14]. As test dataset the chunks of data stream specified by the time intervals of one and three months were employed. These intervals followed a time point t_0, which was set to January 1, 2006, i.e. the point of 2.92 on the x axis in the chart in Fig. 2. As a performance function the mean absolute error (MSE) was used, and as aggregation functions of ensembles arithmetic averages were employed.

Table 1. Parameters of GFS used in experiments

Fuzzy system	Genetic Algorithm
Type of fuzzy system: Mamdani	Chromosome: rule base and mf, real-coded
No. of input variables: 5	Population size: 100
Type of membership functions (mf): triangular	Fitness function: MSE
No. of input mf: 3	Selection function: tournament
No. of output mf: 5	Tournament size: 4
No. of rules: 15	Elite count: 2
AND operator: prod	Crossover fraction: 0.8
Implication operator: prod	Crossover function: two point
Aggregation operator: probor	Mutation function: custom
Defuzzyfication method: centroid	No. of generations: 100

The trends were modelled using Matlab function polyfit(x,y,n), which finds the coefficients of a polynomial p(x) of degree n that fits the y data by minimizing the sum of the squares of the deviations of the data from the model (least-squares fit). Due to the relatively short ageing periods, we used in our study linear trend functions to model the changes of premises prices.

The resulting output of the ensemble for a given instance of the test dataset is computed as the arithmetic mean of the results produced by the component models and corrected by corresponding trend functions. Moreover, weighting component models in an ensemble was applied, using the weights inversely proportional to ageing time. The weights were determined according to the method described in the preceding section and are listed in Table 2, where the number of component models is given in the heading and the model indices in the first column. As can be seen the weights assigned to respective component GFSs are distinct for different size of ensembles.

Table 2. Weight values decreasing with the age of models

#	2	3	4	5	6	7	8	9	10	11	12
0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1	0.50	0.67	0.75	0.80	0.83	0.86	0.88	0.89	0.90	0.91	0.92
2		0.33	0.50	0.60	0.67	0.71	0.75	0.78	0.80	0.82	0.83
3			0.25	0.40	0.50	0.57	0.63	0.67	0.70	0.73	0.75
4				0.20	0.33	0.43	0.50	0.56	0.60	0.64	0.67
5					0.17	0.29	0.38	0.44	0.50	0.55	0.58
6						0.14	0.25	0.33	0.40	0.45	0.50
7							0.13	0.22	0.30	0.36	0.42
8								0.11	0.20	0.27	0.33
9									0.10	0.18	0.25
10										0.09	0.17
11											0.08

The performance of ageing single models created by genetic fuzzy systems (GFS) in terms of MAE is illustrated graphically in Figures 5-9. The x axis shows the age of models, i.e. the how many months passed from time when respective models were created to the time point t_0. The models were generated with training datasets determined by sliding windows of t_l=3, 6, 9, and 12 months respectively. The windows were shifted of t_s=3 months. Two the same test datasets, current for t_0, determined by the interval of 1 and 3 months were employed to all current and aged models. Following denotation was used in the legend of Figures 5-9: noT and withT mean that output produced by respective models for the current test dataset was not updated and updated, respectively, using linear trend functions determined over corresponding ageing intervals t_{ai} plus t_w. In turn, the numbers in round brackets, i.e. (i/j), denote a time span for training and test datasets respectively.

In the charts it is clearly seen that the MAE values for models whose output was not corrected by trend functions grow as ageing time increases. The reverse relation can be noticed when the results produced by models were updated with trend functions. Furthermore, the older models with trend correction reveal better performance than the less aged ones. This can be explained by less fluctuations of premises prices in earlier time intervals (see Fig. 2). Moreover, the shorter time span (starting from t_0) of test data the lower MAE value may indicate that data included in test sets also undergo ageing. In turn, no significant differences in accuracy can be observed between models generated for 3 and 12 month time intervals (see Fig. 9).

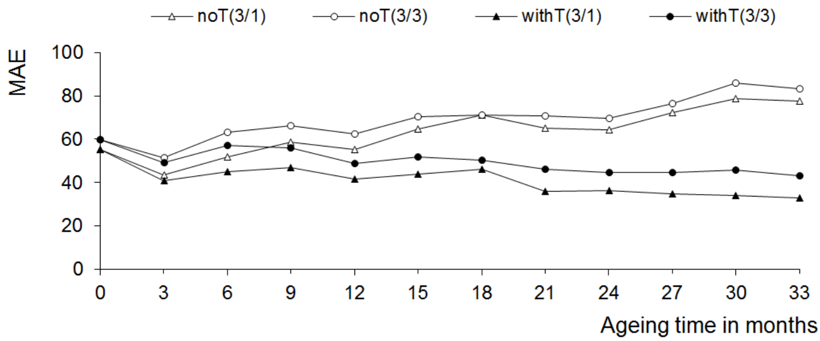

Fig. 5. Performance of ageing models trained over 3 month data windows

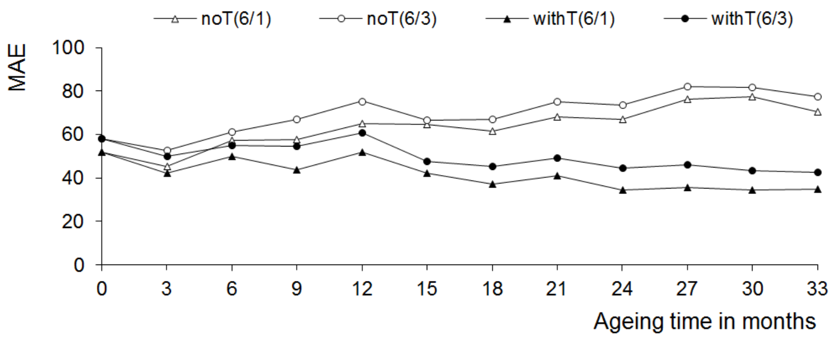

Fig. 6. Performance of ageing models trained over 6 month data windows

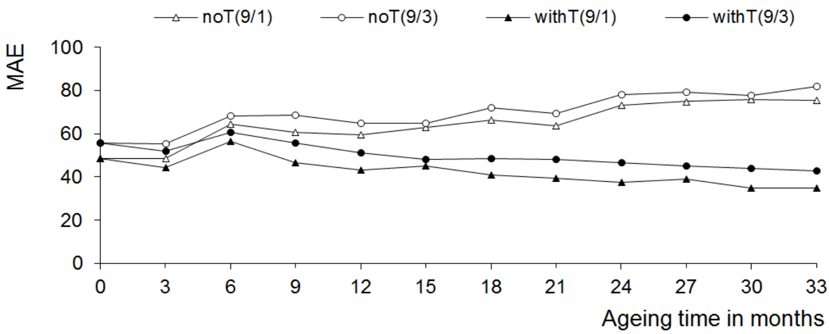

Fig. 7. Performance of ageing models trained over 9 month data windows

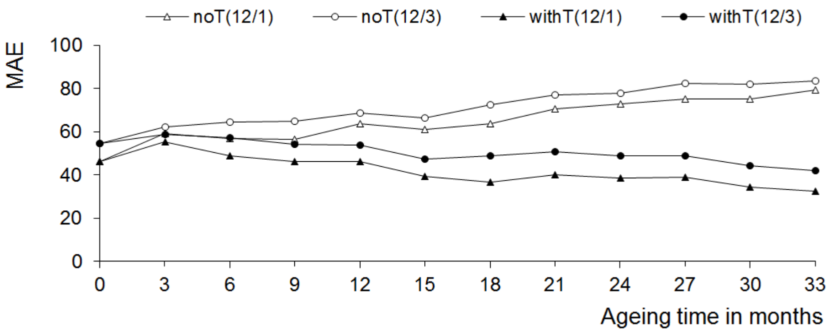

Fig. 8. Performance of ageing models trained over 12 month data windows

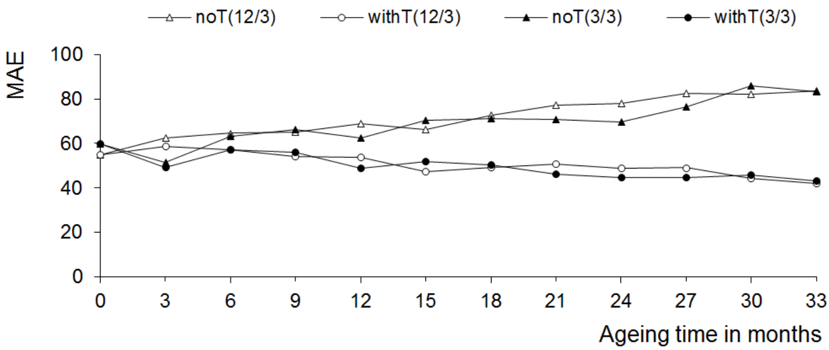

Fig. 9. Performance comparison of ageing models trained over 3 and 12 month data windows

The performance of ensemble models in terms of MAE is depicted in Figures 10-12. The ensembles were composed of stepwise growing number of genetic fuzzy systems (GFS), presented in Fig. 5 and 8. To a single model, current for t_0, more and more aged models, built over training data of the same time span, were added. The same test datasets, current for t_0, determined by the interval of 1 and 3 months were applied to each ensemble. However, in the paper we present only the results for the longer period. Following denotation was used in the legend of Figures 10-12: noT and withT analogously to Fig. 5-9 indicate whether the output provided by component models was updated with trend functions or not. The meaning of the numbers in round brackets remains the same. In turn the letter *w* denotes that component models were weighted using the weights inversely proportional to ageing time.

In the charts can be seen that the MAE values for ensembles where the output of component models was corrected by trend functions decrease as the number of GFSs grows. The reverse relation can be noticed when the results produced by component models were not updated with trend functions. Moreover, adding weights to models without trend correction leads to better performance but has no advantageous effect on ensembles with trend correction. This can be explained by better accuracy of older models with updated output. Finally, the ensembles encompassing models generated for 3 month time intervals reveal better accuracy the ones built over 12 month windows (see Fig. 12).

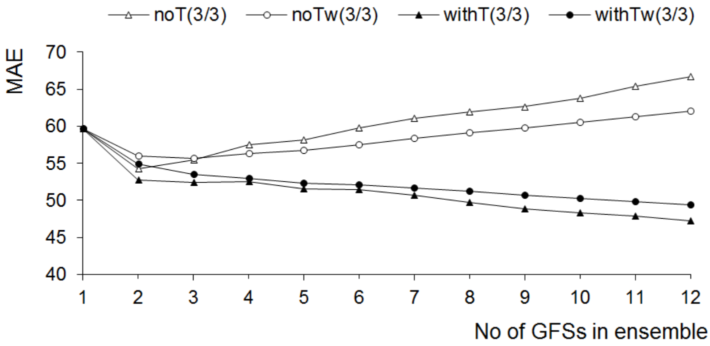

Fig. 10. Performance of ensembles comprising GFSs trained over 3 month data windows

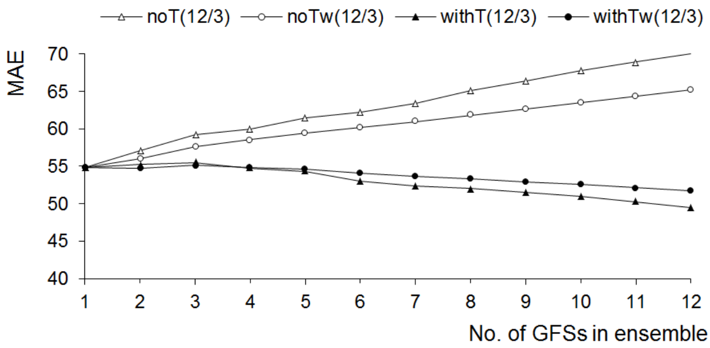

Fig. 11. Performance of ensembles comprising GFSs trained over 12 month data windows

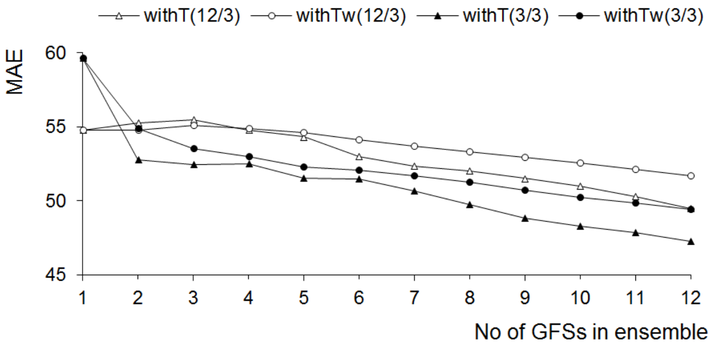

Fig. 12. Performance comparison of ensembles comprising GFSs trained over 3 and 12 month data windows

4 Conclusions and Future Work

An approach to apply ensembles of genetic fuzzy systems to aid in residential premises valuation was proposed. The approach consists in incremental expanding an ensemble by systematically generated models in the course of time. The output of aged component models produced for current data is updated according to a trend function reflecting the changes of premises prices since the moment of individual model generation. An experimental evaluation of the proposed method using real-world data taken from a dynamically changing real estate market revealed its advantage in terms of predictive accuracy.

However, in the study to date each ensemble has been treated as a black box. Further investigation is planned to explore the intrinsic structure of component models, i.e. their knowledge and rule bases, as well as their generation efficiency, interpretability, overfitting, and outlier issues.

Moreover, the weighting component models requires more thorough investigation. The technique we applied in our study consisted in assigning weights that were inversely proportional to component model ageing time. A question arises how big differences among individual weights should be and what should they depend on. It is planned to explore the weights determined according to the estimated accuracy of component models as well as set proportional to the change rate of prices per square metre within the sliding time window.

Another problem to tackle is as follows. When we try to build models from scratch over relatively small amount of data it may happen that data coming within the next period will not fit a given model. Then we should consider to employ clustering, random oracle, or stratification.

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