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Araştırma Makalesi / Research Article

Forecasting Monthly Housing Sales to Foreigners with Type 1 Fuzzy Regression Functions Approach Based on Ridge Regression

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Abstract

Artificial neural networks, fuzzy inference systems, and hybrid methods where these methods are used together have been frequently used in forecasting problems. Although fuzzy inference systems produce very effective results in forecasting problems, the fact that many classical fuzzy inference systems depend on the rule base makes it difficult to implement these methods. The type 1 fuzzy regression functions approach, which is not dependent on the rule base and has a simpler structure than many fuzzy inference systems, is frequently used in forecasting problems. Although the Type 1 fuzzy regression functions approach has superior forecasting performance, it is known that the method has a multicollinearity problem in the application process of this method. The type 1 fuzzy regression functions approach based on ridge regression both eliminates the multicollinearity problem of the Type 1 fuzzy regression functions approach and produce better forecasting results than the Type 1 fuzzy regression functions approach. In this study, the forecasting of monthly house sales to foreigners is carried out for the first time with the Type 1 fuzzy regression functions approach based on ridge regression, and the results of the analysis are compared with many methods suggested in the literature. As a result of the analysis, it is concluded that the forecasting results obtained with the Type 1 fuzzy regression functions approach based on ridge regression produce better results than some other methods in the literature.

Keywords: Fuzzy inference systems, Type 1 fuzzy regression functions approach, Ridge regression, Forecasting, Housing sales.

Ridge Regresyona Dayalı Tip 1 Bulanık Regresyon Fonksiyonları Yaklaşımı ile Yabancılara Yapılan Aylık Konut Satışı Öngörüsü

Öz

Yapay sinir ağları, bulanık çıkarım sistemleri ve bu yöntemlerin birlikte kullanıldığı melez yöntemler öngörü probleminde sıklıkla kullanılmaktadır. Bulanık çıkarım sistemleri öngörü problemlerinde oldukça etkili sonuçlar üretmesine rağmen birçok klasik bulanık çıkarım sisteminin kural tabanına bağlı olması bu yöntemlerin uygulanmasını güçleştirmektedir. Kural tabanına bağlı olmayan ve birçok bulanık çıkarım sisteminden daha basit bir yapıya sahip olan Tip 1 bulanık regresyon fonksiyonları yaklaşımı öngörü probleminde sıklıkla kullanılmaktadır. Tip 1 bulanık regresyon fonksiyonları yaklaşımı, üstün öngörü performansına sahip olmasına rağmen bu yöntemin uygulanma sürecinde yöntemin çoklu bağlantı problemine sahip olduğu bilinmektedir. Bu problemi ortadan kaldırmak amacı ile önerilen ridge regresyona dayalı Tip 1 bulanık regresyon fonksiyonları yaklaşımı, hem Tip 1 bulanık regresyon fonksiyonları yaklaşımının sahip olduğu çoklu bağlantı problemini ortadan kaldırmış hem de Tip 1 bulanık regresyon fonksiyonları yaklaşımından daha iyi öngörü sonuçları üretmiştir. Bu çalışmada yabancılara yapılan konut satışı öngörüsü ilk defa ridge regresyona dayalı Tip 1 bulanık regresyon fonksiyonları yaklaşımı ile gerçekleştirilmiş ve elde edilen analiz sonuçları literatürde önerilen birçok yöntem ile karşılaştırılmıştır. Yapılan analizler sonucunda ridge regresyona dayalı Tip 1 bulanık regresyon fonksiyonları yaklaşımı ile elde edilen öngörü sonuçlarının literatürdeki diğer bazı birçok yöntemden daha iyi sonuçlar ürettiğine varılmıştır.

Anahtar Kelimeler: Bulanık çıkarım sistemleri, Tip 1 bulanık regresyon fonksiyonları yaklaşımı, ridge regresyon, Öngörü, Konut satışı.

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1. Introduction

Housing is a structure that meets the security need, which is one of the most basic needs of the household, and at the same time, it appears as housing, social, cultural, investment goods and consumption goods for the households. The policies implemented by the countries regarding the purchase and sale of housing, the economic level of the societies, the level of welfare, technological developments, and the travels of the people are important factors affecting the purchase and sale of housing. The intense interaction of people, societies, and states living in different parts of the world, especially with globalization, has reshaped the economic order in the world (Bayar (2008)). This situation has caused it to have an important place in the foreign demand as well as the domestic demand in housing sales. Thus, we can say that globalization has significantly affected the housing sales to foreigners in the housing sector.

Many countries, including Turkey, implement support or incentive policies for both their citizens and foreign nationals. The Housing Development Administration (TOKİ) was established in 1984 to implement the policies to support the construction and real estate sector in Turkey, aiming to meet the housing needs of especially low and middle-income citizens, which was established for the production of social housing. In the following years, with the increase in tourism, urban transformation projects, and progress in the construction sector, housing sales in Turkey gained momentum. In addition, the policy of granting citizenship to foreign citizens by acquiring real estate within the scope of the incentive policy has also accelerated the sale of housing. In line with this application, according to the last regulation made in Turkey in 2018, the right to acquire Turkish citizenship was given by acquiring real estate worth $250000. Turkey's natural beauties, livable environmental conditions, especially the depreciation of the Turkish lira against other countries' currencies in recent years, and the incentives in the housing sector have made Turkey a country where foreigners prefer to live. This has led to a rapid increase in the sales of housing to foreigners.

When the studies on house sales to both our citizens and foreigners have been examined, it is seen that the related studies are generally carried out with classical time series analysis methods, artificial neural networks, and some hybrid methods in which these methods are used together. Although these methods are known to produce successful results in many time series forecasting problems, fuzzy inference systems have also been frequently used in forecasting problems in recent years.

If we refer to the studies made with traditional statistical forecasting models; Öztürk and Fitöz (2009) revealed the determinants of housing supply and housing demand in the Turkish housing sector. Lebe and Aktaş (2014) investigated the short and long-term housing demand for Turkey concerning housing policies in Turkey. Aktürk and Tekman (2016) analyzed the consumers residing in Erzurum city centre in their research on the factors affecting their housing purchase decisions. Uysal and Yiğit (2016) investigated the factors affecting the demand for housing in Turkey. Özaktaş (2019) analyzed to what extent the depreciation of the Turkish lira against foreign currencies affects house sales to foreigners, using dynamic least squares, the error correction model, and the Engle-Granger cointegration test.

If the studies made with artificial intelligence forecasting models are mentioned; Nghiep et al. (2001) compared multiple regression analysis and artificial neural network methods to make house price estimation. In the study of Ecer (2014), the artificial neural network method and hedonic regression method were compared in forecasting housing prices in Turkey. The sales prices of the houses in the central districts of Eskişehir were estimated using the artificial neural network method by Yilmazel et al. (2018). In the study of Yılmaz and Tosun (2020), feed-forward artificial neural networks were used for forecasting housing demands in Antalya province.

If the studies with hybrid models are mentioned; Temür et al. (2019) proposed a method using a combination of ARIMA and long-short-term memory (LSTM) artificial neural network methods for the forecasting of home sales.

Fuzzy inference systems are systems that work based on fuzzy sets; they have a structure consisting of fuzzification, rule base determination, and defuzzification stages. It is known that the most important problem of fuzzy inference systems is the rule base determination process. This is the most important problem of the use of fuzzy inference systems such as adaptive network-based fuzzy inference system (ANFIS) proposed by Jang (1993), Mamdani and Assilian (1975), and Takagi and Sugeno (1985).

Unlike many other fuzzy inference systems, the Type 1 fuzzy regression functions (T1FRF) approach proposed by Turksen (2008) is a fuzzy inference system method that does not depend on the rule base and has a simpler structure than many fuzzy inference systems.

The T1FRF method has been frequently used in forecasting problems. Aladag et al. (2014) analyzed the Australian beer consumption data set with the T1FRF method and compared the performance of the T1FRF method with some forecasting methods. Goudarzi et al. (2016) proposed a novel interactively recurrent fuzzy functions for nonlinear chaotic time series prediction Aladag et al. (2016) proposed a fuzzy time series forecasting method based on the fuzzy function approach that uses binary particle swarm optimization to determine the lagged variables of the system. Baser and Demirhan (2017) estimated the yearly mean daily horizontal global solar radiation by using an approach that utilizes fuzzy regression functions with a support vector machine. Tak (2018) proposed the meta fuzzy functions approach to aggregate the methods which are proposed for the same purpose. Dalar and Egrioglu (2018) proposed a new forecasting method that uses fuzzy c-means techniques for clustering T1FRF approach for fuzzy system modelling, and a subsampling bootstrap method for probabilistic inference. Chakravarty et al. (2020) proposed fuzzy regression functions with a noise cluster and compared it with artificial neural networks and support vector machines. Tak (2020a) proposed a novel forecasting approach by combining the T1FRF with the autoregressive moving average model based on a grey wolf optimizer. Pehlivan and Turksen (2020) proposed a multiplicative fuzzy regression function based on a new multiplicative fuzzy clustering algorithm. Tak (2020b) proposed a forecasting method based on T1FRF that employs a possibilistic fuzzy clustering method. Bas and Egrioglu (2022) proposed a T1FRF method that uses the Gustafson-Kessel clustering algorithm instead of the FCM algorithm. Egrioglu and Fildes (2022) proposed a recurrent fuzzy time series function method and its bootstrapped version for forecasting. Tak and İnan (2022) proposed a forecasting method based on T1FFs that employs elastic-net. Chakravarty et al. (2022) proposed a new modified fuzzy regression function that is used against outliers. Chakravarty et al. (2022) proposed a T1FRF for wind speed estimation and compared it with deep neural networks and support vector machine methods.

While relations are established between input and output in the structure of many fuzzy inference systems, in the T1FRF, fuzzy functions corresponding to each fuzzy set are obtained by using multiple regression analysis. In addition to the original inputs of the system in the T1FRF approach; membership values obtained by the fuzzy clustering method and some nonlinear transformations of these membership values are added to the system as an additional input. Thus, more data entry is provided to the system during the application of multiple regression analysis. Although more data input is provided to the system, there is a significant linear relationship between the explanatory variables in the multiple regression method used to obtain fuzzy functions, and this causes the multicollinearity problem. Such a situation causes the variance of the estimators to increase and to obtain inconsistent estimation results.

To eliminate this problem, Bas et al. (2019) proposed Type 1 fuzzy regression functions approach based on ridge regression (RBT1FRF). While classical regression analysis is used to obtain fuzzy functions in the T1FRF method, the ridge regression technique is used instead of classical regression analysis in the RBT1FRF approach proposed by Bas et al. (2019). Although the RBT1FRF approach has been used in many forecasting problems in the literature, it has not yet been used for the forecasting of house sales to foreigners. In this paper, the RBT1FRF approach is used for the first time for forecasting house sales to foreigners.

Under the title of materials and methods, which is the second part of the study, the fuzzy c-means method, ridge regression, multicollinearity, and RBT1FRF method are introduced. Under the title of findings and discussion, which is the third part of the study, the results obtained from the forecasting of house sales to foreigners with the RBT1FRF approach and the analysis results obtained from many methods in the literature are evaluated. Finally, conclusions and recommendations are given in the fourth part of the study.

2. Materials and Methods

Materials and methods used in this paper; fuzzy c means method, multicollinearity problem, and RBT1FRF approach.

2.1. Fuzzy c Means Method

The fuzzy c-means method (FCM), proposed by Bezdek (1981), is a clustering method used to minimize an objective function based on the positions of the cluster centres through iteration. The difference and advantage of the FCM method from the classical clustering method are that it captures the uncertainty encountered when describing real-life data. In the application of the FCM method, first of all, the number of clusters is determined by the researcher. Then, a random membership matrix is generated and cluster centres are obtained as much as the number of fuzzy clusters. Membership values are updated according to the cluster centres, and the algorithm is terminated until the maximum number of iterations is reached or when the variation of the coefficients between the two iterations is not more than ε.

The objective function and constraints used for FCM are given in Equations (1) and (2).

$$J(X,\mu,V)=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{it}^{f}d^{2}(x_k,v_i) \tag{1}$$

$$0\leq\mu_{ik}\leq 1$$
$$\sum_{i=1}^{c}\mu_{ik}=1 \tag{2}$$
$$0<\sum_{k=1}^{n}\mu_{ik}\leq n$$

In these Equations, f is the fuzziness index, $d(x_t,v_i)$ is a measure of similarity between the data and the cluster center. c, v_i $(i=1,2,\dots,c)$ and μ_{ik} $(i=1,2,\dots,c\,;\ k=1,2,\dots,n)$ show the number of fuzzy clusters, cluster centres, and membership values, respectively. At each iteration, v_i $(i=1,2,\dots,c)$ and μ_{ik} $(i=1,2,\dots,c\,;\ k=1,2,\dots,n)$ are updated by Equations (3) and (4).

$$v_i=\frac{\sum_{k=1}^{n}(\mu_{ik})^{f}x_k}{\sum_{k=1}^{n}(\mu_{ik})^{f}}\ ,\ i=1,2,\dots,c \tag{3}$$

$$\mu_{ik}=\left[\sum_{j=1}^{c}\left(\frac{d(x_k,v_i)}{d(x_k,v_j)}\right)^{\frac{2}{f-1}}\right]^{-1}\ ,\ i=1,2,\dots,c\,;\ k=1,2,\dots,n \tag{4}$$

2.2. Multicollinearity problem

The multicollinearity problem is one of the most important problems in regression analysis. The multicollinearity problem is a problem that occurs when an independent variable is highly correlated with one or more of the other independent variables in a multiple regression model. When the independent variables are highly correlated, a change in one variable causes a change in the other variable or variables and therefore the model results are significantly affected. An independent variable that is very highly correlated with one or more independent variables will have a relatively large standard error. In such a case, the statistical significance of an independent variable weakens.

One of the popular methods to check for multicollinearity is to use the Variance Inflation Factor (VIF) for each independent variable. An independent variable with a VIF greater than 10 is generally considered to have a high correlation with other independent variables. The VIF value is obtained by Equation (5).

$$VIF_j = \frac{1}{(1-{R_j}^2)} \ ; j = 1,2,\cdots,p \tag{5}$$

In Equation (5), ${R_j}^2$ is the coefficient of determination obtained from the multiple regression of X_j on the remaining $(p-1)$ regression variables in the model.

2.3. Fuzzy regression functions approach based on ridge regression

The T1FRF approach, proposed by Turksen (2008), is a fuzzy inference system method that stands out with its easy applicability, simple structure, and superior forecasting performance, unlike many well-known fuzzy inference systems in the literature. There is a multicollinearity problem, which is a problem that causes the regression model to produce unreliable results, among the explanatory variables that make up the input data set used in the structure of the regression analysis used to obtain these fuzzy functions.

To eliminate the multicollinearity problem of the T1FRF approach, Bas et al. (2019) proposed the RBT1FRF method. In the RBT1FRF method proposed by Bas et al (2019), unlike the T1FRF method, the ridge regression technique is used as a method of estimating the coefficients of multiple regression models. In addition, it is also concluded that the forecasting performance of the T1FRF method also increased with the use of this technique. The algorithm of the RBT1FRF approach is given step by step with the algorithm below.

Algorithm: RBT1FRF approach

Step 1. In this first step, the data set is first divided into two training and test sets, the number of lags (m) and the number of fuzzy sets (c) are determined by the researcher.

Step 2. By constructing a matrix consisting of inputs and outputs of the system, clustering is done with FCM, and membership values $(u_{ik}, i = 1,2,\cdots,c; k = 1,2,\cdots,n)$ are obtained. Here n represents the length of the training set.

Step 3. Cluster centres are reduced by eliminating the component corresponding to the output and re-membership values are obtained.

Step 4. Normalized membership values (μ) are obtained by Equation (6) and (7) by resetting membership values that are sufficiently small according to the alpha cut-off (α) value.

$$\gamma_{ik} = \begin{cases} u_{ik} & u_{ik} > \alpha \\ 0 & u_{ik} \le \alpha \end{cases} \tag{6}$$

$$\mu_{ik} = \gamma_{ik} / \textstyle\sum_{i=1}^{c} \gamma_{ik} \tag{7}$$

Step 5. The inputs and outputs of the system are created as given in Equations (8) and (9), respectively.

$$X^{(i)} = \begin{bmatrix} \mu_{i1} & {\mu_{i1}}^2 & exp\,(\mu_{i1}) & ln\big((1-\mu_{i1})/\mu_{i1}\big) & x_{11} & . & . & . & x_{p1} \\ \mu_{i2} & {\mu_{i2}}^2 & exp\,(\mu_{i2}) & ln\big((1-\mu_{i2})/\mu_{i2}\big) & x_{12} & . & . & . & x_{p2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \mu_{in} & {\mu_{in}}^2 & exp\,(\mu_{in}) & ln\big((1-\mu_{in})/\mu_{in}\big) & x_{1n} & . & . & . & x_{pm} \end{bmatrix} \tag{8}$$

$$Y^{(i)} = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ . \\ y_n \end{bmatrix} \tag{9}$$

Step 6. Estimate the fuzzy regression functions.

The fuzzy regression functions for each fuzzy set are estimated by Equations (10) and (11).

$$\hat{\beta}_R^{(i)} = (X^{(i)\prime} X^{(i)} + \boldsymbol{kI})^{-1} X^{(i)\prime} Y^{(i)} \tag{10}$$

$$\hat{Y}^{(i)} = X^{(i)} \hat{\beta}_R^{(i)};\ i = 1,2,\dots c \tag{11}$$

In Equation (10), k is the shrinkage parameter proposed by Hoerl and Kennard (1976) given by Equation (12).

$$\mathrm{k} = \frac{\mathrm{p}\hat{\sigma}^2}{\hat{\beta}'\beta} \tag{12}$$

Step 7. The outputs from the fuzzy regression functions are weighted with the corresponding membership values, and the final forecasts of the training set are obtained by using Equation (13).

$$\hat{y}_k = \frac{\sum_{i=1}^{c} \hat{y}_{ik}\mu_{ik}}{\sum_{i=1}^{c} \mu_{ik}}, i = 1,2,\dots,c,\ k = 1,2,\dots,n \tag{13}$$

Step 8. In obtaining the outputs for the test set, the $X^{(i)}$ and $Y^{(i)}$ matrices are updated considering the test set, and Steps 2-7 are repeated to obtain the outputs for the test set.

3. Findings and Discussion

In this paper, the analysis performance of the time series of the monthly house sales to foreigners (MHSF) obtained between the years 2013 and 2020, whose graph is given in Figure 1, is carried out with the RBT1FRF approach. In the analysis phase, the number of inputs of the relevant time series is changed between one and twelve, and the number of fuzzy sets is changed between three and ten. In the analysis of the MHSF time series, the test set length $(ntest)$ is taken as 6.

In the comparison of the methods used in the analysis of the MHSF time series, the Root Mean Squared Error (RMSE) criteria given by Equation (14) and the mean absolute percent error (MAPE) criteria given by Equation (15) are used.

$$RMSE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t-\hat{x}_t}{x_t}\right| \tag{14}$$

$$MAPE = \sqrt{\frac{\sum_{t=1}^{n}(X_t-\hat{X}_t)^2}{n}} \tag{15}$$

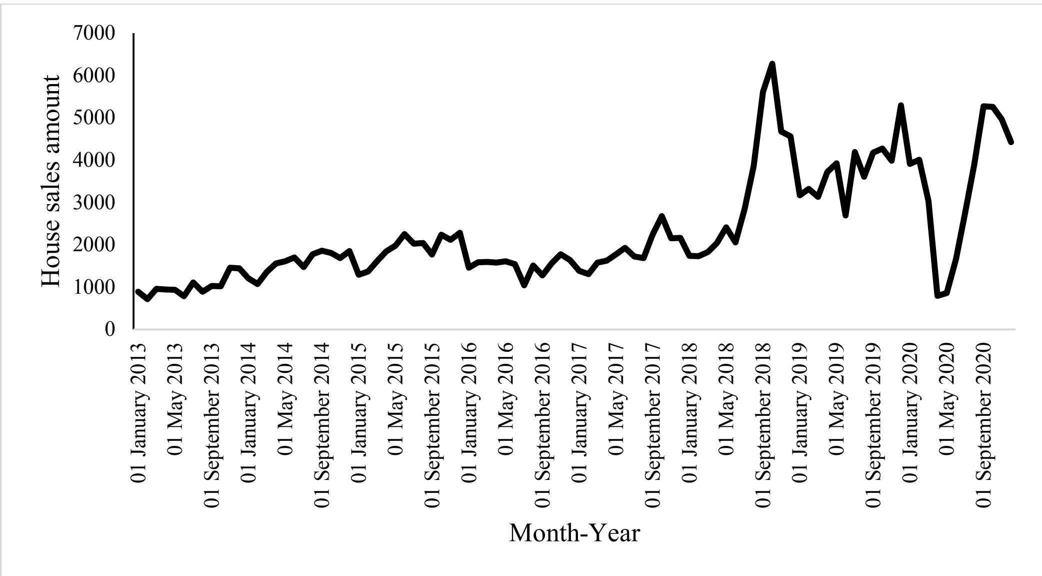


Figure 1. Time series graph of the number of monthly house sales to foreigners between the years 2013 and 2020

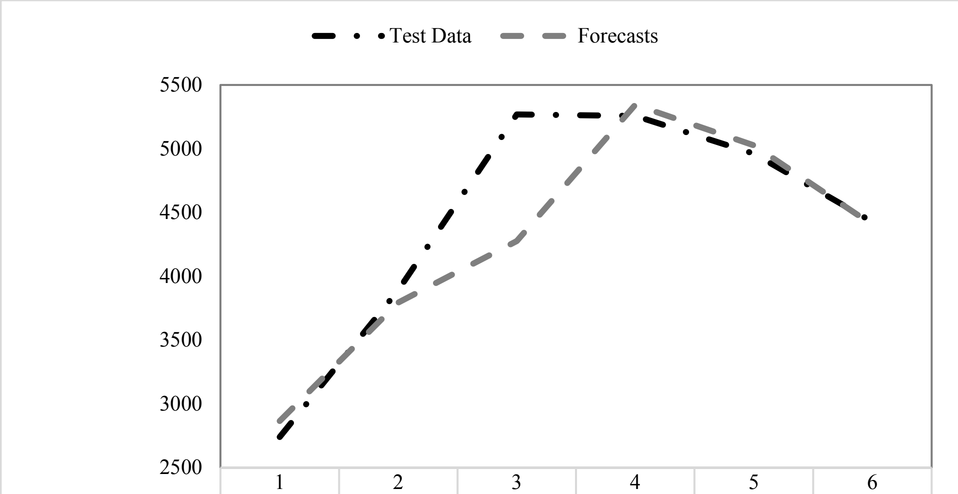
MHSF time series is compared with artificial bee colony based Pi-Sigma artificial neural networks (PS-ANN-ABC), T1FRF approach proposed by Turksen (2008), Chen (1996), feed-forward artificial neural networks based on PSO (FF-ANN-PSO), linear and nonlinear artificial neural networks (L&NL-ANN) proposed by Yolcu et al. (2013), fuzzy time series network (FTS-N) proposed by Bas et al. (2015), recurrent multiplicative neuron model artificial neural networks (R-SNM-ANN) proposed by Egrioglu et al. (2015), Median-Pi artificial neural networks (MP-ANN) proposed by Egrioglu et al. (2019), and Pi-Sigma artificial neural networks (PS-ANN-DEA) based on the differential evolution algorithm proposed by Yılmaz et al. (2021) except the RBT1FRF approach. The number of iterations is also taken as 100 in all methods.

For the case where the test set length of the MHSF time series is 6, the RMSE and MAPE values obtained from each method are given in Table 1. Besides, for the case where the test set length of the MHSF time series is 6, the number of inputs is taken as 5, and the number of fuzzy sets is 3.

Table 1. Analysis results of MHSF test data (ntest=6).

Methods	RMSE	MAPE
PS-ANN-ABC	1262.0202	0.2535
FF-ANN-PSO	1144.3797	0.2368
Chen (1996)	1044.0725	0.2236
R-SNM-ANN	996.8693	0.1977
PS-ANN-DEA	984.0740	0.2125
FTS-N	945.2879	0.2005
MP-ANN	915.2914	0.1988
L&NL-ANN	742.5282	0.1453
T1FRF	467.5143	0.0987
RBT1FRF	413.1833	0.0489

When Table 1 is examined, it can be seen that when the test set length is 6, according to the analysis results of the MHSF time series, the RMSE and MAPE values obtained with the RBT1FRF method are superior to those of other methods. With the RBT1FRF method, lower RMSE and lower MAPE values are obtained compared to other methods. In addition, the graph of the forecasts obtained by the RBT1FRF method and the observations of the test set is given in Figure 2 for the case where the test set length is 6.



	1	2	3	4	5	6
Test Data	2741	3893	5269	5258	4962	4427
Forecasts	2866,3110	3795,5778	4275,5088	5344,3294	5026,5964	4405,1110

Figure 2. Graph of the forecasts obtained by the RBT1FRF method and the test set of the MHSF time series (ntest=6)

Now, let's decide whether the RBT1FRF and T1FRF methods have a multicollinearity problem or not, according to the VIF values. In the case where the test set length is 6, the results of the VIF values obtained from the RBT1FRF and T1FRF methods for the time series of MHSF are given in Table 2.

Table 2. Comparison of the VIF values obtained from the RBT1FRF and T1FRF methods for the MHSF time series when ntest=6

VIF Values	
T1FRF	**RBT1FRF**
764.34998	2.8350378
564.30137	6.2598414
507.02626	5.013496
745.43836	2.4291137
4.09E-08	4.08E-08
6.81E-08	6.78E-08
7.77E-08	7.77E-08
7.59E-08	7.59E-08
5.13E-08	5.13E-08

When Table 2 is examined, it is seen that the T1FRF method has a multicollinearity problem, since some VIF values are greater than 10. For the RBT1FRF method, it is seen that there is no multicollinearity problem since all VIF values are less than 10.

4. Conclusions and Recommendations

It is observed that the policies implemented by the countries regarding the purchase and sale of housing have undergone significant changes in recent years, especially within the framework of the practices that encourage the purchase of housing by foreigners. In this context, the forecasts of housing sales to foreigners in countries have gained importance.

In this paper, for the first time in the literature, monthly house sales to foreigners were estimated with the RBT1FRF approach, and the forecasting performance of the RBT1FRF approach was compared with many well-known forecasting methods in the literature. The analysis results show that the RBT1FRF approach produces better forecasting results than other methods. However, with the RBT1FRF approach, which is used for forecasting monthly house sales to foreigners, the multicollinearity problem of the classical T1FRF approach was avoided and it was concluded that the forecasting performance was increased.

For future studies, the RBT1FRF approach can also be used to forecast house sales to foreigners in different countries.

Authors' Contributions

All authors contributed equally to the study.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The author declares that this study complies with Research and Publication Ethics.

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