Public expenditure forecasting with fuzzy time series

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Abstract

Nowadays, it is of vital importance to make predictions about the future in terms of planning and strategy formulation. This can be realized by accurate and realistic analysis of information and data that have emerged from past to present. Especially, governments must make as possible as accurate and realistic prediction in order to produce an accurate planning and budget based on historical data. Public expenditure forecasting is an important factor for balance of budget. In addition, with its multiplier effect, public expenditure has distinctive role on other components of economy such as national income, employment and private consumption expenditures. That is, public expenditure and forecasting it accurately have vital importance on the economy of countries. Different approaches namely stochastic and non-stochastic approaches have been proposed in the literature for the analysis of time series like this. Particularly, in recent years, the use of non-stochastic models such as fuzzy time series approaches for the analysis of time series has become widespread. In this study, Expenditures of Central Government Budget (ECGB) of Turkey is forecasted with different fuzzy time series approach. The fuzzy time series approach is rarely applied for the forecast of public expenditures, and as far as we know this is the first of such attempts involving Turkish data. Different fuzzy time series forecasting models are applied to the data data from January 2007 to May 2013 in order to reach accurate forecasts. Obtained results from the different fuzzy time series approaches evaluate as a whole. As a result of the implementation, it is shown that fuzzy time series approaches can be effectively used to forecast of ECGB.

Key words:
Forecasting, Expenditures of Central Government Budget, Fuzzy time series.

Introduction

Many studies presented that public expenditures directly or indirectly affect economy. The government's spending policies consisting of economic growth, full employment, price stability and arrangement of fund and distribution of income is really important in terms of its effect on economical behaviors of private sector and outcomes. Public expenditures are decisive on national income and employment by its multiplier effect on the other hand affects the aggregate demand components such as private consumption expenditures (Durukaya, 2012).

There are many studies to research that public expenditures effect on the other components of economy. Blanchard and Perotti (2002) searched that public expenditures effect on the economic activities. According to this study, increase of public expenditures causes a significant increase of product, real wages and consumption whereas it causes decreasing private investment expenditures. Schclarek (2007) obtained similar findings. Fatás ve Mihov (2001) confirm that increase of public expenditures causes a permanent and significant increase of private consumption. D'Alessandro (2010) determined that public expenditures have impact with positive aspect on private consumption. Karras (1994), Hjelm (2002), Okubo (2003), Nieh and Ho (2006) and Gali et al. (2007) put forward that there is complementarity relation between public expenditures and private consumption. Taking all of these studies into account, public expenditure and its' accuracy forecasting are of vital importance with respect to the economy of countries.

Different approaches namely stochastic and non-stochastic approaches have been proposed in the literature for the analysis of time series, like this. In recent years, the use of non-stochastic models such as fuzzy time series approach for the analysis of time series has become widespread. The main advantage of fuzzy time series approaches is that they do not need assumptions that stochastic models do.

The concept of fuzzy time series was first introduced by Song and Chissom (1993 a). Fuzzy time series forecasting models consist of three steps as fuzzification, identification of fuzzy relation and defuzzification which have an influence on forecasting performance of the method. Many researchers have carried out studies using different approaches on these three steps.

In the fuzzification step, Song and Chissom (1993a, 1993b, 1994) and Chen (1996, 2002) determined fixedly interval lengths arbitrarily whereas Huarng (2001) used average and distribution based and Egrioglu et al. (2010, 2011) used optimization based methods. In addition, for the analysis of time series containing trend, a ratio-based length of intervals is proposed by Huarng and Yu (2006a). In addition, Cheng et al. (2008), Li et al. (2008), Aladag et al. (2012), Alpaslan et al. (2012), Egrioglu (2012), Egrioglu et al. (2013) and Alpaslan and Cagcag (2012) were used fuzzy C-means (FCM) and Gustafson-Kessel fuzzy clustering techniques, respectively.

Identification of fuzzy relation is the step in which the appropriate model is determined. Song and Chissom (1993a, 1993b, 1994) used fuzzy relation matrix. Chen (1996) proposed a simpler approach using fuzzy logic group relationships tables. Huarng and Yu (2006b) proposed a first-order fuzzy time series approach which uses feed-forward neural networks (FFANN) in this step. Aladag et al. (2009) proposed a high-order fuzzy time series forecasting model which uses FFANN in the determination of fuzzy relations. Yolcu et al. (2013) proposed an approach which considers the membership values and used FCM technique instead of determining the membership values subjectively.

In this study, we aim to forecast the ECGB from January 2007 to May 2013 by applying different fuzzy time series approaches. When obtained results from the different fuzzy time series approaches evaluate, it is shown that fuzzy time series approaches can be effectively used for forecasting of ECGB. The rest of this paper is designed as follows. In Section 2, the basic concepts of fuzzy time series are briefly reviewed. Section 3 gives the implementation. The last section concludes the paper.

Fuzzy Time Series

The fuzzy time series was firstly defined by Song and Chissom (1993a). The basic definitions of fuzzy time series, and time variant and time invariant fuzzy time series definitions are given below.

Definition 1 Let $Y(t)$ ($t = \ldots, 0, 1, 2, \ldots$), a subset of real numbers, be the universe of discourse on which fuzzy sets $f_j(t)$ are defined. If $F(t)$ is a collection of $f_1(t), f_2(t)$, … then $F(t)$is called a fuzzy time series defined on $Y(t)$.

Definition 2 Suppose $F(t)$ is caused by $F(t-1)$ only, i.e., $F(t-1) \rightarrow F(t)$. Then this relation can be expressed as $F(t) = F(t-1) \circ R(t, t-1)$ where $R(t, t-1)$ is the fuzzy relationship between $F(t-1)$ and $F(t)$, and $F(t) = F(t-1) \circ R(t, t-1)$ is called the first order model of $F(t)$. " ° " represents max-min composition of fuzzy sets.

Definition 3 Suppose $R(t, t-1)$ is a first order model of $F(t)$. If for any t, $R(t, t-1)$ is independent of t , i.e., for any t , $R(t, t-1) = R(t-1, t-2)$, then $F(t)$ is called a time invariant fuzzy time series otherwise it is called a time variant fuzzy time series.

Song and Chissom (1993a) firstly introduced an algorithm based on the first order model for forecasting time invariant $F(t)$. In Song and Chissom's labour, the fuzzy relationship matrix $R(t, t-1) = R$ is obtained by many matrix operations. The fuzzy forecasts are obtained based on max-min composition as below:

$$F(t) = F(t-1) \circ R \tag{1}$$

The dimension of R matrix depends on the number of fuzzy sets. The number of fuzzy sets equals to the number of intervals that compose of universe of discourse. The more fuzzy sets are used, the more matrix operations are needed for obtain R matrix. When the number of fuzzy set is high, using the method proposed by Song and Chissom (1993b) considerably increases the computational cost. In this situation, the method suggested by Song and Chissom is given as below.

Definition 4 Let $F(t)$ be a time invariant fuzzy time series. If $F(t)$ is caused by $F(t-2)$, $F(t-1)$, … , and $F(t-n)$ then this fuzzy logical relationship is represented by

$$F(t-n), \ldots, F(t-2), F(t-1) \rightarrow F(t) \tag{2}$$

and it is called the n^{th} order fuzzy time series forecasting model.

The Application

In this study, we used different fuzzy time series forecasting methods for forecasting of ECGB. These methods are Song and Chissom (1993b) - SC93b, Chen (1996) - C96, Huarng (2001) - $H01^1$ (distribution based) and $H01^2$ (average based), Chen (2002) - C02, Huarng and Yu (2006b) - HY06b, Cheng et al. (2008) - C08, Aladag et al. (2009) - A09 and Yolcu et al. (2013) - Y13. Each of these methods uses different approaches in each steps of analysis process. The graph of monthly ECGB data from January 2007 to May 2013 is given in Figure 1.

In the analysis of ECGB, we used observations of last five month as the out-of-sample observations (test data). The number of fuzzy sets and intervals are varied between 5 and 15 in the analysis of all forecasting method. The number of hidden layer of artificial neural network is taken between 1 and 12 in A09 and Y13. In addition, the model order is taken between 1 and 12 for C02 and A09.

The error criteria obtained from the case where we obtained the best results for the test data are presented in Tables 1. In these tables, RMSE, MAPE, and DA represent root mean square error, mean absolute percentage error, and direction accuracy criteria, respectively. Mentioned performance measures were calculated over the test set.

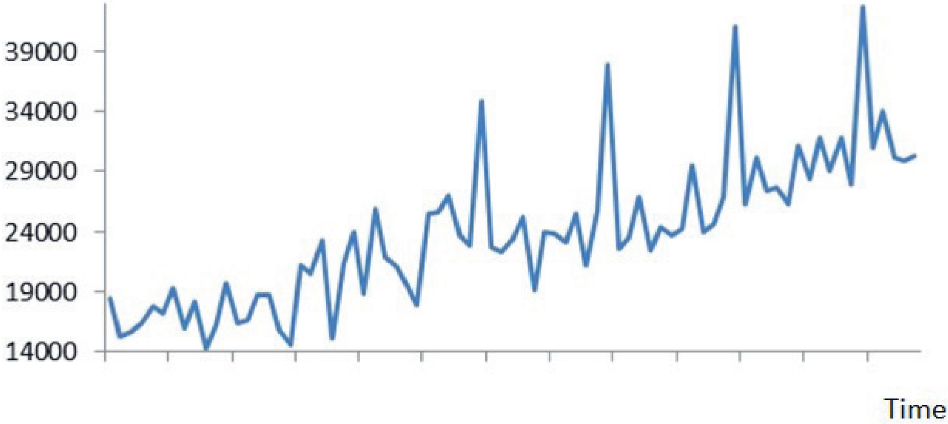

Figure 1. The graph of monthly expenditures of central government budget

Table 1 The error criteria obtained from analysis

	C93b	96	01¹	01²	02	Y06	08	09	13
MSE	479.45	614.13	708.40	384.25	686.81	216.99	577.54	95.14	18.93
APE	.98%	.91%	6.80%	6.66%	.70%	4.75%	1.94%	.93%	.30%
A	0.00%	5.00%	5.00%	0.00%	5.00%	0.00%	0.00%	5.00%	5.00%

We obtained the superlative results given in Table 1 when;

- the interval length was 2500 for the SC93b;
- the interval length was 6000 for the C96;
- the interval length was 4000 for the H01[1] (distribution based);
- the interval length was 200 for the H01[2] (average based);
- the interval length was 5000 and model order twelve for the A09;
- the ratio sample percentile was 0.5 for the H06b;
- the number of the fuzzy sets was twelve for the C08;
- the interval length was 3500, the number of the neurons in the hidden layer was five and model order twelve for the A09;
- the number of the fuzzy sets was thirteen and the number of the neurons in the hidden layer was one for the Y13.

When Table 1 is examined, it is seen that fuzzy time series approaches produce good forecasts for ECGB data. All forecasting results can also be compared to each other according to Table 1. The best results are obtained from the approaches suggested by Aladag et al. (2009) and Yolcu et al. (2013) in terms of all performance measures. The forecasting results can also be examined visually. The graph of observations and forecasts obtained from the best two methods Aladag et al. (2009) and Yolcu et al. (2013) for the test set is given in Figure 2. From this figure, it is clearly seen that the obtained forecasts are very good.

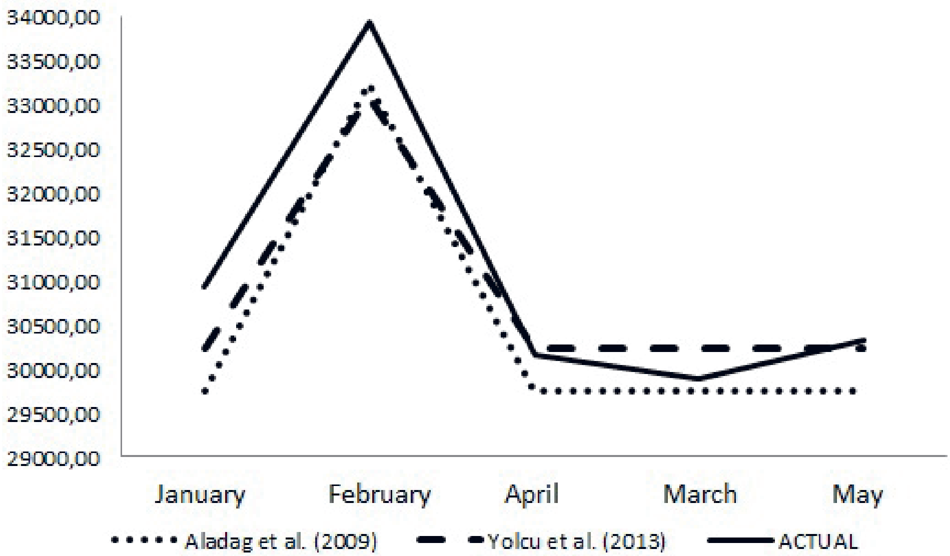

Figure 2. The graph of observations and forecasts obtained from the best two methods.

Conclusions

Public expenditure forecasting problem is an important task. Therefore, various forecasting techniques which are stochastic or non-stochastic have been used to solve public expenditure forecasting problem. The fuzzy time series approach is rarely applied for the forecast of public expenditures, and as far as we know this is the first of such attempts involving Turkish data. To accurately forecast expenditures of central government budget of Turkey, nine different fuzzy time series forecasting approaches available in the literature were applied to the data. As a result of the implementation, it was observed that fuzzy time series approach give accurate for this time series. All forecasting results obtained from these methods are compared to each other in terms of RMSE, MAPE, and DA criteria. The most accurate forecasts were obtained when methods proposed by Aladag et al. (2009) and Yolcu et al. (2013). These findings show that fuzzy time series approach is a good alternative method to forecast public expenditure time series.

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