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Non-classical Algorithm for Time Series Prediction of the Range of Economic Phenomena With Regard to the Interaction of Financial Market Indicators

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The aim of the article is to present non-clasical copyrighted algorithm for prediction of time series, presenting macroeconomic indicators and stock market indices. The algorithm is based on artificial neural networks and multi-resolution analysis (the algorithm is based on Daubechies wavelet). However, the main feature of the algorithm, which gives a good quality of the forecasts, is all included in the series analysis division into, a few partial under-series and prediction dependence on a number of other economic series. The algorithm used for the prediction, is copyrighted algorithm, labeled M.H-D in this article. Application of the algorithm was performed on a series presenting WIG 20. The forecast of WIG 20 was conditional on trading the Dow Jones, DAX, Nikkei, Hang Seng, taking into account the sliding time window. As an example application of copyrighted model, the forecast of WIG 20 for a period of two years, one year, six month was appointed. An empirical example is described. It shows that the proposed model can predict index with the scale of two years, one year, a half year and other intervals. Precision of prediction is satisfactory. An average absolute percentage error of each forecast was: 0.0099%—for two-year forecasts WIG 20; 0.0552%—for the annual forecast WIG 20; and 0.1788%—for the six-month forecasts WIG 20.

Keywords: macroeconomic indicators, stock index, forecasting, wavelet, neural network, wavelet transform, Daubechies wavelet

Introduction

The algorithm for the prediction of time series presenting macroeconomic indicators and stock market indices—M.H-D[1], was based on neural networks and the wavelet analysis, Daubechies wavelets. However, the main feature of the algorithm is to divide the analyzed series into several partial under-series and prediction dependence on a number of other economic series with the appropriate sliding time window (Hadaś, 2005, 2006, 2010; Hadaś-Dyduch, 2013).

Basing the projections presenting a series of stock market index or other macroeconomic indicator on

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[1] In order to simplify the descriptions and comments original model for the prediction of time series presenting macroeconomic indicators and stock market indices designated as the M.H-D.

stock market indices has extensive justification. It is related in particular to the fact that:

(1) Level of economic activity is influenced by the stock market. This is in particular due to the creation of liquidity by the stock market.

According to this logic profitable investments in real assets, usually it is associated with long-term commitment of capital, while investors fear a long-term commitment savings. The liquidity of the stock market reduces cited concerns and provides opportunities for growth. Competitive exchange markets favor increasing the efficiency of the allocation, which also affect the economic growth on a global scale.

(2) Economy affects the stock market by:

- Investors' reactions to the results published by listed companies;
- The reactions of investors about macroeconomic data;
- The reactions of investors led by the state of macroeconomic policies. Investors react to predicted future results, and therefore in accordance with this approach and share price indices, which should be in relation to changes in business behave in the way ahead.

(3) Stock price increase leads to an increase in investment, for example, according to the so-called q-theory, an increase in stock prices means that higher and higher companies' value exceeds their replacement value, and in this situation, managers react in a way that they make additional investments, which increases the demand for investment in the economy.

Literature Review

Prediction of macroeconomic indicators and stock market indices can be determined on the basis of various models, for example, they may be determined on the basis of the forecast models based on autoregression VAR models, and Factor-Augmented Victor Autoregression (FAVAR). In addition, a tool providing synthetic information is a dynamic factor model Dynamic Factor Model (DFM) (Stock & Watson, 2002b). The technique of combining information from a large data set using factor models is used in macroeconomic analysis to solve many fundamental research issues. Examples include inference of a synthetic state of the market or the economy based on disaggregated data (Forni & Lippi, 1997; Del Negro & Otrok, 2007) and modeling monetary policy reaction to information from a large data set (Bernanke & Boivin, 2003; Boivin & Giannoni, 2006). Factor models are also used to construct the ranks of series unobservable directly, such as core inflation, or "pure" inflation (Cristadoro, Forni, Reichlin, & Veronese, 2005; Szyszko, 2009). Common factors as explanatory variables can be basically used as short-term forecasting of the state of economy, including GDP (Giannone, Reichlin, & Small, 2008; Schumacher, 2007) and the state of the economy (Forni & Reichlin, 1998; Aruoba, Diebold, & Scotti, 2008). Factor models have also become a popular tool for monitoring current and short-term forecasting of inflation, for example, in the USA (Stock & Watson, 2002b; Forni, Hallin, Lippi, & Reichlin, 2005; Gavin & Kevin, 2006), in Canada (Gosselin & Tkacz, 2008), in the euro area (Marcellino, Stock, & Watson, 2003) and in Poland (Kotłowski, 2008).

One of the methods of forecasting and series analysis is wavelet transform (Wang & Shan, 2001; Papagiannaki, Taft, Zhang, & Diot, 2005). The starting point for the analysis of wavelet analysis is multi-resolution analysis. Generally, the multi-resolution analysis is implemented based on Mallat's algorithm (Mallat, 1999), which corresponds to the computation of the discrete wavelet transform. Several approaches have been proposed for time-series prediction by the wavelet transform, based on a neural network (Bashir & El-Hawary, 2000; Zheng, Starck, Campbell, & Murtagh, 1999; Lotri˘c, 2004). In views of Zheng et al. (1999)

and Soltani, Boichu, Simard, and Canu (2000), the undecimated Haar transform was used.

This paper proposes a new combined prediction, using Daubechies wavelet with a sliding time window. Moreover, in contrast to previous work, a division of series into under-series is proposed.

Research Methods—Description of Copyright Prediction Model M.H-D

The proposed model M.H-D time series prediction presenting macroeconomic indicators and stock market indices consists of four main stages (see Figure 1), presented graphically in the following figures.

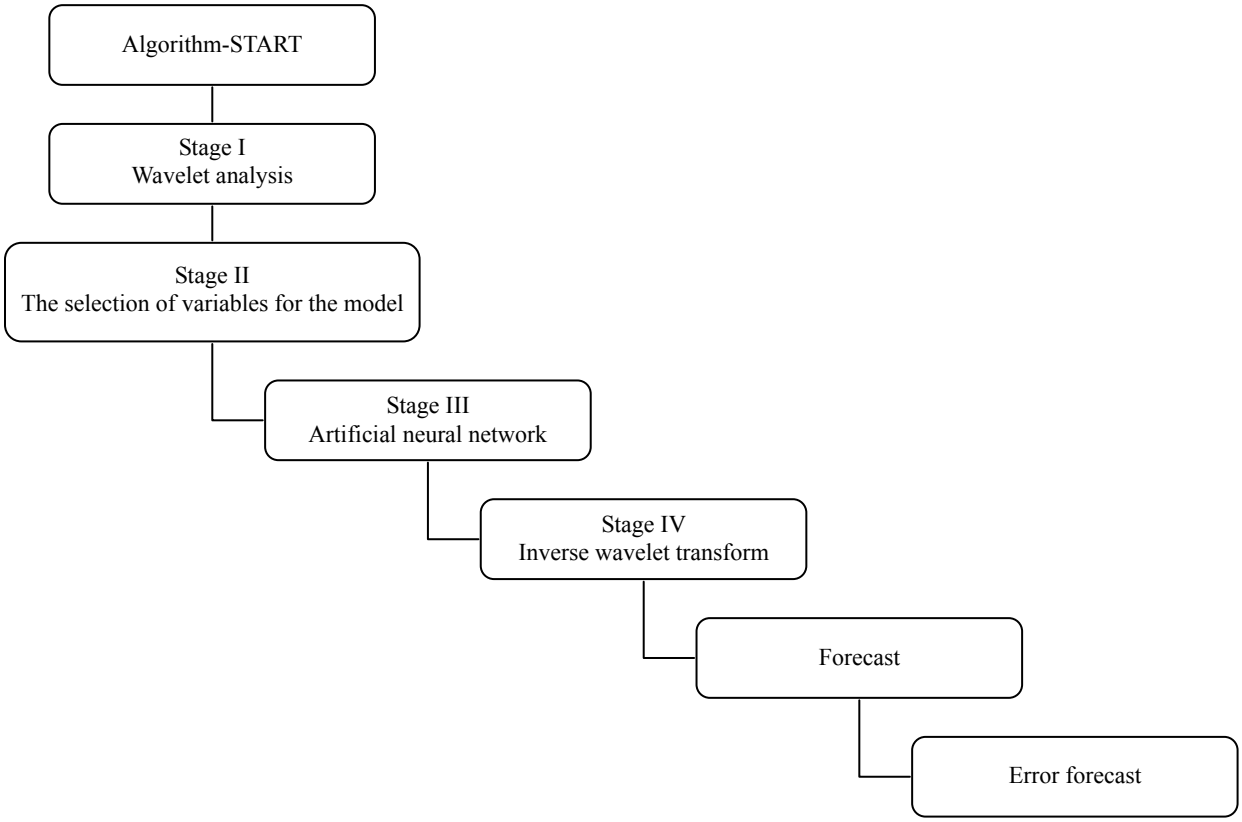

Figure 1. Schematic copyright prediction model M.H-D. Source: Own.

The first stage of the proposed model, shown in Figure 2, can be called a wavelet analysis. It aims to generate scaling functions and wavelets, in this case the Daubechies wavelets. Generated Daubechies wavelet is necessary in subsequent steps, particularly the stage in which the wavelet coefficients are determined for the series of the selected study. Generating scaling functions and wavelets begins with determining the value of the scaling function for integers, which is necessary in determining the value of this function across the field and then the Daubechies wavelets (Hadaś, 2008; Dyduch, 2009).

The second stage shown in Figure 3, the preparation stage, is mainly intended for time series study. During this stage all the operations that precede the process of building the model are proceeded including the standardization of time series. This step involves examining the accuracy and nature of raw data and their operationalization. All the data must be transformed into a suitable form if necessary. In addition, in order to obtain accurate results, each series must be divided into series so-called under-series, samples with an even number of observations, the multiple of two.

Properly prepared ranks, or more precisely under-series are subject to the operation of wavelet transform, after fixing the coefficients of wavelet transform. As a result, wavelet transform for each under-series, is obtained wavelet coefficients of selected under-series at different levels of resolution, which are necessary in learning process about artificial neural network.

In the next step we initialize the model of artificial neural network and execute it according to the diagram shown in Figure 4.

At the output of an artificial neural network we get the coefficients of wavelet transform for future observations of the test series. The wavelet coefficients obtained via inverse wavelet transform operation gain the values of real numbers, i.e., the numbers of future values for a pointed time interval forecasts.

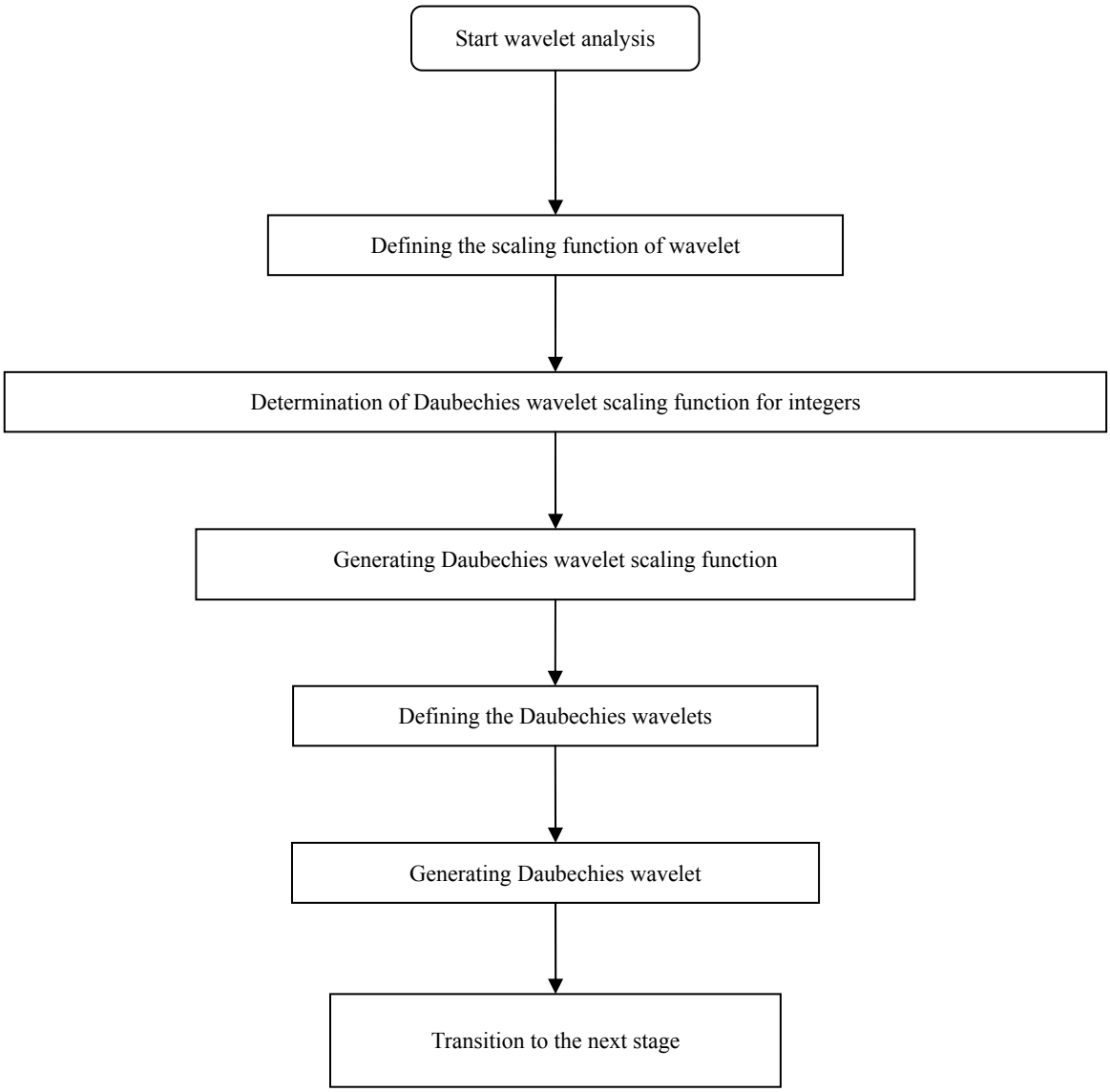

Figure 2. Schematic of a first stage of the algorithm M.H-D. Source: Own.

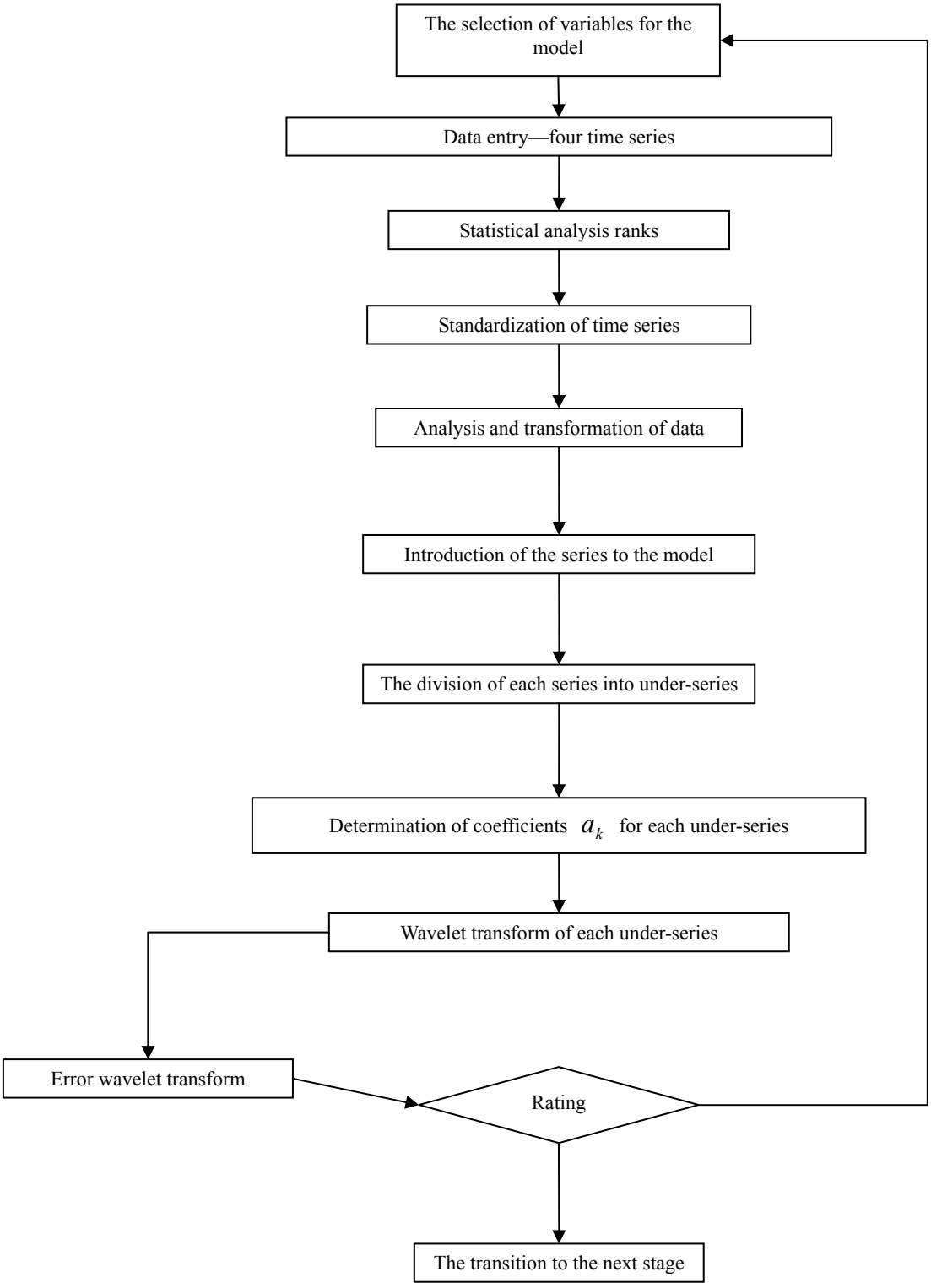

Figure 3. Schematic of the second stage of the algorithm M.H-D. Source: Own.

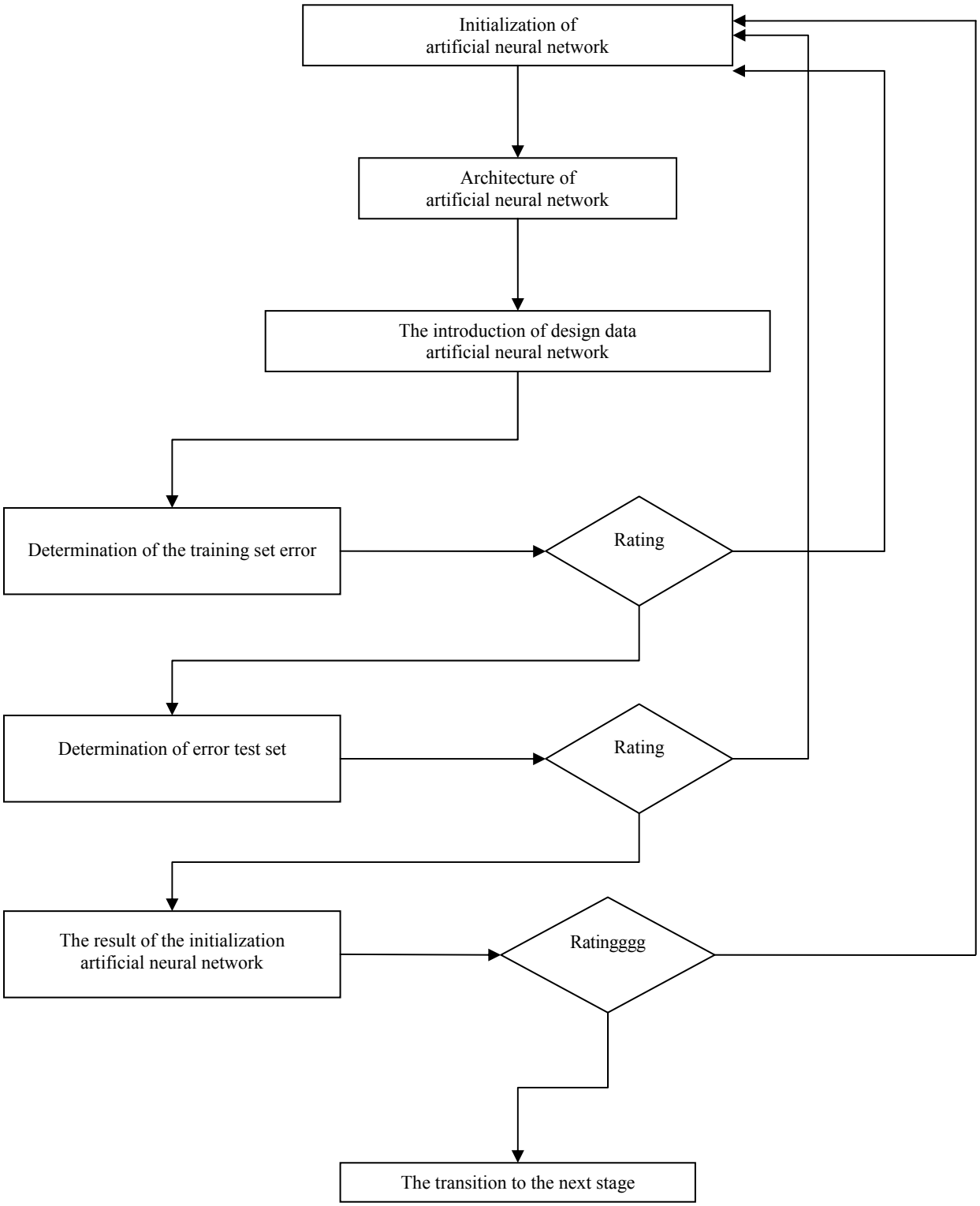

Figure 4. Schematic of the third stage of the algorithm M.H-D. Source: Own.

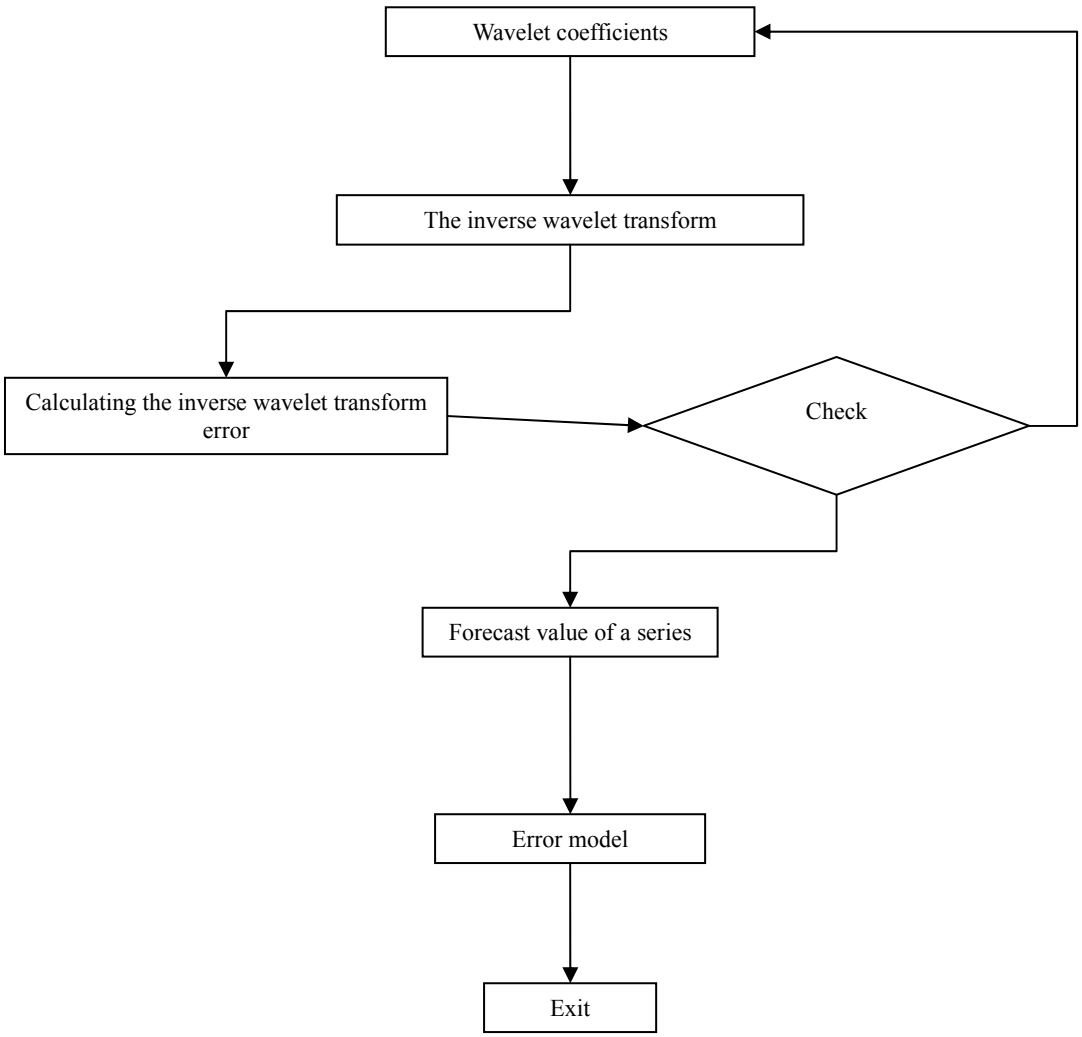

Figure 5. Schematic of the fourth stage of the algorithm M.H-D. Source: Own.

Research Results—The Application of Copyright Prediction Model

Application of the M. H-D model was made for numbers presenting the WIG 20. Prediction is made for a period of two years, one year and a half.

Prediction of the numbers of WIG 20 of the M.H-D algorithm is based on the Japanese, German, American, Polish, and Chinese stock market indices. In simple terms it can be said that on the basis of archival records of Dow Jones, DAX, Nikkei, Hang Seng future values of the WIG 20 index algorithm M.H-D were generated.

The ranks of Dow Jones, DAX, Nikkei, Hang Seng, and WIG 20 studies included in the daily quotations are from the period of the year April 23, 2014-September 16. The ranks are not equipotential and therefore, the standardization of time was done.

After presenting the relevant standardization ranks indexes: Dow Jones, DAX, Nikkei, Hang Seng, WIG 20 and extracting the test set, each series entering into the algorithm M.H-D contains 4,116 observations. Each of the five series was divided into under-series, so-called samples with an even number of observations, which

are multiples of two. There are many possibilities, in which several series of two-element, four-element, eight-element, sixteen-element, etc. under-series can be created. In *n*-series division into under-series:

- 2-piece, 2058 under-series of 2-elements are obtained;
- 4-piece, 1029 under-series 4-elements are obtained;
- 8-piece, 514 under-series 8-elements are obtained;
- 16-piece, 257 under-series 16-elements are obtained;
- 32-piece, 128 under-series 32-elements are obtained;
- 64-piece, 64 under-series 64-elements are obtained;
- 128-piece, 32 under-series 128-elements are obtained.

In the application model, there was adopted the division of each series into two-piece under-series, *n*-th series is:

- Under-series 1 series *n*: 1 observation, 2 observation *n*-th series;
- Under-series 2 series *n*: 3 observation, 4 observation *n*-th series;
- Under-series 3 series *n*: 5 observation, 6 observation *n*-th series;

…

- Under-series 2058 series *n*: 4115 observation, 4116 observation *n*-th series.

For each under-series formed from the original *n*th series, there were determined wavelet coefficients, and then having values of wavelet coefficients for each under-series—artificial neural networks were initialized. The starting point for the initialization of an artificial neural network is a division of data into training set and test. Adopted breakdown of data on these collections are arbital, however, consistent with the rule that the training set is the most numerous and the manner of assigning the following items to the collections of the learner and the test is the same for each series of data.

As the input of artificial neural network there were wavelet coefficients for appropriate under-series. That is, the network was taught on archived data Dow Jones, DAX, Nikkei and Hang Seng shifted in time of two years, a year, six month in relation to the WIG 20. At the entrance of artificial neural network there are given semi-annual forecasts: Wavelet coefficients under-series received from the ranks of the Dow Jones, DAX, Nikkei, Hang Seng, shifted with half a year, and wavelet coefficients under-series algorithm, therefore, M.H-D wavelet coefficients generated a series of WIG 20 for a specified period of the forecast.

The study was divided into sets of learners and the test was considered taking into account the percentage of the expected length of the forecast. Three strategies were adopted:

(1) For a two-year forecasts WIG 20:

- A training set 87.61%;
- A set of test 12.39%.

(2) For the annual forecast WIG 20:

- A training set 94.19%;
- A set of test 5.81%.

(3) For the six-month forecasts WIG 20:

- A training set 97.10%;
- A set of test 2.90%.

A multi-layered network consisting of 70 hidden layers, 20 inputs, and four outputs was designed for testing artificial neural network.

Analysis or Discussion

Average absolute percentage error of wavelet coefficients (the division series listed on two-factor under-series with one level of resolution, the network designed for 70 hidden layers):

(1) For a two-year forecasts WIG 20 were:

- For the test set: 0.0029315%;
- For the output file: 0.0027005%.

(2) for annual forecast wig 20 were:

- For the test set: 0.000239%;
- For the output file: 0.002695%.

(3) for the six-month forecasts wig 20 were:

- For the test set: 0.36829%;
- For the output file: 0.00516%.

Having generated the coefficients of wavelet transform for the future value of the WIG 20 index for the highlighted time periods (one year, half a year, two years) algorithm was used for inverse wavelet transform. The result of inverse wavelet transform, Daubechies wavelets were future values, i.e., the value of the forecast range of WIG 20 respectively for a period of one year, two years, and a half.

An average absolute percentage error of each forecast was:

- 0.0099%—for the two-year forecasts WIG 20;
- 0.0552%—for the annual forecast WIG 20;
- 0.1788%—for the six-month forecasts WIG 20.

Conclusions

The paper presents an original method for time series forecasting based on artificial neural networks and wavelet transform—wavelet Daubechies, including a sliding time window. It also analyzed the distribution of ranks for under-series *n*-elements.

The presented results show that the use of a model based on wavelet analysis and artificial neural networks is justified in the light of the analyzed data. The results show that the proposed M.H-D algorithm can be used for long term prediction, as obtained forecast errors are relatively small. They are in the range from 0.0099% to 0.1788%. In comparison to other time series models, such as AR, MA, or ARMA, the precision of prediction is not the decline trend when the forecasting scale is extended.

It can be concluded that the presented model can be an effective tool for forecasting stock indices and macroeconomic indicators, the prediction is very difficult due to the complexity of the mechanism of these markets, especially the factors affecting the markets.

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