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Multi-classifier based on Elliott wave's recognition

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ABSTRACT

This article deals with prediction by means of Elliott wave recognition. Our goal is to find and recognize important Elliott wave patterns which repeatedly appear in the market history for the purpose of prediction of subsequent trader's action. The pattern recognition approach is based on neural networks. We focus on reliability of Elliott wave pattern recognition made by the developed algorithms which also causes the reduction of the calculation costs.

1. Introduction

The main topic of the article is to develop and optimize the pattern recognition algorithm in order to recognize Elliott wave patterns in time series for the purpose of prediction. Elliott wave patterns are not exact, they are slightly different every time they appear. They can have a different amplitude and different duration, albeit visually the same pattern can look different despite being the same. Moreover, these patterns do not cover every time point in the series, but are optimized so that the developed classifier would be able to learn their key characteristics and accurately recognize them. Such optimized inputs also reduce calculation costs. One of the important challenges is to recognize the input pattern reliably.

Recent studies show that Elliott wave patterns might implicate useful information for stock price forecasting. Currently, there are mainly two kinds of pattern recognition algorithms: an algorithm based on rule-matching [1] and an algorithm based on template-matching [2,3]. Nonetheless, both of these two categories have to design a specific rule or template for each pattern. However, both types of algorithms require the participation of domain experts and lack the ability to learn. For the last few decades, neural networks have been shown to be good candidates for solving problems with market analysis. A typical illustration is the study conducted in [4], where a recognition algorithm for triangle patterns based upon a recurrent neural network was introduced.

Elliott wave patterns can be classified into two categories: continuation patterns and reversal patterns. Continuation patterns indicate that the market price is going to keep its current movement trend; while reversal patterns indicate that the market price will move to the opposite trend. Elliott patterns can be seen as a sort of map which helps us to orientate in certain situations and navigate us to profitable trades.

We focus on prediction by means of Elliott wave's recognition. The article proposes the Elliott waves pattern recognition approach based on a backpropagation neural network. We use an interdisciplinary approach (see Fig. 1), which consists of artificial neural networks, Elliott wave theory and knowledge modeling.

2. Elliott wave-pattern recognition

Elliott wave theory is a form of market analysis based on the theory that market patterns repeat and unfold in cycles. Ralph Nelson Elliott developed this theory in the 1930s. Elliott argued that upward and downward market price action was

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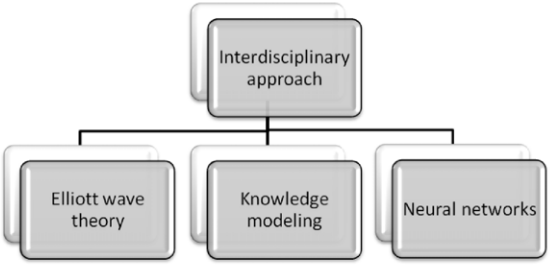

Fig. 1. Our interdisciplinary approach.

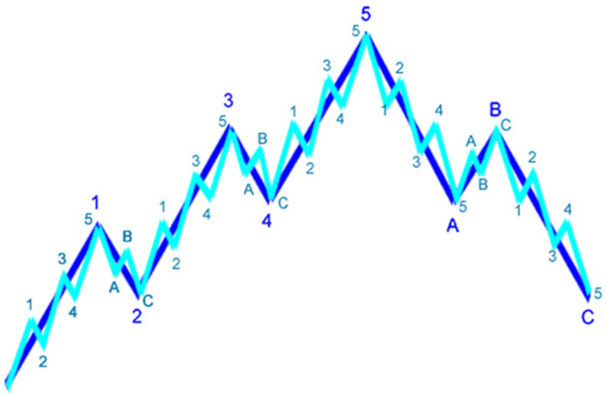

Fig. 2. The fractal character of Elliott wave patterns.
Source: Adapted from Ref. [6].

based on mass psychology and always showed up in the same repetitive patterns. These patterns were divided into what Elliott called "waves". According to Elliott, crowd psychology moves from optimism to pessimism and back again and this is seen in the price movements of market trend which are identified in waves. The Elliott wave theory assumes that a market moves up in a series of five waves and down in a series of three waves. Elliott concluded that markets' moves are not random but follow repetitive cycles driven by mass psychology. The repetitive cycles show up in waves. A wave is a movement in the market either upwards or downwards. Elliott discovered two basic types of wave patterns, impulse waves consisting of five waves and three smaller corrective waves. Impulse waves move in the direction of the main market trend. The corrective wave moves in the opposite direction of the main market trend. Elliott labeled five impulse wave patterns to describe various stages of mass psychology. The waves are subdivided into five smaller waves [5]. Generally, waves three and five are with the trend and two and four are corrections within the trend (Fig. 2).

- *Wave one*—its trend and sentiment is overwhelmingly negative but a few buyers emerge as the market starts to move up. This wave is marked by limited public participation.
- *Wave two* corrects wave one and does not extend beyond the starting point of wave one. The news is negative but shows signs of improving and some early buyers look to take profits, not convinced of the viability of the trend. In wave two, public participation has increased.
- *Wave three* is usually the most powerful wave. There is more positive news and prices begin to rise quickly. The public looks to get on board.
- *Wave four* is corrective and offers an opportunity to buy the market on a pullback. Early buyers look to take profits and some who missed the early move look at the pullback to get into the market.
- *Wave five* is the last stage of the dominant trend. Mass psychology is universally positive reaching euphoric stage and the market becomes over priced. The public are heavy buyers of the market in this stage. The market is ripe for a trend change.

Elliott also concluded that markets move in a three-wave corrective pattern. The corrective wave pattern is normally referred to as the ABC correction [5]. The A wave is hard to identify. In wave B, prices reverse higher. In wave C, prices move lower. Generally wave A and C are trend corrections and wave B a countertrend move within the correction. These waves are known as corrective (Fig. 2).

One of the basic tenets of Elliott wave theory is that market structure is fractal in its character. Elliott wave patterns that show up on long term charts are identical, and will also show up on short term charts, albeit with sometimes more complex structures. This property of fractals is called "self-similarity" or "self-affinity" and it is what this writer is referring to when he says that the market is fractal in character. Elliott waves are fractals because fractal is a geometric object that

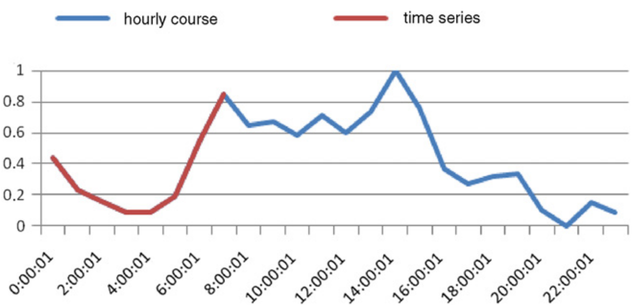

Fig. 3. Hourly Forex course, the red part of the wave is further elaborated in Fig. 4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

after their division into smaller parts of shape shows similarities with the original motives. Each impulse phase consists of three subwaves upward of five breaks and each correction phase consists of two subwaves downward of three breaks. For a detailed view of the Elliott wave, we can find more and more fractures in each subwave. Just such repeating pattern is a fundamental property of fractals, (see Fig. 2), [5]. Using Elliott's waves for determining the future development of prices is quite simple. If Elliott wave occurs in a stock market trends, we can expect break of a price in the opposite direction after the fifth pulse wave or after the third correction wave. Of course, it is not so simple. The Elliott wave is very often distorted differently, and prediction is then very difficult and sometimes impossible. Our use of the word fractal, or Elliott wave fractal, is not a proper use of the property of self-similarity. When we use the term here we mean a "counting fractal", which is really a description of the relative position of a bar on a high–low bar chart [7].

The Elliott wave is another technical tool that may be used to try to identify market trends and determine whether trends are about to change. The Elliott wave can be used to generate short-term trading opportunities and analyze whether current market trends will continue. To apply the Elliott wave to some analysis we need to identify which wave is being formed. The major waves determine the major trend of the market. The minor waves determine the minor trends in the market. Once we identify the main wave look to buy the market in the 1, 3 and 5 waves, and sell the market in waves to 2 and 4. In the corrective phase look to buy wave A and C and look to sell wave B. The most difficult part of Elliott wave analysis is to correctly label the waves. Waves are usually identified by looking back at historic price action. The hard part in applying the Elliott wave is try to anticipate drawing of the waves before the market action takes place. The wave patterns are actually quite simple. All you need to know is markets tend to move in waves and market direction can be identified by identifying the repetitive pattern of waves. Elliott wave theory says markets will move in five waves with up to three waves down. There is no absolute time to complete a cycle. In theory a wave could last for years.

Elliott theory is based on market progressions. As the market also reflects the emotional sentiment of traders around the world, it is clear that this human characteristic projection can have an impact on the wider class of problems than just the progress the stock. It is very important to realize that the market structure is not based solely on price development shares. The actual value of shares is closely associated with many important aspects—one of them is the value of volume. There is clear that this value significantly affects the share price, so we chose the course of volume in our experimental study. Such a kind of time series can be considered as a suitable candidate representing a time series with fractal dynamics. This option is not common, but the experimental results confirm its validity. The proposed classifier is also able to recognize the volume in each Elliott wave structure. Since these values are diametrically opposed to volume, we performed a normalization of the test data set of all used data files.

In Figs. 3 and 4 we can see an example which represents fractal structure in the time series, where Forex EUR/USD from 11 June 2012 (starting and ending at 0:00:01 and 7:30:00) is shown. You can see the original time series in Fig. 3 and its fractal character in Fig. 4 (it is shown in hour, minute and ten-minute courses), which represents the fractal structure of the red part from the hour course from Fig. 3. Values on the y-axis are normalized.

3. Backpropagation neural networks

A neural network is a parallel, distributed information processing structure consisting of processing elements (which can possess a local memory and can carry out localized information processing operations) interconnected together with unidirectional signal channels called connections. Each processing element has a single output connection which branches into as many collateral connections as desired (each carrying the same signal—the processing element output signal). The processing element output signal can be of any mathematical type desired. All of the processing that goes on within each processing element must be completely local: i.e., it must depend only upon the current values of the input signals arriving at the processing element via impinging connections and upon values stored in the processing element's a local memory.

The backpropagation neural network architecture is a hierarchical design consisting of fully interconnected layers or rows of processing units with each unit itself comprised of several individual processing elements. Backpropagation belongs to the class of mapping neural network architectures and therefore the information processing function that it

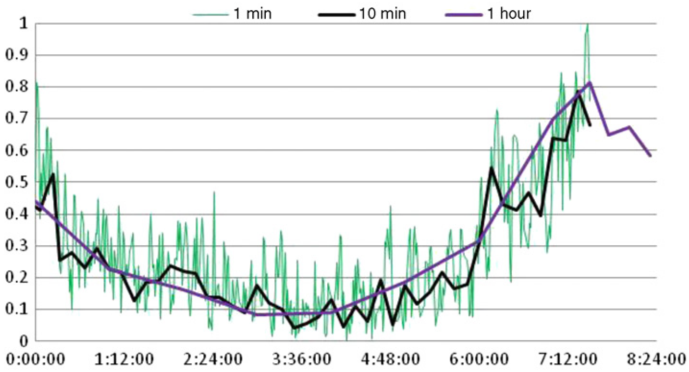

Fig. 4. Fractal structure of the course of Forex (hours, 10 min, 1 min).

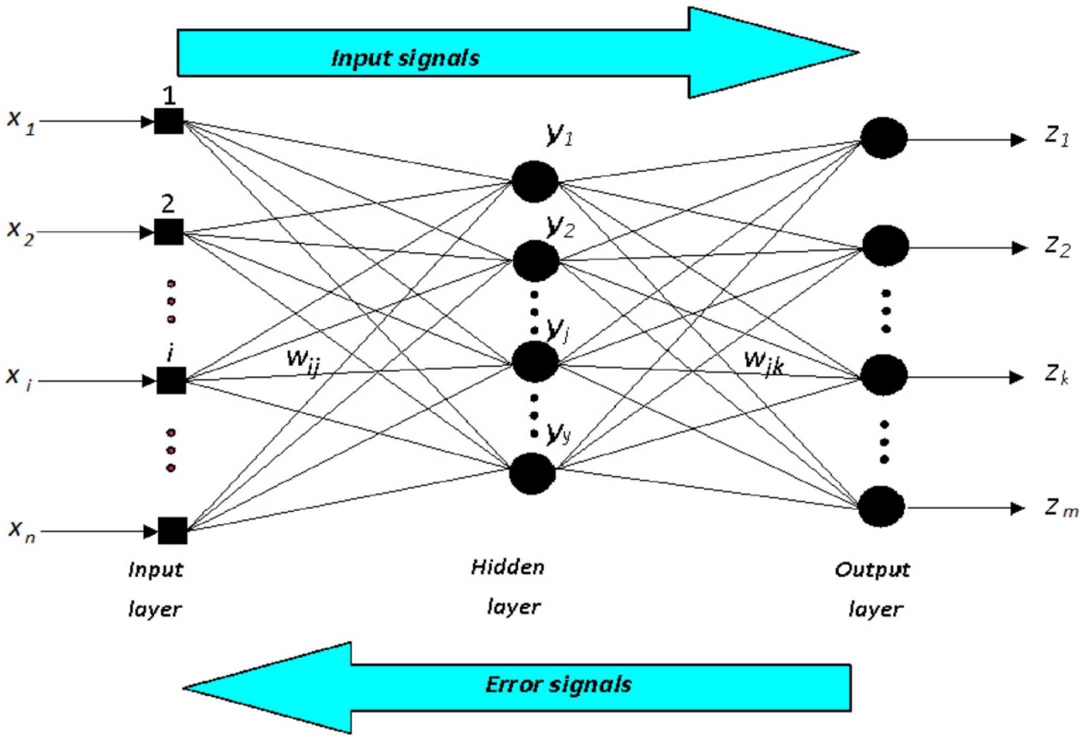

Fig. 5. A backpropagation network architecture.

carries out is the approximation of a bounded mapping or function $f : A \subset R^n \rightarrow R^m$, from a compact subset $\boldsymbol{A}$ of n-dimensional Euclidean space to a bounded subset $f[\boldsymbol{A}]$ of m-dimensional Euclidean space, by means of training on examples $(x_1, z_1), (x_2, z_2), \ldots, (x_k, z_k) \ldots$. It will always be assumed that such examples of a mapping f are generated by selecting $\boldsymbol{x}_k$ vectors randomly from $\boldsymbol{A}$ in accordance with a fixed probability density function $p(\boldsymbol{x})$. The operational use to which the network is to be put after training is also assumed to involve random selections of input vectors $\boldsymbol{x}$ in accordance with $p(\boldsymbol{x})$. The backpropagation architecture described in this paper is the basic, classical version (Fig. 5). The backpropagation learning algorithm is composed of two procedures: (a) feed-forward and (b) back-propagation weight training.

Feed-forward. Assume that each input factor in the input layer is denoted by x_i, y_j and z_k represent the output in the hidden layer and the output layer, respectively. And, y_j and z_k can be expressed as follows (1):

$$y_j = f(X_j) = f\left(w_{oj} + \sum_{i=1}^{I} w_{ij} x_i\right) \quad \text{and} \quad z_k = f(Y_k) = f\left(w_{ok} + \sum_{j=1}^{J} w_{ik} y_j\right) \tag{1}$$

where the w_{0j} and w_{0k} are the bias weights for setting threshold values, f is the activation function used in both hidden and output layers, and X_j and Y_k are the temporary computed results before applying activation function f. In this study, a sigmoid function is selected as the activation function. Therefore, the actual outputs y_j and z_k in hidden and output layers, respectively, can be also written as:

$$y_j = f(X_j) = \frac{1}{1+e^{-X_j}} \quad \text{and} \quad z_k = f(Y_k) = \frac{1}{1+e^{-Y_k}}. \tag{2}$$

The activation function f introduces the non-linear effect to the network and maps the result of computation to a domain (0, 1). This sigmoid function is differentiable. The derivative of the sigmoid function in Eq. (2) can be easily derived as: $f' = f(1 \pm f)$.

Back-propagation weight training. The error function is defined as [8] (3):

$$E = \frac{1}{2}\sum_{k=1}^{K} e_k^2 = \sum_{k=1}^{K} (t_k - z_k)^2 \tag{3}$$

where t_k is a predefined network output (or desired output or target value) and e_k is the error in each output node. The goal is to minimize E so that the weight in each link is accordingly adjusted and the final output can match the desired output. To get the weight adjustment, the gradient descent strategy is employed. In the link between hidden and output layers, computing the partial derivative of E with respect to the weight w_{jk} produces, as (4)

$$\frac{\partial E}{\partial w_{jk}} = -e_k f'^{(Y_k) y_j} = -\delta_k y_j \quad \text{where } \delta_k = (t_k - z_k) f'(Y_k). \tag{4}$$

The weight adjustment in the link between hidden and output layers is computed by $\Delta w_{jk} = \alpha \times y_j \times \delta_k$, where α is the learning rate, a positive constant between 0 and 1. The new weight herein can be updated by the following $w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n)$, where n is the number of iterations. Similarly, the error gradient in links between input and hidden layers can be obtained by taking the partial derivative with respect to w_{ij}, as (5):

$$\frac{\partial E}{\partial w_{ij}} = -\Delta_j x_j = f'(X_j) \sum_{k=1}^{K} \partial_k w_{jk}. \tag{5}$$

The new weight in the hidden-input links can be now corrected as: $\Delta w_{ij} = \alpha \times x_i \times \Delta_j$ and $w_{ij}(n+1) = w_{ij}(n) + \Delta_j$. Training the BP-networks with many samples is sometimes a time-consuming task. The learning speed can be improved by introducing the momentum term η [9]. Usually, η falls in the range $\langle 0, 1\rangle$. For the iteration n, the weight change Δw can be expressed as $\Delta w(n+1) = \eta \times w(n) + \alpha \times \frac{\partial E}{\partial w(n)}$. The backpropagation learning algorithm used in artificial neural networks is shown in many textbooks [10].

4. Multi-classifier

The core of the multi-classifier consists of the detection system for the pattern recognition of structures with fractal dynamics. The multi-classifier (Fig. 6) is based on neural networks which are adapted by backpropagation.

- The first neural network is designed to recognize selected Elliott wave's patterns. Emphasis is placed on the ability of a network to evaluate the found patterns with a degree of consensus of similarity with the defined pattern from training set. It is also necessary to network guarantee information about a quality of the found pattern.
- The second neural network evaluated prediction of the trend component on the basis of the recognized pattern. The whole prediction is based on the IF–THEN rules from which the training set is composed for the second neural network. In essence, the neural network represents a rule-based of knowledge system that is able to decide whether a time series respects corrective or impulse direction.

4.1. Pattern recognition classifier

For the purpose of adaptation of the pattern recognition classifier, it is necessary to remark that determination of training patterns is one of the key tasks. Improperly chosen patterns can lead to confusion of neural networks. The search for the training set patterns is a complicated process which is usually performed manually by the user. During our experimental work, we made some study that included Elliott wave pattern recognition.

We use four different patterns of Elliott wave theory. Impulse waves are five-wave patterns. Impulse waves always unfold in the same direction as the larger trend—the next higher degree impulse or corrective wave. Waves 1, 3 and 5 within an impulse are themselves impulse waves of lower degree which should also subdivide into a five-wave pattern. One of the impulse waves within an impulse wave will usually be extended or much longer than the other two. Most extensions in the currency markets occur in wave three. When one of the impulse waves extends the other two will frequently be of an equal size. Waves 2 and 4 within an impulse waves are corrective waves. Once an impulse wave is completed it will be followed by a corrective wave. An impulse wave is always followed by a corrective wave of the same degree unless the impulse wave completes a higher degree wave. Patterns of impulsive character are represented in Fig. 7 as P6, P8, P10, P12 first part.

Corrective waves are three- or five-wave patterns. Corrective waves always unfold in the opposite direction to the larger trend—the next higher degree impulse or corrective wave. There are two different groups of corrective waves: simple corrective waves (zigzags, flats and irregulars) and complex corrective waves (triangles, double and triple threes). Corrective

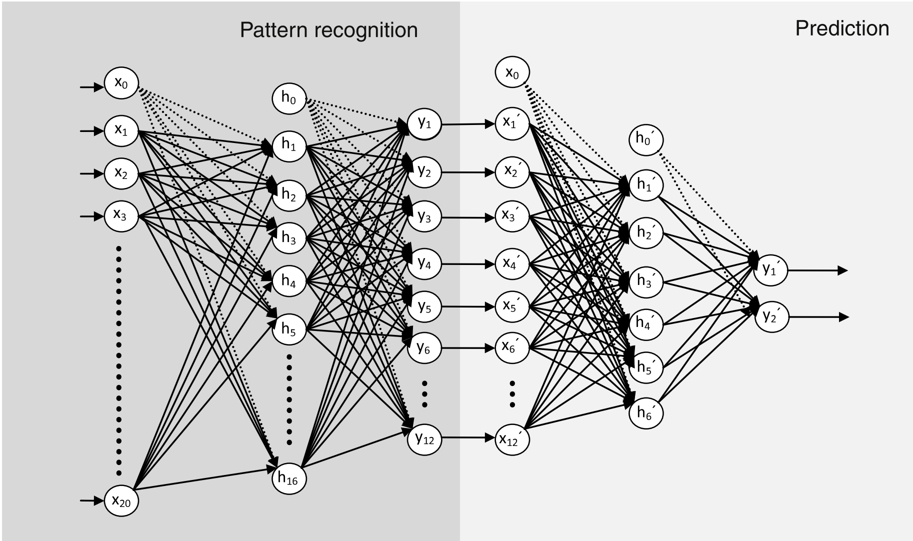

Fig. 6. The multi-classifier proposal for the purpose of pattern recognition with consecutive prediction.

waves have much more variation than impulse waves which makes it less easy to identify them while they are still being formed. Patterns of corrective character are represented in Fig. 7 as P7, P9, P11, P12 second part.

ZigZag waves are broadly called ABC corrections. They differ by the distance their subwaves move in relation to each other and by the way they subdivide. A zigzag consists of a 5–3–5 sequence in which wave B does not move past the start of wave A and wave C moves far beyond the end of wave A. A flat is formed by a 3–3–5 sequence in which all the three subwaves are of the same length. An irregular is made up of a 3–3–5 sequence in which wave B exceeds the start of wave A and waves C moves close to or beyond the end of wave A. It is useful to know that in all the three ABC corrections wave C subdivides into a five-wave pattern, or an impulse wave. This information can be very helpful when making timing decisions for entering your trades at the start of the higher impulse waves. ABC corrections most commonly act as the second subwaves of the impulse waves. Patterns of ZigZag character are represented in Fig. 7 as P1, P2, P5.

Triangles are complex corrective waves which are formed by five progressively smaller three-wave patterns. Elliott wave theory uses the same method for classifying and measuring triangles as does the traditional technical analysis. Under the Elliott wave principle triangles most often act as the fourth subwaves of impulse waves, preceding the final move in the direction of the larger trend.

Therefore, if you see a triangle in the fourth wave of an impulse wave you can apply the standard price objective calculation method used for triangles to calculate the possible end of wave five (completion of the whole impulse wave)—in addition to the projection methods described below. If a triangle occurs in the wave B of an ABC correction you can project the end of wave C by using the same technique [5–7,11,12]. Patterns of triangular character are represented in Fig. 7 as P3, P4.

The pattern recognition classifier is based on backpropagation neural networks and is able to recognize Elliott wave structures in a given time series. Artificial neural networks need training sets for their adaptation. In our experimental work, the training set consisted of 12 patterns representing the basic structure of the various phases of Elliott waves that include patterns containing impulse phase (P2, P5, P6, P8 and P10), the correction phase (P1, P7, P9 and P11), special triangular pattern (P3 and P4) and the basic structure of the whole Elliott wave (P12), see Fig. 7. Input data is sequences always including n consecutive numbers, which are transformed into interval $\langle 0,\ 1\rangle$ by the formula (6). Samples are adjusted for the needs of backpropagation networks with a sigmoid activation function in this way [11,12].

$$x'_j = \frac{x_j - \min(x_i, \dots, x_{i+n-1})}{\max(x_i, \dots, x_{i+n-1}) - \min(x_i, \dots, x_{i+n-1})}, \quad (j = i, \dots, i+n-1) \tag{6}$$

where x'_j is normalized output value of the j-th neuron ($j = i, \dots, i+n-1$) and $(x_i, \dots, x_{i+n-1})$ are $n-1$ consecutive output values that specify sequences (patterns) from the training set (e.g. training pairs of input and corresponding output vectors).

The input vector contains 20 components. We used 20 input neurons so that each component of the input vector was accepted with the same weight, therefore the used training set contains, together with each component, its complement to value "**1**", i.e. $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, 1-x_1, 1-x_2, 1-x_3, 1-x_4, 1-x_5, 1-x_6, 1-x_7, 1-x_8, 1-x_9, 1-x_{10})$. Such a proposed input vector representing patterns is a guarantee that equal emphasis is placed on each value, because the backpropagation algorithm usually has a tendency to put less emphasis on inputs near zero. The output vector has 12 components and each output unit represents one of 12 different types of Elliott wave samples. A neural network architecture is 20–16–12 (e.g. 20 units in the input layer, 16 units in the hidden layer, and 12 units in the output layer). The net is fully connected. Adaptation of the neural network starts with randomly generated weight values.

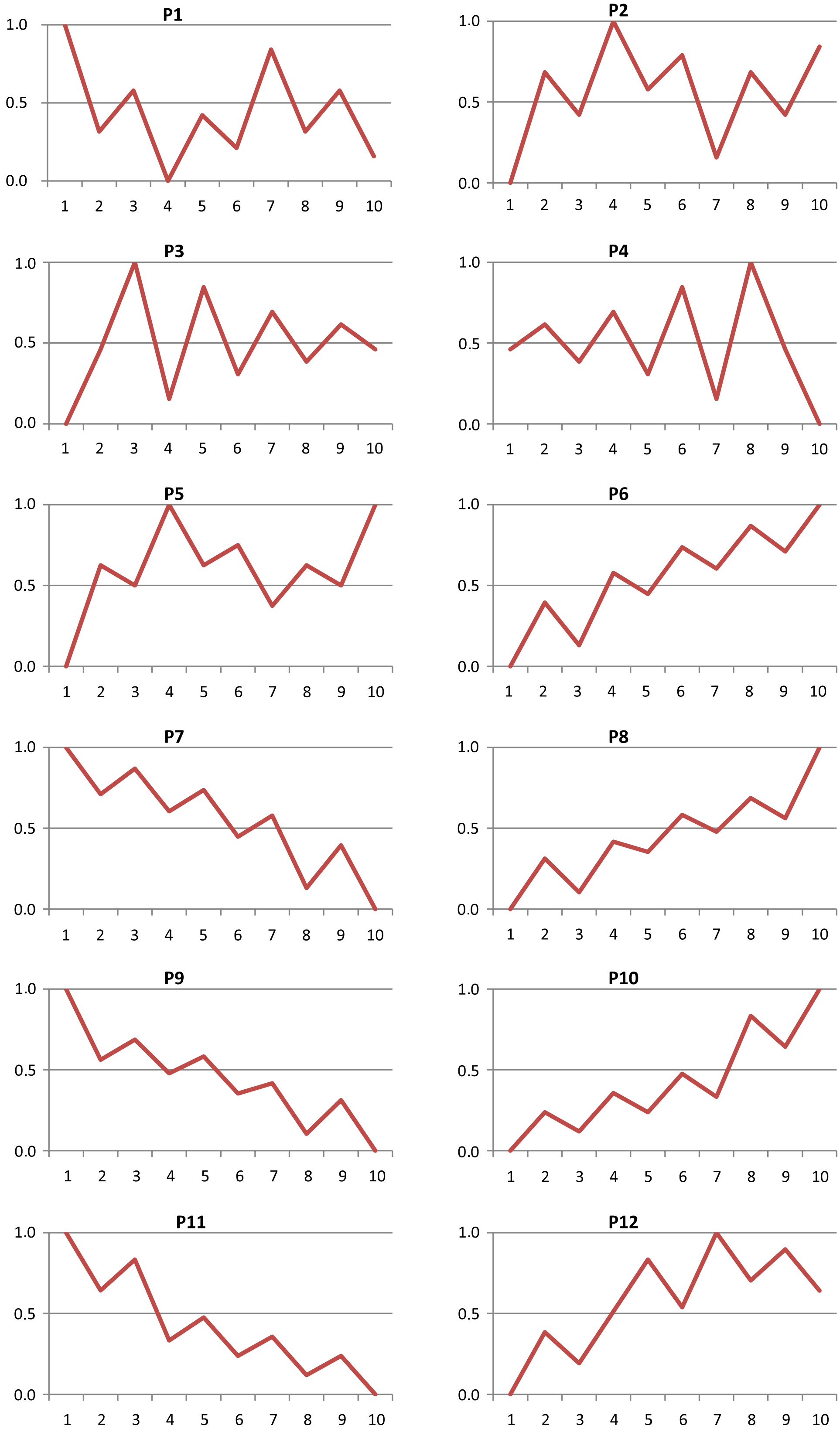

Fig. 7. Different types of Elliott wave samples represented in the training set.

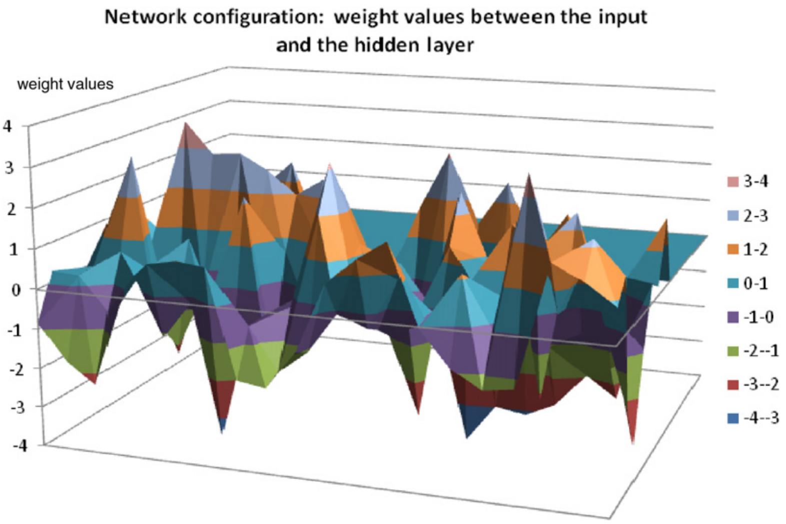

Fig. 8. The final network configuration of weight values between input (20 units) and hidden (16 units) layer—pattern recognition classifier.

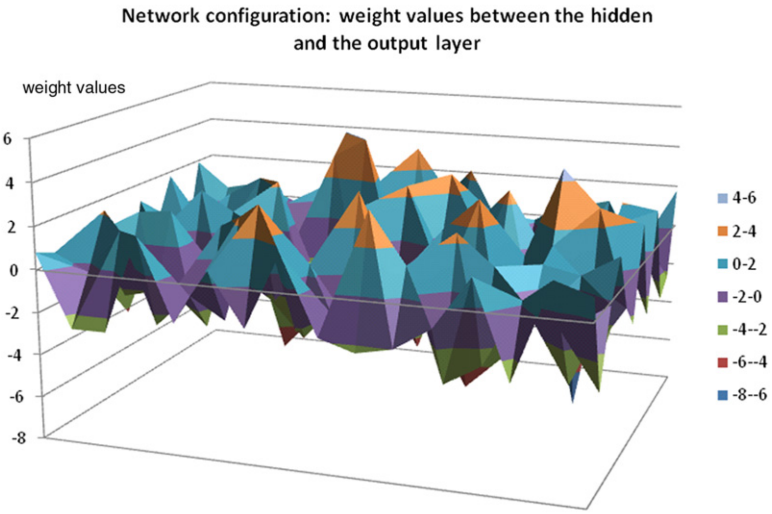

Fig. 9. The final network configuration of weight values between hidden (16 units) and output (12 units) layer—pattern recognition classifier.

We used the backpropagation method for the adaptation with the following parameters: first 5000 iterations have the learning rate value 0.5, and for the next 2000 iterations the learning rate value is 0.1, momentum is 0. The conducted experimental studies also showed that in each cycle of adaptation is to present an adequate network of training patterns mixed randomly to ensure their greater diversity, but also acts as a measure of system stability. Uniform system in a crisis usually collapses entirely, while in the diversion system through a crisis of its individual parts, but the whole remains functional. The condition of end of the adaptation algorithm specified the limit value of the overall network error, $E < 0.07$. It concerns the perfect the training set adaptation from Fig. 7. The final network configuration is shown in Figs. 8 and 9.

4.2. Prediction classifier

The second neural network of the proposed multi-classifier simulates the knowledge system. Knowledge modeling is the concept of representing information and the logic of putting it to use in a digitally reusable format for purpose of capturing, sharing and processing knowledge to simulate intelligence. A knowledge base is designed in the form of rules. Each rule consists of a conditional and a consequential part. All rules are expressed in the following form: *IF a THEN b*. The left side of each rule represents a conditional part of the rule whereas its right side represents consequential part of the rule. For our purposes, it was essential to create suitable form of rules which should include all important features of the designed knowledge system. The rules in our system were presented in the following form:

IF *found pattern* & *fulfillment of consensus of similarity* **THEN** *trend direction*.

Table 1
The proposed knowledge base.

Number of rule	IF	Found pattern	&	Consensus of similarity	THEN	Trend prediction
1	If	P1	&	>90	Then	UT
2	If	P2	&	>90	Then	DT
3	If	P3	&	>90	Then	UT
4	If	P4	&	>90	Then	UT
	If	⋮	&	⋮	Then	⋮
m	If	P5&P11	&	>98	Then	UT

Table 2
The training set for the second neural network.

Input neurons												Output neurons	
x'_1	x'_2	x'_3	x'_4	x'_5	x'_6	x'_7	x'_8	x'_9	x'_{10}	x'_{11}	x'_{12}	y'_1	y'_2
1	0	0	0	0	0	0	0	0	0	0	0	1	0
0	1	0	0	0	0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	0	0	0	1	0
0	0	0	0	1	0	0	0	0	0	0	0	0	1
0	0	0	0	0	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	1	0	0	0	0	0	1	0
0	0	0	0	0	0	0	1	0	0	0	0	0	1
0	0	0	0	0	0	0	0	1	0	0	0	1	0
0	0	0	0	0	0	0	0	0	1	0	0	0	1
0	0	0	0	0	0	0	0	0	0	1	0	1	0
0	0	0	0	0	0	0	0	0	0	0	1	1	0

There are two basic variables in the antecedent. It means fulfillment of consensus of similarity and found patterns which we gained as results (outputs) from the first part of the classifier. After prediction of trend direction the consequent is composed like this: UT—upward trend, DT—downward trend. Consensus of similarity was set at 90% or more. The proposed knowledge base is shown in Table 1.

Here, the main task is how the knowledge base could be transformed into a training set for a neural network. Although the knowledge base from Table 1 is too extensive, we consider 12 basic rules, where each represents one pattern in the used training set. It means one rule for one pattern of the used Elliott wave from Fig. 4. It is sufficient because the neural network is able to generalize relationships from the training set into the weight values. Two neurons form the output of the second network. The first neuron predicts a pulse and the second one predicts the correction phase of the monitoring quantity in the graph. The whole training set is shown in Table 2. There are knowledge rules encoded in the weight values after the neural network adaptation. Then, the control mechanism is adequate for the adapted neural network, which creates the second part of the multi-classifier. The adapted neural network is able to predict breaks in the monitored graph behaviors on the basis of the found Elliott wave patterns. When determining the topology of the second neural network, we proceeded as follows: (a) the number of neurons in the input and output layer is again based on the training set, (b) the number of neurons in the hidden layer is based on heuristics described in [13], (c) the neural network is fully interconnected, (d) the sigmoid activation function was used. In summary, the topology of the neural network contains 12 input, 6 hidden and 2 output neurons. In the active phase, outputs of the first of neural networks are entering, which represent the degree of consensus of recognized Elliott wave pattern P1–P12 from Fig. 7 [14].

The parameters of the backpropagation algorithm are the following: the first 1000 iterations have a learning rate value of 0.5, and for the next 3000 iterations the learning rate value is 0.1, momentum is 0. These learning rates were set according to the experimental study. Calculation is halted after every 1000 cycles and the coefficient of the learning rate is set to a smaller value, resulting in subsequent weight gain soft. The condition of the end of the adaptation algorithm specified the limit value of the overall network error, $E < 0.07$. It concerns the perfect the training set adaptation. The final network configuration is shown in Figs. 10 and 11.

5. Results and comparative study

Inorder to test the efficiency of the method, we applied a database from the area of financial forecasting [15] that is a set of data that reflects the situation of the market. Data shows volume behavior of the following companies: Coca Cola, Boeing, Google, eBay and Carrefour, and the development of EUR/USD forex, which reflect the exchange rate between EUR and USD. We used four different kinds of financial time series, daily, hourly, 10 min. and minutes. Our Neural network was able to recognize all given types of Elliott wave samples represented in the training set (Fig. 7).

Outputs from the first classifier produce sets of values that are assigned to each recognized training pattern in the given test time series. It is important to appreciate what can be considered as an effective criterion related to consensus of similarity. The proposed threshold resulting from our experimental study was determined as at least 90%. The neural

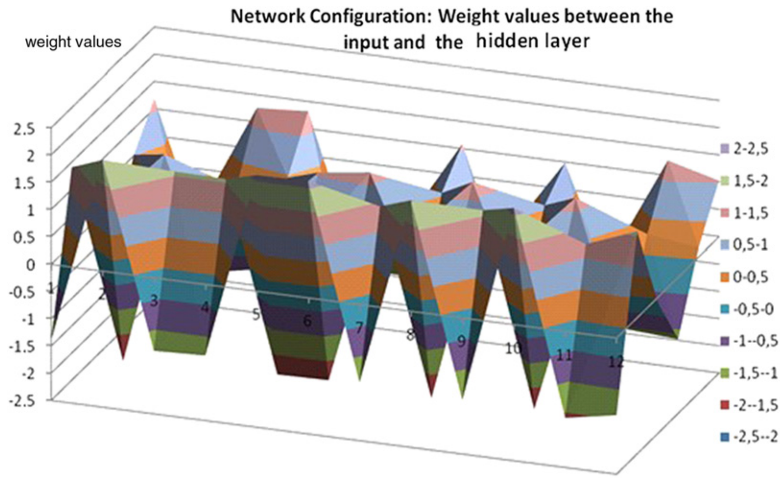

Fig. 10. The final network configuration of weight values between input (12 units) and hidden (6 units) layer.

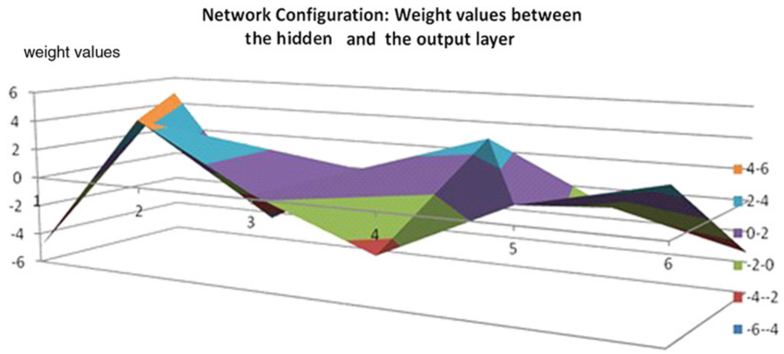

Fig. 11. The final network configuration of weight values between hidden (6 units) and output (2 units) layer—prediction classifier.

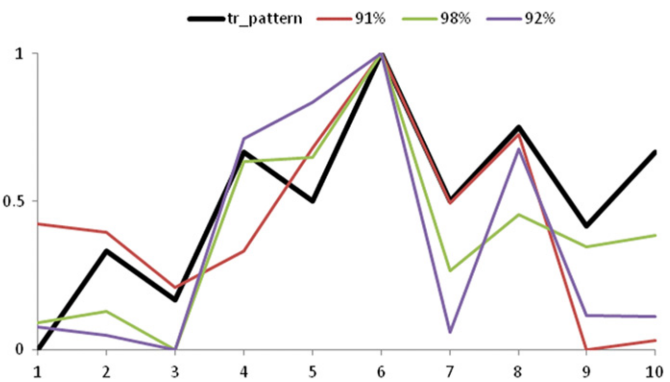

Fig. 12. Three found behaviors with consensus of similarity greater than 90%.

network is able to discover some connections, which are almost imperceptible. For example, experts could find a consensus of similarity between training patterns and recognized patterns less than 90% in Fig. 12. Therefore, a situation may occur, when consensus of similarity marked with neural networks is greater than 90% and an expert estimation is much less. An illustration of some recognized patterns that occur in financial time series is shown in Fig. 13.

Outputs from the second classifier carry a predictive character. The neural network determines whether the trend direction should have an increasing or decreasing character on the basis of recognized Elliott wave patterns which appear in the market history. We examined a total of 25 data sets. Each of them contained 500 values. Table 3 demonstrates a summary of classification and prediction results of the proposed multi-classifier. That has recognized 9326 patterns with a consensus of similarity greater than 70%, the next 6859 patterns with a consensus of similarity greater than 80%, and 2361 patterns with a consensus of similarity greater than 90%. Trend prediction was verified only for patterns with consensus of

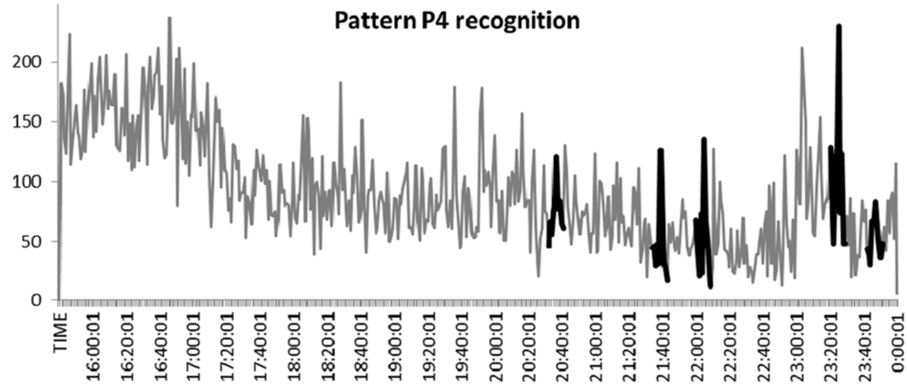

Fig. 13. Some recognized patterns that occur in a financial time series.

Table 3
A summary of classification and prediction results.

The number of recognized patterns with consensus of similarity greater than 70%	The number of recognized patterns with consensus of similarity greater than 80%	The number of recognized patterns with consensus of similarity greater than 90%	The number of successful trend predictions based on found patterns with consensus of similarity greater than 90%	Successful prediction in total
9326	6859	2361	1440	61%

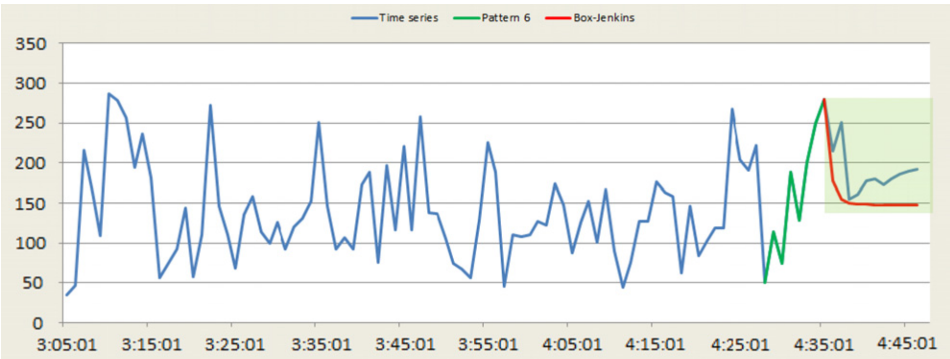

Fig. 14. Trend prediction of a minute time series. The green rectangle represents an area, where the trend direction is located according to the proposal multi-classifier after pattern P6 detection. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

similarity greater than 90% and their number is 1440, which is a 61% successful prediction in total. In this case, the proposed multi-classifier is justifiable because the prediction percentage greater than 50% means success in the case of predictive exchange software.

Our comparative study was aimed at comparing outputs from the proposed multi-classifier with other approaches. We focused on the classification of Elliott figures in the chart with a follow-up prediction of trend in the graph of the monitored system. Software NCSS with implemented Box–Jenkins methodology comprised an alternative approach for prediction. The Box–Jenkins forecasting method introduces a self-projecting time series forecasting method. The underlying goal is to find an appropriate formula so that the residuals are as small as possible and exhibit no pattern. The model-building process involves four steps, repeated as necessary, to end up with a specific formula that replicates the patterns in the series as closely as possible and also produces accurate forecasts [16]. This methodology is implemented in many different models and is very well known for its success and variability of use.

The graph in Fig. 14 shows the trend prediction of a minute time series that shows the course of EUR/USD Forex from 11 March 2010 containing 500 min values. The first proposed classifier detected pattern P6 with consensus of similarity 98%. On the basis of P6 pattern recognition (green line), the second proposed classifier predicted that the trend direction should have decreasing character (green rectangle). For comparison, the Box–Jenkins methodology also predicted a downward trend of the minute time series (red line).

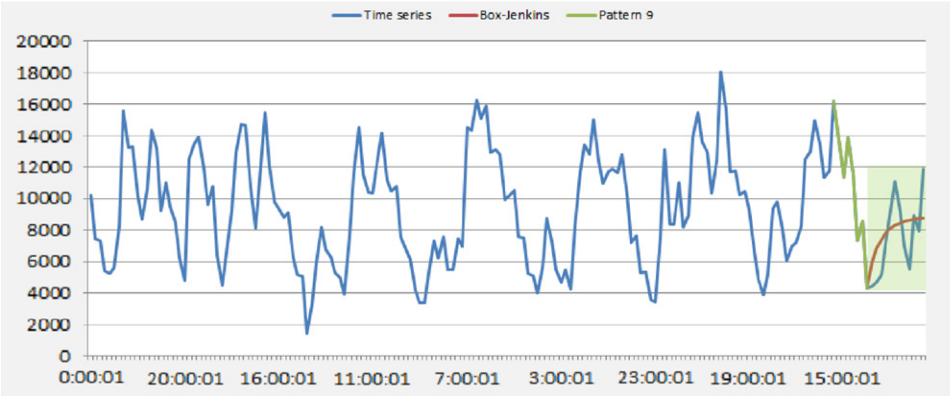

Fig. 15. Trend prediction of a hour time series. The green rectangle represents an area, where the trend direction is located according to the proposal multi-classifier after pattern P9 detection. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

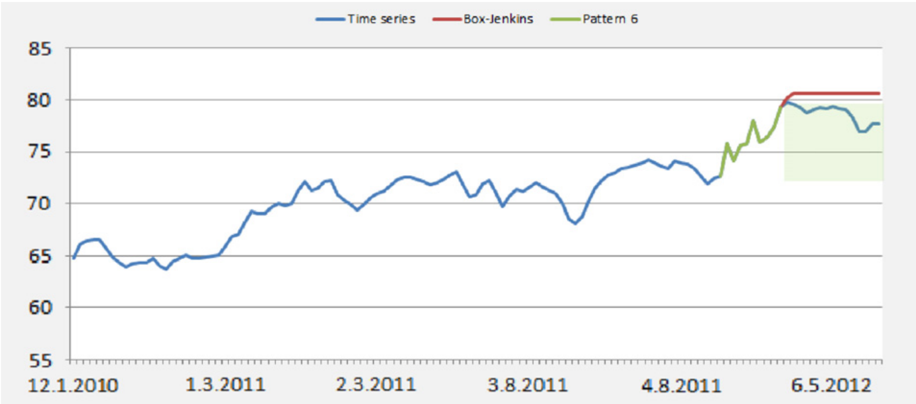

Fig. 16. Trend prediction of a daily time series. The green rectangle represents an area, where the trend direction is located according to the proposal multi-classifier after pattern P6 detection. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The graph in Fig. 15 shows the trend prediction of an hourly time series that shows the volume behavior of Coca Cola corp. from 1 January 2012 containing 500 hourly values. The first proposed classifier detected pattern P9 with consensus of similarity 93%. On the basis of P9 pattern recognition (green line), the second proposed classifier predicted that the trend direction should have an increasing character (green rectangle). For comparison, the Box–Jenkins methodology also predicted an upward trend of the minute time series (red line).

The graph in Fig. 16 shows the trend prediction of a daily time series that shows the stock price development of Boeing corp. 1 January–6 May 2012. The first proposed classifier detected pattern P6 with a consensus of similarity of 89%. On the basis of P6 pattern recognition (green line), the second proposed classifier predicted that the trend direction should have decreasing character (green rectangle). In comparison with it, the Box–Jenkins methodology incorrectly predicted a downward trend of the daily time series (red line).

Other experimental simulations provided similar numerical results.

6. Conclusion

In this paper, a short introduction into the field of Elliott wave recognition using a backpropagation neural network has been given. According to the results of experimental studies, it can be stated that Elliott wave patterns were successfully extracted in the given time series in a varied time scale and recognized using the suggested method, as can be seen from the figures in the results section. It might result in better mapping of the time series behavior for better prediction. Elliott wave recognition allows time series trend prediction, as follows. If we recognize the impulse phase of an Elliott wave, trend prediction is downwards. If we recognize the correction phase of an Elliott wave or triangle patterns, trend prediction is upwards. We were able to demonstrate using Elliott wave theory in the course of Volume. As far as we know this has been not tested yet. This is the reason we think Elliott wave theory is feasible and will be recognizable in other types of time series and we will research it in our future work.

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