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METHODS OF FUZZY LOGIC AS AN INSTRUMENT FOR FORECASTING OF TAX REVENUES

Summary: Updating of forecasting for tax revenues is one of the most important directions to increase the efficiency of fiscal bodies' operations within the budget process. Scientifically substantiated forecasting plays an important role both in the formation of middle-term budget revenues on different levels and is of major influence upon managerial decision-making being under way. The article deals with the comprehensive research of modified approach to forecasting budget revenues volumes based on the usage of obscure time rows (OTR). The authors presented the main terms dealing with obscure time rows, made a digest of the major known methods of OTR forecasting, described the modified approach to forecasting, and analyzed the obtained results.

Key words: forecasting of tax revenues, methods of fuzzy logic.

One of the most important directions to increase the efficiency of financial bodies' activity concerning the budget process is modernization of tax revenues forecasting. Scientifically substantiated forecasting both contributes to the middle-term revenues of local budgets and influences ultimately the on-going decision-making process.

The discrepancy of out-coming information, insufficiency of database (shortcoming data files), the unknown character of correlation between in-coming and out-coming ratios and absence of normal distribution among statistical data are viewed as substantial peculiarities of economic processes in Ukraine. The latter restricts the usage of classic methods of statistic analysis i.e. ARIMA and other mono-factor extrapolative regressive models and require the elaboration of new non-traditional approaches and methods based on ideas of artificial intellect, the main features of which are:

– possibility to process the a priori fuzziness of input data,
– enlisting quantitative and qualitative variables and criteria,
– possibility to enter expert data in the form of eventual relevance directly into the system,
– possibility to teach the fuzzy logic system and to contribute essential rules (ER) and parameters of fuzzy conclusion rules directly straight during the system application.

Theoretic methods of fuzzy sets have been applied in economics since the late 1970's. Nowadays, fuzzy logic (viewed as one of the most advanced scientific directions in analysis, forecasting, modelling of economic phenomena and processes) is Math's interpretation and diversification of classic Bull's logic being based on the partial truth concept – truth which is located somewhere between 'and' – 'there's no'. Lofti Zaden, the founder of fuzzy logic, used to emphasize that the theory of fuzzy phrases should not be postulated as an independent, separated sphere of thought [Zadeh 1965]. Hence, it is a methodological expansion of any other specific theory obtained via fuzzification of it's basic objects (e.g. numbers) i.e. their transferring from a discreet condition into a noninvertible one. The latest research has been made in the area of fuzzy calculations, fuzzy differential equations, etc.

Recently, fuzzy logic (FL) systems have been widely used [Mamdani 1974; Sugeno 1985; Zimmerman 1991; Hguen et al. 1995; Mudi 2000; Mendel 2001; Naeemi 2004]. Model of fuzzy time series is a sub-type of the fuzzy logic method [Заде 1976, Song 1993, Hwang 1996]. Some scholars claim this method has the minimum prognosis deviation. Thus, the prognosis models of fuzzy time series (FTS), suggested by Chen [1996], did not actually amend the prognosis deviation obtained in the previous model and made up some 3.23 per cent. Hwang, Chen and Lee FTS model [1998] provided relative departure of prognosis data at 3.12 per cent. Chen and Hsu [2004] succeeded to lower the average relative departure down to 0.36 per cent. Besides, the algorithms to apply the following methods were suggested by Mamedova [Мамедова 2005] and Fedorova [Федоров 2006; 2007].

Despite the fact that FL systems are being widely used, their application for the forecasting of general scientific – e.g. economic processes – is likely to be sporadic, in particular it is still obscure, which algorithms of fuzzy conclusion are most efficient for economics itself, and there is no information about the interference of rules number and quantity of values for linguistic variables upon modelling (prognosis) efficiency.

It should also be mentioned that all approaches listed-above use either university registered data or number of population for the certain country, or variations of this data without any provisional processing and obtaining additional information.

In our research project the fuzzy time series was accepted to forecast the tax revenues as a model as was mentioned before. The tax revenues to the State budget of Ukraine for the fixed period of time, i.e. dynamics and corresponding variations for the same period, are considered to be known. The task is to obtain the prognosis data of the studied ratio due to variations for the last period and to choose the most efficient prognosis model due to the corresponding number of linguistic variables.

According to the set task we applied the following prognosis algorithm:

1. Definition of the universal set U which is an interval between the smallest and largest rates of tax revenues.

2. Division of the universal set U on the same length intervals being relevant to the rates of growth of tax revenues.

3. Definition of the corresponding linguistic values of the studied variable, i.e. definition of fuzzy sets F(t).

4. Fuzzification of input data, i.e. transformation of precise cardinal values into fuzzy ones.

5. Calculation of fuzzy correlation matrix RW(t) and forecasting of tax revenues.

6. Defuzzification of the obtained results, i.e. transformation of fuzzy values into precise (cardinal) ones.

Due to the fact that the method of fuzzy time series is based on the application of linguistic variables and definition of their corresponding values, the latter are represented by a variable, which is a tax revenues surplus.

We have considered and drafted 3 prognosis models with a different number of linguistic values:

1. Application of 3 linguistic variables: average rate of revenues; low rate of revenues, high rate of revenues.

2. Application of 5 linguistic variables: very low rate of revenues; low rate of revenues, average rate of revenues; high rate of revenues, very high rate of revenues.

3. Application of 7 linguistic variables: very low rate of revenues; low rate of revenues, average rate of revenues; unchangeable rate of revenues, normal rate of revenues, high rate of revenues, very high rate of revenues.

Let us formalize and solve the problem of tax revenues forecasting. For this purpose let us take a sample for the period from October 2007 to December 2009 and accomplish the prognosis for January 2010 on its base [*Показники*…]. We have to take the following steps:

Step 1. We have to define the complete set *U*, which contains the intervals of tax revenue surplus. In Table 1 there are presented the tax revenues and their surplus in every successive month.

Table 1. Tax revenues and surplus

Date	Revenue, million UAH	Surplus, million UAH	Date	Revenue, million UAH	Surplus, million UAH
Oct/07	7 921.3		Dec/08	15 627.4	1 874.5
Nov/07	9 812.5	1 891.2	Jan/09	13 021.5	–2 605.9
Dec/07	14 133.2	4 320.7	Feb/09	9 508	–3 513.5
Jan/08	13 401.6	–731.6	Mar/09	11 642.7	2 134.7
Feb/08	9 473.7	–3 927.9	Apr/09	14 353.3	2 710.6
Mar/08	13 588.9	4 115.2	May/09	10 832.7	–3 520.6
Apr/08	11 405	–2 183.9	Jul/09	12 646.3	1 813.6
May/08	13 519.4	2 114.4	Jun/09	8 686.3	–3 960
Jun/08	18 436.9	4 917.5	Aug/09	10 887.8	2 201.5
Jul/08	11 298.2	–7 138.7	Sept/09	14 672	3 784.2
Aug/08	12 990.5	1 692.3	Oct/09	8 587.1	–6 084.9
Sept/08	20 942.1	7 951.6	Nov/09	13 289.9	4 702.8
Oct/08	13 826.9	–7 115.2	Dec/09	16 705.9	3416
Nov/08	13 752.9	–74			

Source: National Bank of Ukraine.

Universal set U has the following ultimate values of revenues: the tiniest –7138.7 and the largest – 7951.6. We have to expand the set ultimate measures (during the next step the set will be divided into 3 intervals) and obtain U = [–7140; 7953].

Step 2. We have to divide the set U into 3 same length intervals whose length equals 5031 million UAH.

$U = \{u_1, u_2, u_3\}$: u_1 = [–7140; –2109], u_2 = [–2109; 2922], u_3 = [2922; 7953]. These intervals are bisected by points: $\bar{u}_1 = -4624.5$; $\bar{u}_2 = 406.5$; $\bar{u}_3 = 5437.5$.

Step 3. We have to define the sets of fuzzy sets in universal set U. At this stage we will introduce a linguistic variable and define the corresponding values of this variable. Linguistic variable (tax revenues surplus) can have the following values:

– low (negative) revenue surplus (NRS),
– average (low) revenue surplus (LRS),
– high revenue surplus (HRS).

Every linguistic variable corresponds to fuzzy variable:

‹NRS, [–7140; –2109], A_1›,
‹LRS, [–2109; 2922], A_2›,
‹HRS, [2922; 7953], A_3›.

Fuzzy sets in complete set U are defined by means of the following independent function:

$$\mu_{A_t}(u_j) = \frac{1}{1 + (0.0001(V_t - \bar{u}_j))^2}, \qquad (1)$$

where: V_t – numeric values of tax revenue surplus in month t,
j – index of interval for surplus values ($j = \overline{1,3}$).

Fuzzy sets are presented by:

$$A_1 = \{(1/u_1), (0.8/u_2), (0.5/u_3)\},$$

$$A_2 = \{(0.8/u_1), (1/u_2), (0.8/u_3)\},$$

$$A_3 = \{(0.5/u_1), (0.8/u_2), (1/u_3)\},$$

where V_t gradually represents average values of intervals.

Step 4. We have to transform precise cardinal values of revenue surplus into fuzzy ones. We will run fuzzification of tax revenues surplus for every month from November 2007 to December 2009 and obtain fuzzy sets of revenue surplus – $A^{11.07}$, $A^{12.07}$, …, $A^{12.09}$, whose attachment functions are calculated analytically by formula (1) (Table 2).

Table 2. Fuzzification of revenue surplus

Date	Revenue, million UAH	Surplus, million UAH	Fuzzification of tax revenues surplus
10.07	7 921.3	–	–
11.07	9 812.5	1 891.2	$A^{11.07}=\{(0.7/u_1),(0.98/u_2),(0.89/u_3)\}$
12.07	14 133.2	4 320.7	$A^{12.07}=\{(0.56/u_1),(0.87/u_2),(0.99/u_3)\}$
01.08	13 401.6	–731.6	$A^{01.08}=\{(0.87/u_1),(0.99/u_2),(0.72/u_3)\}$
02.08	9 473.7	–3 927.9	$A^{02.08}=\{(1/u_1),(0.84/u_2),(0.53/u_3)\}$
03.08	13 588.9	4 115.2	$A^{03.08}=\{(0.57/u_1),(0.88/u_2),(0.98/u_3)\}$
04.08	1 1405	–2 183.9	$A^{04.08}=\{(0.94/u_1),(0.94/u_2),(0.63/u_3)\}$
05.08	13 519.4	2 114.4	$A^{05.08}=\{(0.69/u_1),(0.97/u_2),(0.9/u_3)\}$
06.08	18 436.9	4 917.5	$A^{06.08}=\{(0.52/u_1),(0.83/u_2),(1/u_3)\}$
07.08	11 298.2	–7 138.7	$A^{07.08}=\{(0.94/u_1),(0.64/u_2),(0.39/u_3)\}$
08.08	12 990.5	1 692.3	$A^{08.08}=\{(0.71/u_1),(0.98/u_2),(0.88/u_3)\}$
09.08	20 942.1	7 951.6	$A^{09.08}=\{(0.39/u_1),(0.64/u_2),(0.94/u_3)\}$
10.08	13 826.9	–7 115.2	$A^{10.08}=\{(0.94/u_1),(0.64/u_2),(0.39/u_3)\}$
11.08	13 752.9	–74	$A^{10.08}=\{(0.83/u_1),(1/u_2),(0.77/u_3)\}$
12.08	15 627.4	1 874.5	$A^{12.08}=\{(0.7/u_1),(0.98/u_2),(0.89/u_3)\}$
01.09	13 021.5	–2 605.9	$A^{10.09}=\{(0.96/u_1),(0.92/u_2),(0.61/u_3)\}$
02.09	9 508	–3 513.5	$A^{02.09}=\{(0.99/u_1),(0.87/u_2),(0.56/u_3)\}$
03.09	11 642.7	2 134.7	$A^{03.09}=\{(0.69/u_1),(0.97/u_2),(0.9/u_3)\}$
04.09	14 353.3	2 710.6	$A^{04.09}=\{(0.65/u_1),(0.95/u_2),(0.93/u_3)\}$
05.09	10 832.7	–3 520.6	$A^{05.09}=\{(0.99/u_1),(0.87/u_2),(0.55/u_3)\}$
06.09	12 646.3	1 813.6	$A^{06.09}=\{(0.71/u_1),(0.98/u_2),(0.88/u_3)\}$
07.09	8 686.3	–3960	$A^{07.09}=\{(1/u_1),(0.84/u_2),(0.53/u_3)\}$
08.09	10 887.8	2 201.5	$A^{08.09}=\{(0.68/u_1),(0.97/u_2),(0.91/u_3)\}$
09.09	14 672	3 784.2	$A^{09.09}=\{(0.59/u_1),(0.9/u_2),(0.97/u_3)\}$
10.09	8 587.1	–6 084.9	$A^{10.09}=\{(0.98/u_1),(0.7/u_2),(0.43/u_3)\}$
11.09	13 289.9	4 702.8	$A^{11.09}=\{(0.53/u_1),(0.84/u_2),(0.99/u_3)\}$
12.09	16 705.9	3 416	$A^{12.09}=\{(0.61/u_1),(0.92/u_2),(0.96/u_3)\}$

Source: own calculations.

Step 5. We have to forecast the tax revenues in fuzzy logic symbols.

The prognosis will be carried out on the basis of the mentioned-above sample. We have to calculate the fuzzy correlation matrix $R(t)$, which is an intersection of two fuzzy sets represented by the matrix of fuzzy tax revenues surplus $S(t)$ while $(t-2)$, $(t-3)$, …, $(t-22)$) – month and matrix of fuzzy tax revenues surplus at $(t-1)$ – a month correspondingly:

$$R(t)[i,j] = S(t)[i,j] \cap N(t)[i,j] = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1j} \\ r_{21} & r_{22} & \cdots & r_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ r_{i1} & r_{i2} & \cdots & r_{ij} \end{bmatrix}.$$

Now we have to calculate the forecast value of tax revenue surplus for t month in the form of fuzzy set:

$$F(t) = \left[\max(r_{11}, r_{21}, ..., r_{i1}) \max(r_{12}, r_{22}, ..., r_{i2}) ... \max(r_{1j}, r_{2j}, ..., r_{ij}) \right].$$

Thus for September 2009

$$S(09.09) = \begin{bmatrix} 0.7 & 0.98 & 0.89 \\ 0.56 & 0.87 & 0.99 \\ 0.87 & 0.99 & 0.72 \\ 1 & 0.84 & 0.53 \\ 0.57 & 0.88 & 0.98 \\ 0.94 & 0.94 & 0.63 \\ 0.69 & 0.97 & 0.9 \\ 0.52 & 0.83 & 1 \\ 0.94 & 0.64 & 0.39 \\ 0.71 & 0.98 & 0.88 \\ 0.39 & 0.64 & 0.94 \\ 0.94 & 0.64 & 0.39 \\ 0.83 & 1 & 0.77 \\ 0.7 & 0.98 & 0.89 \\ 0.96 & 0.92 & 0.61 \\ 0.99 & 0.87 & 0.56 \\ 0.69 & 0.97 & 0.9 \\ 0.65 & 0.95 & 0.93 \\ 0.99 & 0.87 & 0.55 \\ 0.71 & 0.98 & 0.88 \\ 1 & 0.84 & 0.53 \end{bmatrix} R(09.09) = \begin{bmatrix} 0.68 & 0.97 & 0.89 \\ 0.56 & 0.87 & 0.91 \\ 0.68 & 0.97 & 0.72 \\ 0.68 & 0.84 & 0.53 \\ 0.57 & 0.88 & 0.91 \\ 0.68 & 0.94 & 0.63 \\ 0.68 & 0.97 & 0.9 \\ 0.52 & 0.83 & 0.91 \\ 0.68 & 0.64 & 0.39 \\ 0.68 & 0.97 & 0.88 \\ 0.39 & 0.64 & 0.91 \\ 0.68 & 0.64 & 0.39 \\ 0.68 & 0.97 & 0.77 \\ 0.68 & 0.97 & 0.89 \\ 0.68 & 0.92 & 0.61 \\ 0.68 & 0.87 & 0.56 \\ 0.68 & 0.97 & 0.9 \\ 0.65 & 0.95 & 0.91 \\ 0.68 & 0.87 & 0.55 \\ 0.68 & 0.97 & 0.88 \\ 0.68 & 0.84 & 0.53 \end{bmatrix}$$

$$N(09.09) = \begin{bmatrix} 0.68 & 0.97 & 0.91 \end{bmatrix},$$
$$F(09.09) = \begin{bmatrix} 0.68 & 0.97 & 0.91 \end{bmatrix}.$$

The same way we will calculate the forecast value of tax revenue surplus for the rest of the month:

$$F(10.09) = \begin{bmatrix}0.59 & 0.90 & 0.97\end{bmatrix},$$

$$F(11.09) = \begin{bmatrix}0.98 & 0.70 & 0.43\end{bmatrix},$$

$$F(12.09) = \begin{bmatrix}0.53 & 0.84 & 0.99\end{bmatrix},$$

$$F(01.10) = \begin{bmatrix}0.61 & 0.92 & 0.96\end{bmatrix}.$$

Step 6. Transformation of fuzzy values for tax revenues surplus into precise values.

We will conduct the defuzzification of tax revenue surplus by formula:

$$V(t) = \frac{\sum_{j=1}^{3} F_t(u_j)\overline{u}_j}{\sum_{j=1}^{3} F_t(u_j)} \tag{2}$$

where $F_t(u_j)$ – value of the attachment function for *t* month, calculated in step 5.

Thus, for September 2009

$$V(09.09) = \frac{0.68 \times (-4624.5) + 0.97 \times 406.5 + 0.91 \times 5437.5}{0.68 + 0.97 + 0.91} = \frac{2161.3}{2.56} = 845.5$$

million UAH.

Now we will add the obtained value of tax revenue surplus to that value of tax revenue surplus in August 2009 and get the forecast value:

F(09.09) = 10887.8 + 845.5 = 11733.3 mln UAH Absolute approximation deviation:

$$A_{09.09} = \left|\frac{Y(09.09) - F(09.09)}{F(09.09)}\right| \times 100\% = \left|\frac{14672 - 11733.3}{14672}\right| * 100\% = 20.03\%.$$

The same way we will calculate the tax revenue surplus, the forecast value of tax revenue surplus and absolute approximation deviations for the following months:

October 2009 : $V(10.09) = 1200.2$, $F(10.09) = 15872.2$, $Y(10.09) = 8587.1$, $A_{10.09} = 84{,}84\%$,

November 2009 : $V(11.09) = -902.3$, $F(11.09) = 7684.8$, $Y(11.09) = 13289.9$, $A_{11.09} = 42.18\%$,

December 2009 : $V(12.09) = 1381.2$, $F(12.09) = 14671.1$, $Y(12.09) = 16705.9$, $A_{12.09} = 12{,}18\%$.

Average approximation deviation: A = 39.81%.

The forecast values of tax revenue surplus will be:

$V(01.10) = 1121.9$, $F(01.10) = 17827.8$ million UAH.

We will calculate the forecast values for models with 5 and 7 linguistic variables the same way. Calculation results and the corresponding approximation deviation are presented in the next table:

Table 3. Estimated values for data-based models

Period	Data	Forecast data	Deviation	Average deviation
3 linguistic variables				
09.09 10.09 11.09 12.09 01.10	14 672 8 587.1 13 289.9 16 705.9 –	11 733.3 15 872.2 7 684.8 14 671.1 17 827.8	0.2003 0.8484 0.4218 0.1218 -	0.3981 or 39.81 per cent
5 linguistic variables				
09.09 10.09 11.09 12.09 01.10	14 672 8 587.1 13 289.9 16 705.9 –	11 743.5 15 891.0 7 656.6 14 699.9 17 845.0	0.1996 0.8506 0.4239 0.1201 -	0.3985 or 39.85 per cent
7 linguistic variables				
09.09 10.09 11.09 12.09 01.10	14 672 8 587.1 13 289.9 16 705.9 –	11 744.9 15 897.0 7 626.5 14 706.0 17 849.1	0.1995 0.8513 0.4262 0.1197 -	0.3992or 39.92 per cent

Source: own calculations.

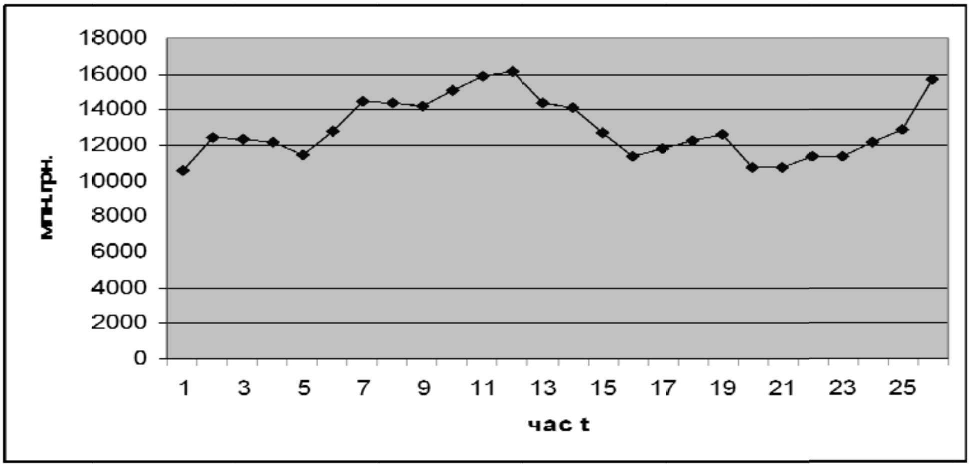

Figure 1. Fuzzificated with trinomial sliding average tax revenues

Source: [*Показники…*].

As it can be seen, absolute average deviation in each of the listed models is 39 per cent which proves their satisfactory fidelity [Дуброва 2003]. Hence, it can be connected with considerable fluctuations of dynamic series levels. To clarify development trends and minimize fluctuations of series levels, we will fuzzificate the time series by trinomial sliding average. The results are displayed in Figure 1.

We will calculate the forecast values for the models with a different number of linguistic variables using the mentioned algorithm [Sugeno 1985; Hguen et al. 1995; Mendel 2001]. The calculation results and corresponding approximation deviation are shown in Table 4.

Table 4. Calculated values for the models built on the fuzzificated data

Data	Forecast data	Deviation	Average deviation
3 linguistic variables			
11 382.30	11 997.31	0.0540	0.0628 or 6.28 per cent
12 183.00	11 552.75	0.0517	
12 860.97	12 839.00	0.0017	
15 699.80	13 444.44	0.1437	
–	17 232.31	–	
5 linguistic variables			
11 382.30	12 026.2	0.0566	0.0639 or 6.39 per cent
12 183.00	11 506.0	0.0556	
12 860.97	12 880.9	0.0016	
15 699.80	13 473.7	0.1418	
–	17 243.5	–	
7 linguistic variables			
14 672	12 029.4	0.0569	0.0639 or 6.39 per cent
8 587.1	11 507.0	0.0555	
13 289.9	12 883.9	0.0018	
16 705.9	13 476.9	0.1416	
–	17 200.0	–	

Source: own calculations.

Having analyzed the information mentioned above, we can come to the following conclusions:

1. Methods of prognosis using the means of FTS model make it possible to forecast the tax revenues under conditions of the discrepant fuzzy data.

2. Application of different number of linguistic variables does not affect the quality of prognosis model. Either in the first (Table 3) or the second (Table 4) case average absolute deviation does not vary in successive models.

3. It should also be noted that in the case of the excessive fluctuation of dynamic series levels, one has to accomplish the relevant transformations i.e. fuzzification of time series, to create a successful prognosis model.

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METODA LOGIKI ROZMYTEJ JAKO NARZĘDZIE DO PROGNOZOWANIA DOCHODÓW PODATKOWYCH

Streszczenie: Jednym z głównych kierunków wzrostu efektywności pracy organów finansowych dotyczących procesu budżetowania jest poprawa prognozowania wpływów z podatków. Naukowo udowodniona prognoza odgrywa istotną rolę nie tylko w kształtowaniu dochodo-

wej części budżetów na dowolnym poziomie w średnim okresie, ale ma również zasadniczy wpływ na podejmowanie decyzji dotyczących zarządzania w trakcie ich realizacji. Wśród istotnych cech procesów ekonomicznych w gospodarce Ukrainy możemy wyróżnić niekompleksowość informacji wstępnych, ograniczoność danych (krótkie próby), brak danych dotyczących charakteru relacji pomiędzy zmiennymi wejściowymi i wyjściowymi oraz brak rozkładu normalnego wśród danych statystycznych. Te cechy ograniczają zastosowanie klasycznych metod analizy statystycznej, między innymi modelu ARIMA oraz innych ekstrapolacyjnych modeli autoregresji z jedną zmienną. Co więcej, wymagają opracowania nowych, nietradycyjnych rozwiązań i metod opartych na idei sztucznej inteligencji, do których możemy zaliczyć metody logiki rozmytej. W niniejszej pracy zostało przedstawione zmodyfikowane podejście do prognozowania wpływów podatkowych, które polega na wykorzystaniu rozmytych szeregów czasowych. Zaprezentowano główne terminy dotyczące rozmytych szeregów czasowych, dokonano przeglądu najbardziej znanych metod prognostycznych z wykorzystaniem rozmytych szeregów czasowych, opisano zmodyfikowane podejście prognozowania oraz dokonano analizy otrzymanych wyników.