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Forecasting the Unemployment Rate: Application of Selected Prediction Methods

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Abstract:

Purpose: *Unemployment rate prediction has become critically significant, because it can be used by governments to make decision and design accurate policies. The paper's main objective is to compare the most significant predictive methods for modeling the unemployment rate.*
Design/Methodology/Approach: *In this work, the selected predictive methods (naive method, regression model, ARIMA, Holt model and Winters model) were described, developed and compared using data collected by Central Statistical Office.*
Findings: *The considered methods enable to predict the unemployment rate with high accuracy. The results of experiments allow to conclude that the most suited methods of forecasting the unemployment rate are the quadratic regression model and the Winters multiplicative model.*
Practical Implications: *Forecasting the unemployment rate is one of the important elements in economy and presented methods can be easily used by labor market entities to predict and verify the situation in the market.*
Originality/Value: *Forecasting the unemployment rate is an extremely difficult and demanding task, but on the other hand, it can be an effective tool that supports planning processes. The conducted research showed the quadratic regression model and the Winters multiplicative model provide high accuracy in terms of modeling the unemployment rate*

Keywords: *Forecasting, time series, regression model, ARIMA, Winters model.*

JEL classification: *C01, C22, C53.*

Paper Type: *Research paper.*

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1. Introduction

Unemployment is a social phenomenon where some people who are able to work and who declare taking it up cannot find employment (Begg *et al.,* 1994; Kłos, 2014; Kwiatkowski, 2002). This phenomenon is, therefore, the result of a maladjustment of supply and demand in the labor market. It also illustrates the situation on the labor market in the country. The issue of unemployment and counteracting it is one of the most important social problems. Public debate is devoted not only to the effects of unemployment, but also to the search for effective ways to reduce this phenomenon in the future (Budzyńska, 2007; Nehring, 2010). There are some barriers to finding effective methods, including, the lack of reliable information about the labor market, and the attempts made by the Institute of Labor and Social Affairs do not have certain reliability (Kryńska, 2001; Kryńska *et al.,* 1998). Building an appropriate tool for forecasting the unemployment phenomenon requires many years of observation and systematic data collection.

Developed countries have labor market models based on which they predict the demand for workers in various configuration, and their results are often used in regional politics (Błaszkiewicz, 2015; Gruchociak, 2013). Such a procedure helps candidates to properly prepare for work even several years in advance, which may reduce the number of unemployed, which results from the mismatch between employees' competences and the needs of the labor market. The unemployment rate reflects the situation on the labor market in the country. Economic growth affects the creation of new jobs, which implies an increase in employment, while a slowdown in the economy reduces the demand of enterprises for work, leading in consequence to an increase in unemployment (Gawrycka, 2006; Kuczewska, 2013).

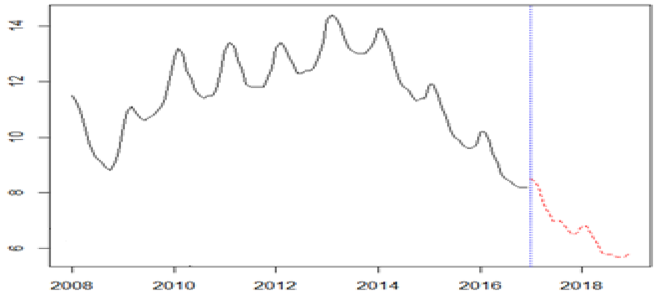
Forecasting the unemployment rate is one of the important elements allowing economic entities in the labor market to reduce the uncertainty resulting from the socio-economic situation of the country (Chakraborty *et al.,* 2021; Błażejowski, 2009; Głuszczuk, 2016). In the face of changes, as well as the impact of structural factors, it becomes more and more complicated to make decisions regarding the day-to-day functioning of employees, employers and trade unions, as well as the actions of public authorities to solve the problem of unemployment (Li *et al.,* 2014; Xu *et al.,* 2013).

Therefore, attempts to predict future trends and phenomena that will take place in the labor market are more and more difficult, both for the long-term and short and medium-term horizons (Kucharski, 2015). However, the monitoring of the labor market itself seems to be a much less complicated process due to the access to indicators describing the market, made available by the system of official statistics. One of the indicators enabling the analysis of unemployment is the unemployment rate calculated by the Central Statistical Office. According to the Central Statistical Office, the unemployment rate in Poland is currently low and has remained at a low level for a long time. Forecasting phenomena occurring in the labor market helps labor market entities to verify and initiate a development path aimed at meeting the expected state in the future (Jakimiuk, 2017). It also provides a wealth of information and knowledge on which to base strategic thinking and acting in the sphere of public management (Frączek and Laurisz, 2010).

2. Data

Data collected by the Central Statistical Office in 2008-2018 were used for the analysis. The data refer to monthly unemployment rates for the period from January 1, 2008 to December 31, 2018. In order to be able to reliably assess the accuracy of forecasts and their comparison, the data set has been divided into two parts: train and test. It is usually assumed that the training set accounts for about 80% of all observations of the series. Therefore, it was decided that with the total number of 132 observations collected from the Central Statistical Office, the first 108 observations were used to construct models and forecasts, and the remaining 24 observations were used to assess the accuracy of forecasts. The division into the training and test part is shown in Figure 1, and the basic descriptive statistics of the data set used for the analysis are presented in Table 2.

Figure 1. *A series of the unemployment rate divided into training and test parts.*



Source: *Own preparation.*

Table 1. *Basic descriptive statistics.*

	Minimum	**1st Quartile**	**Median**	**Mean**	**3rd Quartile**	**Maximum**
Total	5,7	9,05	11,3	10,61	12,43	14,4
Train set	8,2	10,28	11,7	11,49	12,9	14,4
Test set	5,7	5,8	6,6	6,675	7	8,5

Source: *Own preparation.*

3. Selected Forecasting Methods

3.1 Naive Methods

Naive methods are based on simple premises that relate to the future. This means that changes will not occur in the current way of influencing the factors that determine the values of the forecast variable. These methods make it possible to construct short-term forecasts for one period ahead. They also assume that there will be no significant changes in the most important factors in the series under study. They can be used when there are small random fluctuations in the series of the forecast variable. Naive methods are easy and quick to apply, but the quality of forecasts with their use is usually low.

The best known of these methods is to construct a forecast for a period *t* at the level of the observed value of the forecast variable at the moment *t-1* (Cieślak, 2005). This model takes the following form:

$$\boldsymbol{y_t^* = y_{t-1}}, \qquad (1)$$

where:
y_t^* - the forecast of the variable *Y* determined for the period *t*,
y_{t-1} - the value of the forecast variable *Y* in the period *t-1*.

3.2 Trend Model

In the development of trend models, there is a development tendency and random fluctuations, and the time variable is the explanatory variable. The temporal variable is not a direct cause of changes in the values of the predicted variable, but summarizes the effect of unknown factors and provides the opportunity to describe these changes in a quantitative manner. It exists in the form of a sequence of natural integers that represent successive moments or periods to which the values of the time series of the forecast variable correspond. The model notation looks as follows:

$$\boldsymbol{y_t = f(t) + \varepsilon_t}, \qquad t = 1,\ldots,n, \qquad (2)$$

where:
f(t) - time (trend) function that characterizes the development tendency of the series,
ε_t - random variable, it characterizes the effects of the impact of random fluctuations on the forecast variable.

The main task of determining the function *f(t)* is called time series smoothing. This is done by determining the form of the function characterizing the development tendency of the series and determining its parameters. The determination of the trend function is finding the function *f(t).* The hypothesis determining the form of the function can be based on theoretical premises that refer to a specific development mechanism of a variable. Determining this mechanism will determine the analytical form of the trend. The most common form of a trend function is a linear function:

$$\boldsymbol{y_t = \alpha + \beta t}, \qquad (3)$$

It represents a constant direction of development of the studied phenomenon, which is determined by the slope of the straight line (*β*). This parameter is the coefficient of constant increment of the value of the forecast variable over a time unit. In many situations, the use of linear trend functions is incorrect. In some cases, the more complex functions should be used, for example the function of a second order polynomial, which has the advantage of high flexibility. It results from having three parameters, thanks to which the model better reflects various non-linear development trends. An example of the form of a function for a second order polynomial is given by the formula:

$$y_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2, \quad \alpha_2 > 0. \tag{4}$$

This function may be appropriate for the construction of short-term forecasts, long-term forecasts involve the risk of constructing forecasts that are burdened with large errors (Cieślak, 2005).

3.3 ARIMA Class Models

A significant part of economic time series are non-stationary series. Non-stationarity can be caused, for example, by the presence of a trend and seasonal fluctuations. They can be eliminated by including the mentioned factors in the equation or by differentiation. As a result of calculating the differences in the time series, the stationarity of the tested process is achieved. It is then assumed that the process is integrated to a degree *d* (Borkowski and Krawiec, 2009; Borkowski and Marcinkowski 1999; Osińska 2006). ARIMA models are a very general class of time series, and their structure is based on the autocorrelation phenomenon (Ramli *et al.,* 2018; Stoklasová 2012). They can be used to model stationary or non-stationary time series. There are three basic types of models in this class, autoregressive (AR) models, moving average (MA) models, and mixed autoregressive and moving average (ARMA) models. The letter I used in the name means that the time series was subjected to the differentiation operation (Chrabołowska and Nazarko, 2003; Pawełek, 2013). The ARIMA model is written with the use of notations specifying the order of the individual components of the model. Thus, the ARIMA model (p, d, q) is an autoregressive process of the *p* order, a moving average of the *q* order and integrated to the *d* degree. This model can be written as:

$$\Delta^d Y_t = c + \alpha_1 \Delta^d Y_{t-1} + \ldots + \Delta^d Y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_q \varepsilon_{t-q}. \tag{5}$$

Forecasting with the ARIMA model is iterative. It starts with the analysis of the time series structure, and then it is necessary to select an appropriate model and verify it. The adoption of the ARIMA model does not exclude non-stationarity with respect to the mean value. There are no unambiguous methods that would allow unambiguous differentiation of non-stationarity in terms of mean or variance. The inclusion of the trend in the model eliminates systematic fluctuations with the longest period, and the differentiation of the series allows to remove the trend in the mean and variance (Borkowski and Krawiec, 2009). The Akaike information criterion can be used to compare ARIMA class models to select the best one. Among the different values of this criterion for selected model variants, the one for which the value has the lowest value is selected (Piłatowska, 2010).

3.4 Holt's Linear Model

If there is a development trend in the series, the linear Holt model can be used to smooth it. The first order polynomial is used to describe the development trend in the Holt model. This model is represented by the following equations:

$$\boldsymbol{F_{t-1} = \alpha y_{t-1} + (1-\alpha)(F_{t-2} + S_{t-2})} \quad (6)$$

and

$$\boldsymbol{S_{t-1} = \beta(F_{t-1} - F_{t-2}) + (1+\beta)S_{t-2},} \quad (7)$$

where:
F_{t-1} - the smoothed value of the predicted variable per moment or period *t-1,*
S_{t-1} - the smoothed value of the trend increment per moment or period *t-1,*
α,β - the model parameters with values between 0 and 1.

α, β parameters can be treated as a percentage of taking into account the errors of previous forecasts. α refers to the value of the variable, and β to the trend increment. Determining the values of these parameters consists in carrying out a series of experiments using various combinations of the values of these parameters, and then selecting the one that minimizes the average error of expired forecasts (Cieślak, 2005; Witkowska *et al.*, 2012). Assuming *t>n* moment or period forecast equation has the following form:

$$\boldsymbol{y_t^* = F_n + (t-n)S_n, \qquad t > n,} \quad (8)$$

where:
y_t^* - forecast value of variable Y determined for the moment or period *t,*
F_n - the smoothed value of the predicted variable at the moment *n,*
S_n - the smoothed value of the trend increment per moment or period *n,*
n – the number of elements in the time series of the variable being forecasted.

3.5 Winters Model

The Winters model can be used in the case of time series containing a development trend, periodic (seasonal) fluctuations and random fluctuations. This model is available in an additive or multiplicative version, in the first case it is expressed by equations:

$$F_{t-1} = \alpha(y_{t-1} - C_{t-1-r}) + (1-\alpha)(F_{t-2} + S_{t-2}), \quad (9)$$

$$S_{t-1} = \beta(F_{t-1} - F_{t-2}) + (1+\beta)S_{t-2}, \quad (10)$$

$$C_{t-1} = \gamma(y_{t-1} - F_{t-1}) + (1-\gamma)C_{t-1-r} \quad (11)$$

and in the second:

$$F_{t-1} = \alpha\left(\frac{y_{t-1}}{C_{t-1-r}}\right) + (1-\alpha)(F_{t-2} + S_{t-2}), \quad (12)$$

$$S_{t-1} = \beta(F_{t-1} - F_{t-2}) + (1+\beta)S_{t-2}, \quad (13)$$

$$C_{t-1} = \gamma\left(\frac{y_{t-1}}{F_{t-1}}\right) + (1-\gamma)C_{t-1-r} \quad (14)$$

where:
F_{t-1} - the smoothed value of the predicted variable per moment or period *t-1,* after eliminating seasonal fluctuations,
S_{t-1} - the smoothed value of the trend increment per moment or period *t-1,*
C_{t-1} - an assessment of the seasonality index for a moment or period *t-1,*
α,β,γ - the smoothing constants for the trend level, trend changes and seasonal fluctuations, respectively, and take a value from 0 to 1.

Forecast equation for the additive version of the model per moment or period *t>n* is presented by the following formulas.

$$y_t^* = F_n + S_n(t-n) + C_{t-r} \quad (15)$$

$$y_t^* = [F_n + S_n(t-n)]C_{t-r}, \quad (16)$$

where *n* is the number of terms in the time series of the variable being forecasted (Cieślak, 2005; Zagdański and Suchwałko 2016).

The choice of the additive and multiplicative version depends primarily on the nature of the seasonality. If the seasonal changes remain at a similar level, then the additive model is chosen, while if the amplitude of changes increases or decreases, then the multiplicative model

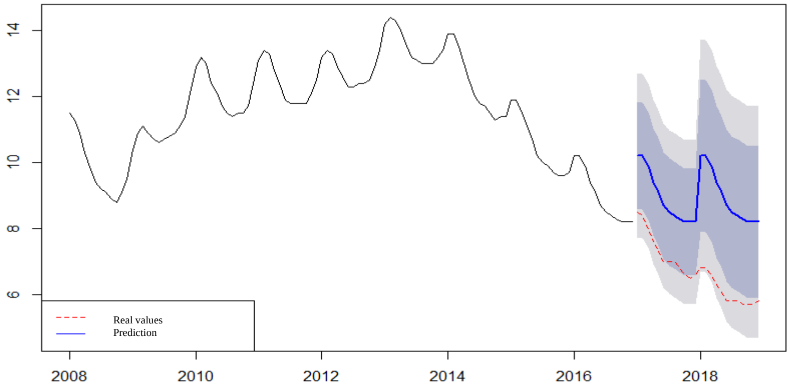
4. Results

One of the main tasks of the analysis of the unemployment rates is to forecast its future values on the basis of the past ones (Hanias *et al.*, 2012). Forecasts, as the final step in the forecasting process, are to provide reasonable information about the future development of a given phenomenon.

4.1 Forecasting Using the Naive Method

In the naive method, it is assumed that the selected value of the observations in the series is the best forecast for the next, unknown value of this series. Figure 2 shows a comparison of the forecast with the actual values. The length of the time horizon was determined on the basis of the number of observations in the test set. The forecasted values differ significantly from the real values and this may indicate large prediction errors. The forecast errors for the naive method are presented in Table 2. The MAPE and MPE values for the test set confirm the previous conclusions, the average difference between the forecasted and actual values is high and amounts to approx. 35%.

Figure 2. *The forecast determined on the basis of the naive method.*



Source: *Own preparation.*

Table 1. *Forecast errors for the naive method.*

Naive method	MAE	RMSE	MAPE	MPE
Test set	2,27	2,36	35,02	-35,02
Train set	1,07	1,27	9,72	-1,83

Source: *Own preparation.*

4.2 Forecasting Using a Model with a Quadratic Trend

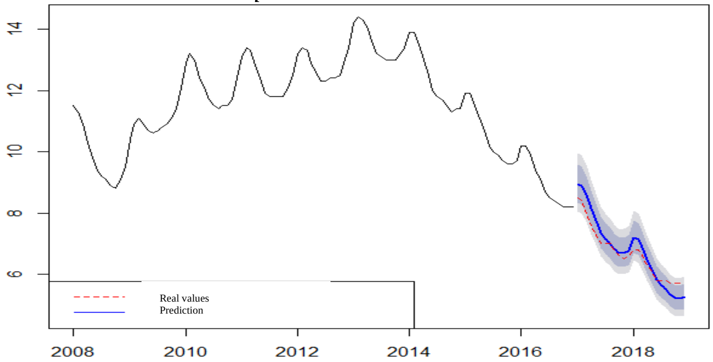
Figure 3 shows the forecast based on the quadratic trend model. The forecast errors for the training and test set are shown in Table 3. Figure 3 clearly shows that the forecasts made on the basis of the quadratic trend model agree with the real values. This model reflects well the trend and seasonal fluctuations in the series. Forecast errors for the quadratic trend model, compared to the naive method, are much smaller and can be considered satisfactory. This is also evidenced by the MAPE value, which is lower than the forecast acceptability value of 5%, and the remaining errors are close to 0.

Table 3. *Forecast errors for the quadratic trend model.*

Quadratic trend model	MAE	RMSE	MAPE	MPE
Test set	0,30	0,35	4,41	-1,01
Train set	0,42	0,53	3,61	-0,10

Source*: Own preparation.*

Figure 3. *Forecast based on the quadratic trend model.*

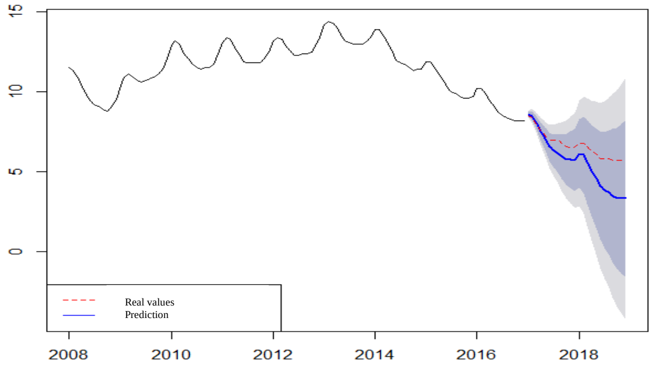


Source: *Own preparation.*

4.3 Forecasting with the Use of ARIMA Models

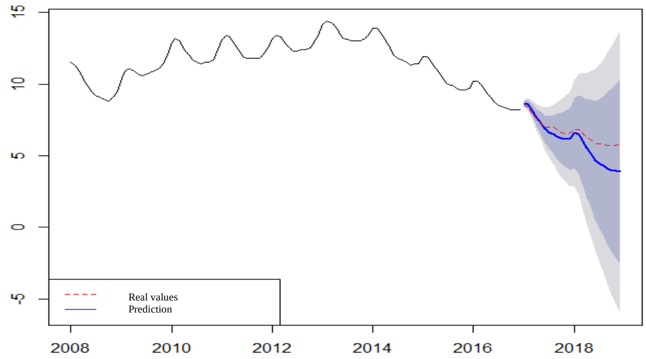
On the basis of the conducted research, it was found that the following ARIMA models will be used to forecast the unemployment rate: ARIMA model with seasonality taken into account (ARIMA (1,1,2) (0,1,0)) and ARIMA auto (ARIMA (3,1,1) (2,1,0)). Figure 4 shows the forecasts and prediction intervals for the auto ARIMA model, and Figure 5 for the ARIMA model. Comparing the graphs, it can be seen that despite a better fit of the auto ARIMA model to the data, the forecasts for this method seem to be slightly worse than the forecasts obtained with the ARIMA model. This may mean that the forecast errors for the ARIMA model will turn out to be smaller than for the ARIMA auto model. In order to more precisely compare the forecasts for both models, they are presented in one graph (Figure 6).

Figure 4. *Forecast and predictive intervals for the auto ARIMA model.*



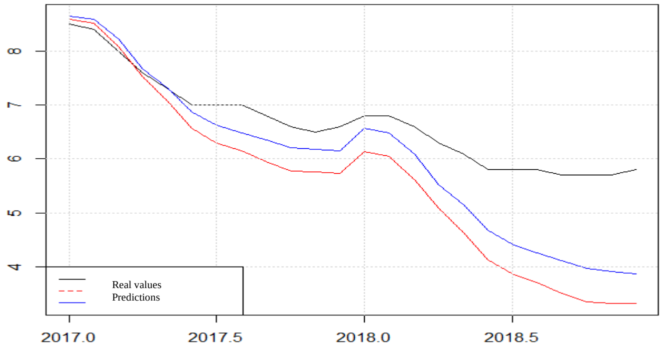
Source: *Own preparation.*

Figure 5. *Forecast and prediction intervals for the ARIMA model.*



Source: *Own preparation.*

Figure 6. *Comparison of forecasts for unemployment rates, determined on the basis of ARIMA models.*



Source: *Own preparation.*

Figure 6 shows that the ARIMA model fits the data better than the ARIMA auto model. As for other methods of forecast construction, prediction errors for ARIMA models were determined and presented in Tables 4 and 5. The results confirm the earlier assumptions. The forecast errors for the ARIMA model, selected on the basis of expert knowledge, are smaller than the forecast errors determined for the ARIMA auto model. This may be due to the fact that the model fitted on the basis of the automatic parameter selection procedure requires diagnostic verification in terms of the correctness of fit, therefore the model selected on the basis of expert knowledge in this situation turned out to be a better suited model.

Table 4. *Forecast errors for the auto ARIMA model*

Auto ARIMA	MAE	RMSE	MAPE	MPE
Test set	1,09	1,34	17,79	17,5
Training set	0,07	0,01	0,62	-0,04

Source: *Own preparation.*

Table 5. Forecast errors for the ARIMA model

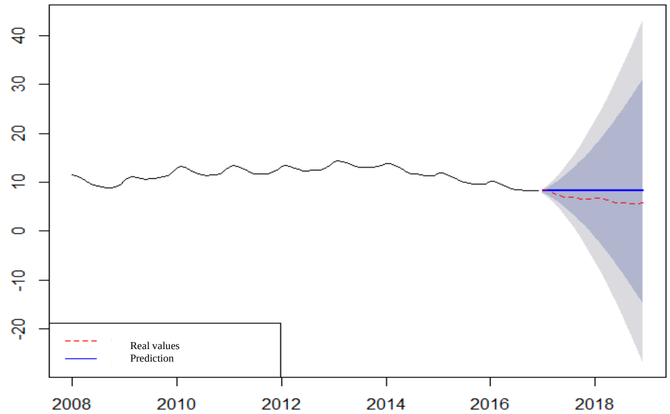
ARIMA	MAE	RMSE	MAPE	MPE
Test set	0,71	0,94	11,77	11,10
Training set	0,09	0,11	0,74	-0,06

Source: *Own preparation.*

4.4 Forecasting using the Holt's Model

The values of α nad β parameters have been selected with an accuracy of 0.0001 by minimizing the value of the mean square error of the forecasts. The optimal values of the coefficients were determined using the automatic parameter selection procedure available in the R package, and the following values were obtained: α=β=0,9926. Figure 6 shows that the obtained forecasts differ significantly from the actual values. In the case of Holt's linear model, attention is also drawn to the wider prediction ranges that increase with the forecast horizon. Large values of the MAPE and MPE criteria may be the result of not taking into account seasonal fluctuations in the Holt's linear model. Large error values may also be related to the long-term forecast horizon. Holt's linear model is most often used for short-term forecasting up to 12 months. The predictions obtained using the Holt's method can therefore be considered erroneous.

Figure 6. *Forecasts and prediction ranges for the linear Holt's model.*



Source: *Own preparation.*

Table 6. Forecast errors for the linear Holt's model.

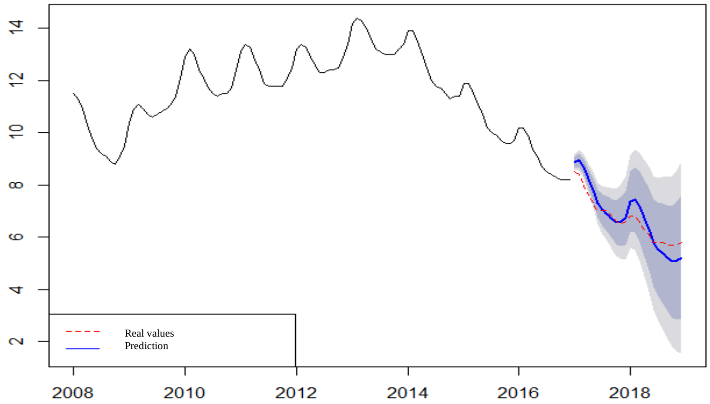
Holt	MAE	RMSE	MAPE	MPE
Test set	1,58	1,74	25,24	-24,75
Train set	0,20	0,25	1,70	0,11

Source: *Own preparation.*

4.5 Forecasting using the Winters Model

As in Holt's linear model, α, β and γ parameters have been selected with an accuracy of 0.0001 by minimizing the value of the mean square error of the forecasts, using the procedure of automatic selection of coefficients available in the R package. The values of α, β and γ parameters are respectively: 0.6391, 0.1397, 0.2493. In Figure 7, it can be seen that the forecasts obtained on the basis of the Winters additive model reflect the studied series much better than Holt's linear model. The forecast errors for the additive model are shown in Table 7. The forecasts can be considered acceptable if, for the MAPE coefficient, the critical value is assumed at the level of 10%.

Figure 7. *Forecast for the unemployment rate series based on the additive Winters model.*



Source: *Own preparation.*

Table 7. *Forecast errors for the Winters additive model.*

Additive Winters	MAE	RMSE	MAPE	MPE
Test set	0,38	0,44	5,68	-0,997
Train set	0,11	0,14	0,99	0,09

Source: *Own preparation.*

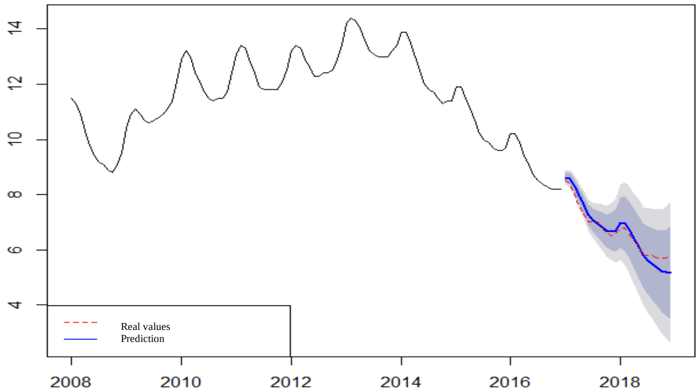
Seasonal fluctuations may follow the trend in an additive or multiplicative manner. The multiplicative model is used less frequently for forecasting than the additive model. This is due to the assumption that the relative increments of the trend value for the explained variable change in a regular manner or are constant. Forecasts based on Winters' multiplicative model for parameters α = 0,6120, β = 0,1407 and γ = 0,2607, were used in this paper to compare their values with the forecasts made with the use of the additive model. The forecasts based on the multiplicative model are presented in Table 8.

Table 8. *Forecast errors for the Winters multiplicative model.*

Multiplicative Winters	MAE	RMSE	MAPE	MPE
Test set	0,21	0,27	3,32	0,38
Train set	0,11	0,15	0,95	0,12

Source: *own preparation.*

***Figure 8**. Forecast for a series of unemployment rates based on Winters' multiplicative model.*



***Source:** Own preparation.*

Comparing the forecast errors for the additive model and the multiplicative model, it can be noticed that the forecasts determined on the basis of the Winters additive model are burdened with a slightly greater error than the forecasts determined on the basis of the multiplicative model. Smaller criteria values (MAE, RMSE, MAPE, MPE) for the multiplicative method show its advantage over the additive method.

4.6 Forecasts Comparison

Table 9 shows all the methods used to forecast the unemployment rate and forecast errors for the training and test sets. When analyzing the table below, it can be seen that the errors for the test set are sometimes greater than those for the train set. This is due to the fact that assessing the accuracy of forecasts only on the basis of the training set may lead to an unreliable summary, therefore it is also important to compare the errors on the test set. For the test set, assuming that the forecast acceptability coefficient is 5%, the best results were achieved using the multiplicative Winters models and the quadratic trend model. On the other hand, when analyzing the error values for the training set, the best results were achieved with the auto ARIMA model, although the forecast values for the test set raise some controversy.

The value of the MAPE criterion for the above-mentioned model is one of the largest in the statement and exceeds each of the assumed forecast acceptability thresholds (5%, 10%, 15%), the same is true in the case of the MPE error. Very good results on both the train and test set were achieved with the quadratic trend model. The difference between the MAPE values for this method was 0.8 pp. As far the Winters multiplicative model, this difference is small (for the multiplicative model the difference was 2.37 pp), which may indicate a good fit of the model to the data. The forecast made with the Winters additive model also turned out to be quite satisfactory. The forecast errors are slightly greater than the errors for the quadratic trend model, and the MAPE value can be considered appropriate assuming that it is not greater than 10%.

Table 9. *Forecast errors for the test and train set for selected methods (horizon = 24).*

Method	MAE		RMSE		MAPE		MPE	
	Test set	Train set	Test set	Train set	Test set	Train set	Test set	Train set
Naive method	-2,27	1,07	2,36	1,27	35,02	9,72	-35,02	-1,83
Quadratic trend model	0,3	0,42	0,35	0,53	4,41	3,61	-1,01	-0,1
Auto ARIMA	1,09	0,07	1,34	0,01	17,79	0,62	17,5	-0,04
ARIMA	0,71	0,09	0,94	0,11	11,77	0,74	11,1	-0,06
Holt	1,58	0,2	1,74	0,25	25,24	1,7	-24,75	0,11
Additive Winters	0,38	0,11	0,44	0,14	5,68	0,99	-0,997	0,09
Multiplicative Winters	0,21	0,11	0,27	0,15	3,32	0,95	0,38	0,12

Source: *Own preparation.*

In many cases, the errors on the train and test sets do not coincide with the predetermined maximum acceptability of forecasts (15%). The worst model turned out to be Holt's linear model, which confirmed the earlier observations that high error values may be the result of not taking into account seasonal fluctuations in the model. In the previous chapter, it was considered that the predictions obtained using the Holt method can be considered erroneous. Based on the presented results, the following can be considered as acceptable models: the quadratic trend model and the Winters multiplicative model

5. Concluding Remarks

The aim of the study was to develop a forecast of the unemployment rate in Poland and to test its accuracy in comparison to historical data. The naive method, trend models, autoregressive and linear Holt’s models and Winters models were used to forecast the unemployment rate. The analysis used data collected by the Central Statistical Office. The data concerned monthly unemployment rates for the period from January 1, 2008 to December 31, 2018. In order to be able to reliably assess the accuracy of forecasts and their comparison, the data set has been divided into two parts: training and testing. For the time horizon of 24 months, the best models turned out to be: the multiplicative Winters model and the model with a quadratic trend.

Forecasting the unemployment rate is an extremely difficult and demanding task, but on the other hand, it can be an effective tool that supports planning processes. However, the conducted study does not completely solve the above problem, because it is difficult to obtain a forecast whose result would perfectly reflect the actual value. There are many predictive models, but no perfect predictions. Each of them is burdened with a greater or lesser error caused by random factors, but it is possible to analyze the quality and acceptability of forecasts.

In this study, in the case of selected methods, the errors of most of the forecasts were within the admissibility limits, so they could be considered admissible. The work uses the most popular time series models, although the comparison of modern predictive models such as regression trees, neural networks or deep-learning models seems to be an extremely interesting issue. Such an analysis may constitute a further continuation of the research presented in this paper.

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