Expert Systems with Applications 41 (2014) 6235–6250

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Financial forecasting using ANFIS networks with Quantum-behaved Particle Swarm Optimization

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ARTICLE INFO

Keywords:
Financial forecasting
Financial pattern recognition
Adaptive Network-based Fuzzy Inference System (ANFIS)
Quantum-behaved Particle Swarm Optimization (QPSO)
Dynamic Time Warping (DTW)
Wavelet Transform (WT)

ABSTRACT

To be successful in financial market trading it is necessary to correctly predict future market trends. Most professional traders use technical analysis to forecast future market prices. In this paper, we present a new hybrid intelligent method to forecast financial time series, especially for the Foreign Exchange Market (FX). To emulate the way real traders make predictions, this method uses both historical market data and chart patterns to forecast market trends. First, wavelet full decomposition of time series analysis was used as an Adaptive Network-based Fuzzy Inference System (ANFIS) input data for forecasting future market prices. Also, Quantum-behaved Particle Swarm Optimization (QPSO) for tuning the ANFIS membership functions has been used. The second part of this paper proposes a novel hybrid Dynamic Time Warping (DTW)-Wavelet Transform (WT) method for automatic pattern extraction. The results indicate that the presented hybrid method is a very useful and effective one for financial price forecasting and financial pattern extraction.

1. Introduction

The FX is the largest global market today. According to the September 2013 report of the Bank for International Settlements (2013), Global FX turnover reached $5.3 trillion a day in 2013. There are two main groups that trade on the FX market. The first group is companies and governments that use the FX market to convert domestic currency into a foreign currency for international business transactions. The second group consists of investors that trade in order to make a profit on the Forex market. Speculators on the FX market range from large banks to home-based operators (Archer, 2010).

As with other financial markets, the most important factor for being successful in FX trading is the ability to correctly predict future market fluctuations. If a speculator can "buy low and sell high", then he or she will make a profit. There are wild variations in exchange rates on the FX market, and it is difficult for traders to make the right decision to buy or sell. Forecasting future FX exchange rates is an intriguing subject for many speculators. They use artificial intelligent models to forecast future market values and look for complex chart patterns. The objective of this paper is to propose a hybrid artificial intelligence model as a trading advisory system. An ANFIS-QPSO hybrid system is used as a one-step-ahead forecasting method. Wavelet coefficients of time series are used as the ANFIS input parameters. The paper also presents a hybrid Dynamic Time Warping (DTW)-Wavelet Transform (WT) method for automatic pattern extraction from a financial time series. This study attempts to make correct trading signals based on forecasted market values and identified chart patterns. The proposed model can help traders to reduce trading risks and to increase their profit.

According to the efficient market theory, it is nearly impossible to accurately make long-term predictions based on historical market data. But in the short-term, there are some hidden repeating patterns that, if we can identify them, could help us make a profit from the market (Liu & Kwong, 2007). Professional traders use two major types of analysis to make accurate decisions in financial markets: fundamental and technical. Fundamental analysis is based on the overall state of the economy, the state of the industry and a company's overall financial situation. Technical analysis, on the other hand, relies on charts and historical data, and is based on the idea that history will repeat itself. Therefore, by analyzing

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http://dx.doi.org/10.1016/j.eswa.2014.04.003
0957-4174/

past data, we can forecast future market trends. The two main methods used for technical analysis are statistical-based indicators and chart patterns. Statistical methods include the use of moving averages to find a mathematical relationship between past data that can be used for evaluating future market values. Finally, if a specific pattern appears in a chart, chart patterns analysis can be used to predict the future trends.

There are many papers dealing with financial market forecasting. Many of them employ soft computing techniques, such as genetic algorithms, neural networks, and neuro-fuzzy systems. Most previous works have presented methods to try to accurately predict the market. Obviously, based on the current human knowledge, it is impossible to correctly predict the exact market values. Therefore, researchers have used complicated methods to minimize forecasting error. To be successful in real market trading, professional traders place great value on predicting future market trends. Instead of trying to forecast an exact market value, the model proposed in this paper provides a trading advisory signal generated from predicted market trends.

The innovations of the presented method are as follows:

- The majority of earlier papers used just one of the technical indicators or chart patterns as a forecasting method. The proposed method uses wavelet decomposition of time series and extracted chart patterns as the system inputs.
- An ANFIS-QPSO hybrid method has rarely been used for financial forecasting. A novel method for tuning ANFIS membership functions by QPSO has been proposed. Experimental results have shown that this model is very accurate and highly efficient for forecasting in financial markets, especially in the Forex market.
- DTW has rarely been used for finding patterns in financial time series. In this paper a state-of-the-art hybrid algorithm, combining Dynamic Time Warping and Wavelet Transform, is presented to extract the shaped patterns in financial time series.
- The majority of earlier papers employed a single shape template or time series as a target pattern. These patterns are generally independent from the input time series. The presented method creates an adaptive pattern based on the main features of pattern and input time series to accurately predict the current data.

Section 2 of this paper provides the literature review, Section 3 reviews basic methods. The proposed method is described in Section 4. Section 5 describes the experiments and makes comparisons. Finally, Section 6 examines the conclusions of the study.

2. Literature review

Many previous studies used statistical technical indicators to predict the price variations. Some of the proposed methods used soft computing techniques as a forecasting system. Escobar, Moreno, and Munera (2013) presented a new technical indicator based on fuzzy logic. Current indicators used only mathematical models, but Escobar et al. incorporated some aspects of trader behavior, such as risk tendency. They used fuzzy logic to make decisions an ordinary investor.

Cheng, Wei, Liu, and Chen (2013) used ANFIS to forecast stock prices on the Taiwanese stock markets. They advocated that making forecasts based on several past periods of stock prices is much better than using a single previous period, and observed that it is difficult to find the best weight for each period. They incorporated high-order data into the values of single attributes by using the method of ordered weighted averaging (OWA). Wei (2013a, 2013b) proposed an ANFIS model that optimized an adaptive expectation genetic algorithm for predicting stock prices. Wei (2013a, 2013b) in another study used a novel genetic algorithm (GA) weighted ANFIS model to forecast the Taiwan stock index. Because of strong connections with the Taiwan economy and international trade, Wei (2013a, 2013b) used fluctuations in other stock markets as forecasting factors in his proposed model. Chang, Wei, and Cheng (2011) proposed a hybrid ANFIS model based on auto regression and volatility to forecast stock prices. (Vanstone & Finnie, 2006; Vanstone et al., 2004a, 2004b) used neural networks to forecast stock prices on the Australian stock markets.

Kazem, Sharifi, Hussain, Saberi, and Hussain (2013) used optimized support vector regression with a chaos-based firefly algorithm for stock price forecasting. Tan, Quek, and Cheng (2011) proposed an ANFIS model that was supplemented by reinforcement learning (RL) for identifying trend movement and making investment decisions. Atsalakis and Valavanis (2009) used fifteen different combinations of past stock prices to find the best ANFIS inputs for forecasting short-term trends in stock markets. Esfahanipour and Aghamiri (2010) used technical indices as the input variables for ANFIS on a Takagi Sugeno Kang (TSK) type fuzzy system and fuzzy C-mean clustering for stock price prediction. Boyacioglu and Avci (2010) used six macroeconomic variables and three indices as ANFIS input variables for predicting the Istanbul Stock Exchange index. For predicting stock prices, Atsalakis, Dimitrakakis, and Zopounidis (2011) presented the Wave Analysis Stock Prediction (WASP) system, an ANFIS system based on Elliot Wave Theory. Wei, Chen, and Ho (2011) separated past forecasting models into two main types: models based on artificial intelligence algorithms, and statistical models based on mathematical equations. They proposed an ANFIS model which used multi-technical indicators to predict stock price trends. Melin, Soto, Castillo, and Soria (2012) presented an ensemble of ANFIS for the prediction of chaotic time series. Svalina, Galzina, Lujic, and Šimunovic (2013) proposed an ANFIS to forecast the close prices for the next five days for the Zagreb Stock Exchange Crobex index. They used a separate ANFIS for each day. Ebrahimpour, Nikoo, Masoudnia, Yousefi, and Ghaemi (2011) combined three Multilayer Perceptron (MLP) neural networks and an ANFIS to forecast trends on the Tehran stock exchange. Vanstone, Finnie, and Hahn (2012) used a neural network to create a stock trading system based on fundamental variables. Chen (2013) used particle swarm optimization for tuning subtractive clustering parameters, and the ANFIS model for predicting business failures. Ansari, Kumar, Shukla, Dhar, and Tiwari (2010) proposed an uncertainties detection system to be used during a period of recession, an ANFIS based on economic and statistical analysis. Cheng, Wei, and Chen (2009) proposed a new fusion ANFIS based on multi-stock volatility causality for forecasting stock prices in Taiwan. (Liu, Leng, & Fang, 2014)(Chiang, 2013) and (Lin et al., 2012) used ANFIS with QPSO as a membership tuning function. Choudhry, McGroarty, Peng, and Wang (2012) used a neural network to forecast FX exchange rates based on past bid and ask prices. Marghescu, Sarlin, and Liu (2010) applied the fuzzy c-means method, Sarlin and Marghescu (2011b) used a self-organizing map (SOM). Sarlin and Marghescu (2011a) in another study used a neuro-genetic hybrid model for predicting currency crises. Trinkle (2005) proposed an ANFIS model for forecasting annual excess stock returns, and compared the results using the neural network and the Autoregressive Integrated Moving Average (ARIMA) model. Vojinovic, Kecman, and Seidel (2001) compared a radial basis function neural network model with a linear autoregressive model for forecasting the USD/NZD exchange rate. Albanis and Batchelor (2007) proposed a hybrid method based on neural network and recursive partitioning for combining heterogeneous classifiers in stock selection. Leung, Chen, and Mancha (2009) used two independent neural network architectures to make trading decisions on the FX market. Vanstone and Finnie (2011) proposed an artificial neural network model for foreign currency trading .Schott and Kalita (2011) used ANFIS to identify patterns on time series data in stock analysis. Quek, Yow, Cheng, and Tan (2009) utilized a novel fuzzy neural system, named the Generic Self-organizing Fuzzy Neural Network (GenSoFNN), for portfolio balancing on the New York Stock Exchange and NASDAQ. (Vanstone & Finnie, 2009, 2010; Vanstone & Hahn, 2008) used a neural network to forecast stock market index.

In some other papers wavelet-based systems were used to forecast market fluctuations. Li and Kuo (2008) used the Discrete Wavelet Transform (DWT) for feature extraction, and a self-organizing map network for model forecasting. Kao, Chiu, Lu, and Chang (2013) created a stock index forecasting system by integrating wavelet-based feature extraction with Multivariate Adaptive Regression Splines (MARS) and Support Vector Regression (SVR). Reboredo and Rivera-Castro (2014) used wavelet multiresolution analysis to examine the relationship between oil prices and stock returns in Europe and the USA. Zhao, Zhang, and Qi (2008) combined wavelet and neural network architecture to predict stock market returns. Huang (2011a, 2011b) proposed a financial forecasting model based on integration spectral clustering, incorporating wavelet-based kernel partial least squares regression. Hsieh, Hsiao, and Yeha (2011) forecasted the stock market by using WT and the recurrent Neural Networking (NN) system, integrated with the Artificial Bee Colony (ABC) algorithm. Granéa and Veiga (2010) used wavelets for detecting outliers in financial time series. Sun and Meinl (2012) proposed a denoising algorithm based on wavelets for high-frequency financial data mining. Catalão, Pousinho, and Mendes (2011) proposed a hybrid wavelet-PSO-ANFIS method for electricity price forecasting. Caetano and Yoneyama (2009) used wavelet transformation to detect imminent abrupt changes in financial time series.

Dynamic Time Warping (DTW) is a well-known technique for finding the best alignments between two time series. Barbon et al. (2009) used DTW based on Discrete Wavelet Transform (DWT) for pattern recognition in spoken languages. Li (2014) proposed an Asynchronism-based Principal Component Analysis (APCA), based on Dynamic Time Warping, in order to obtain the estimation of a time series which derives from the original form. Jalalian and Chalup (2013) proposed using a hybrid of Potential Support Vector Machines (P-SVMs) and a Gaussian Dynamic Time Warping (GDTW) for variable-length time series analysis. Lee, Oh, and Kim (2012) employed Dynamic Time Warping to find the appropriate number of templates in futures market investing.

There are not many studies dealing with financial patterns extraction. According to (Bulkowski, 2005) financial charts display 53 different patterns. Some of the popular chart patterns are shown in Fig. 1. Liu and Kwong (2007) proposed a model to find chart patterns based on wavelet analysis and radial basis function neural networks. Wang and Chan (2009) developed a template grid model to extract rounding top and saucer patterns. Ładyzynski and Grzegorzewski (2013) proposed a system based on fuzzy geometric protoforms and classification trees to detect patterns in price time series. Zapranis and Tsinaslanidis (2012) developed a rule-based mechanism for identifying the rounding bottoms pattern and resistance levels. Lan, Zhang, and Xiong (2011) used fuzzy logic theory and the Japanese candlestick theory to find reversal points of stock prices. Jagnjic, Bogunovic, Pizeta, and Jovic (2009) proposed a classification method based on qualitative space fragmentation.

3. Basic methods

3.1. Adaptive-Network-Based Fuzzy Inference System (ANFIS)

Zadeh (1965) proposed fuzzy logic and Fuzzy Inference Systems (FIS) for the first time in 1965. In fuzzy logic, data can be a member of more than one set. In fuzzy logic, models are represented by if-then rules and linguistic variables. Every fuzzy inference system has three main parts: fuzzy rules, membership functions and a reasoning mechanism. There are three types of fuzzy inference systems: the Mamdani system, where the fuzzy output has to be defuzzified (Mamdani, 1976), the Takagi–Sugeno system, which gives a real number as output (Takagi & Sugeno, 1983), and the Tsukamoto system, which uses monotonous functions.

Jang (1993) proposed the Adaptive Network-based Fuzzy Inference System (ANFIS) in 1993. The ANFIS architecture uses a Takagi–Sugeno type fuzzy system. For instance, a fuzzy inference system with two rules of the Takagi–Sugeno type is shown in Eq. (1) (Zadeh, 1965):

$$\begin{aligned} &Rule1: \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1 \\ &Rule2: \text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2 \end{aligned} \tag{1}$$

Fig. 2 shows the ANFIS system's general architecture for a fuzzy inference system with two inputs, x and y, and one output, f.

The details of the functioning of each layer of the ANFIS are as follows:

Layer 1. This layer is the input layer and contains adaptive nodes with node functions. Each node in this layer corresponds to a linguistic label, and the output is the value of the membership function described in Eq. (2):

$$O_{1,i} = \mu A_i(x) \quad \text{for } i = 1,2 \tag{2}$$

For every level, $O_{k,i}$ is the node in the *i-th* position of the *k-th* layer.

There are many types of membership function, but a bell-shaped function is the one usually adopted. It can be written as follows in Eq. (3):

$$\mu A(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{3}$$

where a_i, b_i and c_i are known as premise parameters.

Layer 2. Every node in this layer multiplies the incoming signals with output given by:

$$O_{2,i} = w_i = \mu A_i(x)\mu B_i(y), \quad i = 1,2 \tag{4}$$

Layer 3. The *i-th* node of this layer calculates the ratio of the firing strength of the *i-th* rule to the sum of all the firing strengths, with output:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{5}$$

Layer 4. In this layer, node i has the following node function:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{6}$$

Layer 5. The single node in this layer computes the overall output as the sum of all incoming signals, as follows:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

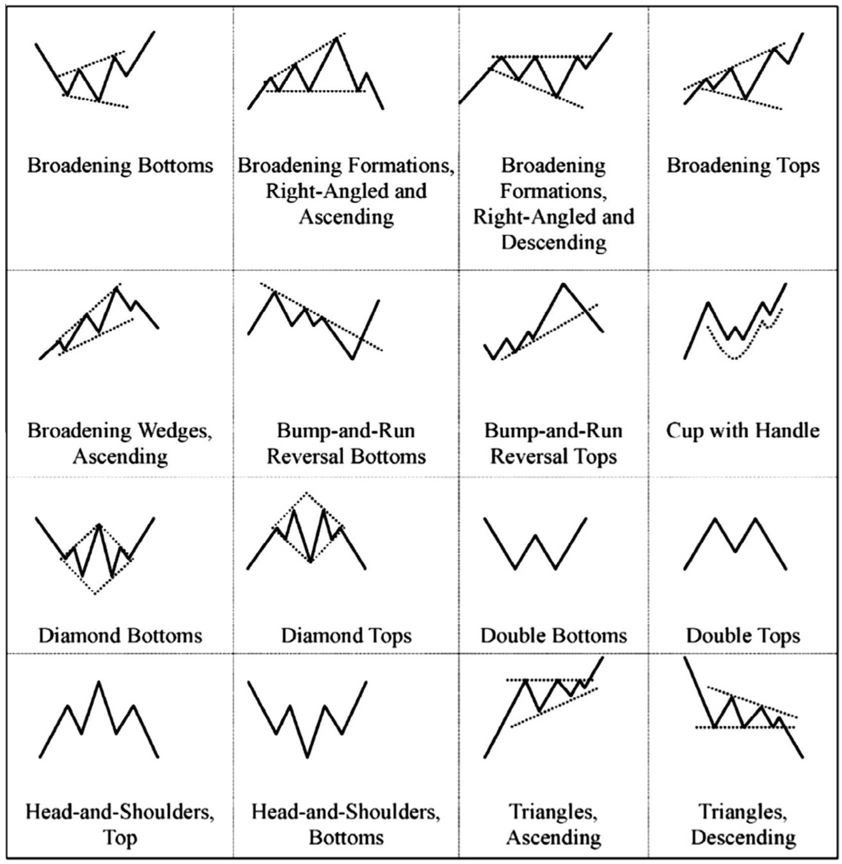

Fig. 1. Popular chart patterns (Liu & Kwong, 2007).

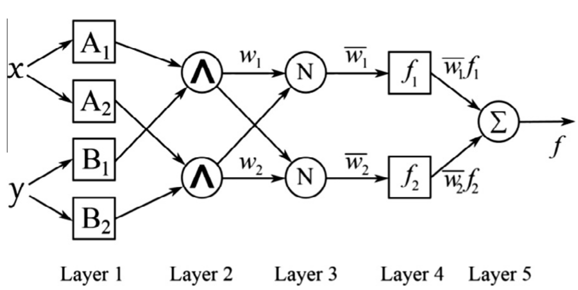

Fig. 2. The general architecture of ANFIS.

3.2. PSO and QPSO

3.2.1. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization algorithm was first proposed by Kennedy and Eberhart (1995). The PSO is a random search technique based on a population of particles. The main idea of PSO comes from the social behavior of schools of fish and flocks of birds. In PSO each particle moves in a D-dimensional space based on its own past experience and those of other particles. Each particle has a position and a velocity represented by the vectors $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ for the i-th particle. At each iteration, particles are compared with each other to find the best particle. Each particle records its best position as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$. The best position of all particles in the swarm is called the global best, and is represented as $G = (G_1, G_2, \ldots, G_D)$. The velocity of each particle is given by Eq. (8).

$$V_{id} = w, v_{id} + c_1 \cdot rand_1() \cdot (pbest_{id} - x_{id}) + c_2 \cdot rand_2() \cdot (gbest - x_{id}) \tag{8}$$

In this equation $i = 1, 2, \ldots, M$, $d = 1, 2, \ldots, D$, C_1 and c_2 are positive constants (known as acceleration constants), $rand_1()$ and $rand_2()$ are random numbers in [0 1], and w, introduced by Shi and Eberhart (Clerc & Kennedy, 2002) is the inertia weight. The new position of the particle is determined by Eq. (9):

$$x_{id} = x_{id} + v_{id} \tag{9}$$

3.2.2. Quantum-behaved Particle Swarm Optimization (QPSO)

Sun, Feng, and Xu (2004a) (Sun, Xu, & Feng, 2004b, 2005) proposed the Quantum-behaved Particle Swarm Optimization. In QPSO every particle has a quantum behavior, and moves around the center of the potential field. Instead of position and velocity, QPSO assigns each particle with a wave function $\psi(x,t)$. The behavior of particles in QPSO is very different from PSO, as shown in Fig. 3. The probability of the appearance of the particle i in position x is calculated from the probability density function $\psi(x,t)$. Each particle moves according to Eqs. (10) and (11)

$$P_{id} = \varphi \cdot P_{id} + (1 - \varphi) \cdot P_{gd}, \quad \varphi = rand() \tag{10}$$

$$X_{id} = P_{id} \pm \alpha \cdot |mbest_d - X_{id}| \cdot \ln(1/u), \quad u \sim U(0,1) \tag{11}$$

where, *mbest* is the mean best position of the particles.

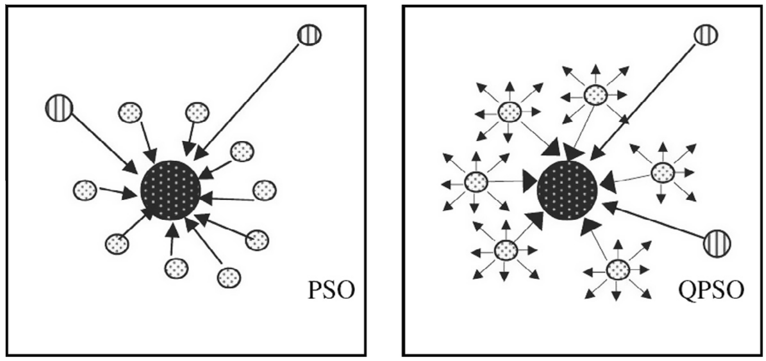

Fig. 3. The movements of particles in PSO and QPSO (Sun, Fang, Palade, Wu, & Xu, 2011).

$$mbest = \frac{1}{M}\sum_{i=1}^{M} P_i = \left(\frac{1}{M}\sum_{i=1}^{M} P_{i1}, \frac{1}{M}\sum_{i=1}^{M} P_{i2}, \ldots, \frac{1}{M}\sum_{i=1}^{M} P_{in}\right) \quad (12)$$

P_{id} is a random point between P_{id} and P_{gd} and a local attractor for the i-th particle on the d-th dimension. φ and u are random numbers in [0 1] and α is one of the QPSO parameters, called the contraction–expansion coefficient.

3.3. Dynamic Time Warping (DTW)

Sequential data classification is widely applied in financial data mining (Liao & Wang, 2010; Wang, Huang, & Wang, 2012). Common distance measures in sequential pattern matching are of three different types (Jalalian & Chalup, 2013):

- Non-elastic metric (Euclidean Distance, lp-norms and Correlation (Deza & Deza, 2009))
- Elastic non-metric (Dynamic Time Warping (Kalaba, 1959) and Longest Common Sub-sequence(V. Chvatal & Sankoff, 1975))
- Elastic metric (Edit Distance with Real Penalty Chen and Raymond (2004))

In the past, Dynamic Time Warping was proposed for automatic speech recognition (Velichko & Zagoruyko, 1970). DTW is a well-known technique used to measure the similarity between two time series. It also works on time series with different lengths. By using DTW, we can find the optimum path between two time series. To describe DTW, assume two time series $X = (x_1, x_2, \ldots, x_N)$ of length $N \in \mathbb{N}$ and $Y = (y_1, y_2, \ldots, y_M)$ of length $M \in \mathbb{N}$. In the following, we construct an $N \times M$ matrix where the element in the (i-th,j-th) position is the distance $D(x_i, y_j)$, using Euclidean distance. Typically $D(x_i, y_j)$ is small if x_i and y_j are of a similar size, and vice versa. The goal is to find the alignment between X and Y with minimal overall cost. An (N,M)-warping path is a sequence $P = (p_1, p_2, \ldots, p_l)$, with $P_l = (n_l, m_l) \in [1:N] \times [1:M]$for $l \in [1:L]$ satisfying the following three conditions:

- Boundary condition: $\boldsymbol{p_1} = (\mathbf{1}, \mathbf{1})$ and $\boldsymbol{p_L} = (\boldsymbol{N}, \boldsymbol{M})$. The alignment path starts at the bottom left and ends at the top right.
- Monotonicity condition: $\boldsymbol{n_1} \leqslant \boldsymbol{n_2} \leqslant \ldots \leqslant \boldsymbol{n_L}$ and $\boldsymbol{m_1} \leqslant \boldsymbol{m_2} \leqslant \ldots \leqslant \boldsymbol{m_L}$. The alignment path does not go back in time.
- Step size condition: $\boldsymbol{p_{\ell+1}} - \boldsymbol{p_\ell} \in \{(\mathbf{1},\mathbf{0}), (\mathbf{0},\mathbf{1}), (\mathbf{1},\mathbf{1})\}$ ***for*** $\ell \in [\mathbf{1} : L - \mathbf{1}]$. This prevents the warping path from taking long jumps (shifts in time), while aligning sequences.

The cost function associated with a warping path is computed with respect to the local cost matrix (which represents all pairwise distances) shown in Eq. (13):

$$c_p(X, Y) := \sum_{\ell=1}^{L} C(x_{n\ell}, y_{m\ell}) \quad (13)$$

The warping path, which has a minimal cost associated with each alignment, is called the optimal warping path named P^*. The $DTW(X,Y)$, the total cost of P^*, is defined as follows:

$$DTW(X, Y) := c_p * (X, Y) = min\{c_p(X, Y) | p \in P^{N\times M}\} \quad (14)$$

where $P^{N\times M}$ is the set of all possible warping paths, and leads to the accumulated cost matrix, or global cost matrix D, which is defined as follows (see Fig. 4):

$$(1) \quad \text{First row}: \ \boldsymbol{D}(\mathbf{1}, \boldsymbol{j}) = \sum_{\boldsymbol{k}=\mathbf{1}}^{\boldsymbol{j}} \boldsymbol{c}(\boldsymbol{x_1}, \boldsymbol{y_k}), \quad \boldsymbol{j} \in [\mathbf{1}, \boldsymbol{M}]. \quad (15)$$

$$(2) \quad \text{First column}: \ \boldsymbol{D}(\boldsymbol{i}, \mathbf{1}) = \sum_{\boldsymbol{k}=\mathbf{1}}^{\boldsymbol{i}} \boldsymbol{c}(\boldsymbol{x_k}, \boldsymbol{y_1}), \quad \boldsymbol{i} \in [\mathbf{1}, \boldsymbol{N}]. \quad (16)$$

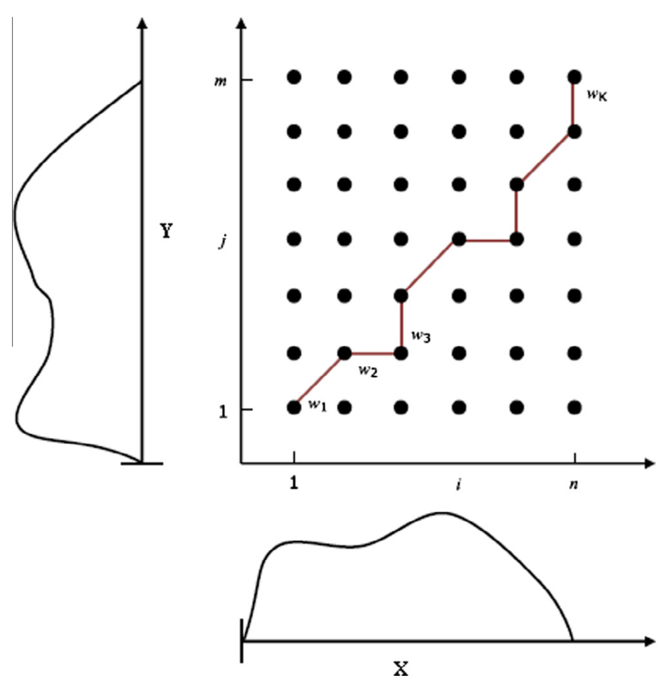

Fig. 4. An example of a warping path on the x–y plane (Keogh, 2001).

(3) All other elements:

$$D(i,j) = min\{D(i-1,j-1), D(i-1),j), D(i),j-1)\} + c(x_i, y_j), \quad i \in [1,N], j \in [1,M] \tag{17}$$

3.4. Wavelet Transform (WT)

Wavelet Transform is used mainly for extracting information from signals, and is also a type of signal processing technique (Cohen, Daubechies, & Vial, 1993). In fact, wavelets are made up of mathematical functions that decompose signals into components with different frequencies. We can decompose any function $f(t)$ by a sequence of projections based on the wavelet basis, as follows:

$$f(t) = \sum_k s_{j,k}\emptyset_{j,k}(t) + \sum_k d_{j,k}\psi_{j,k}(t) + \sum_k d_{j-1,k}\psi_{j-1,k}(t) + \ldots + \sum_k d_{1,k\psi 1,k}(t) \tag{18}$$

where Φ is the father wavelet and ψ is the mother wavelet, defined as follows:

$$\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi(2^{-j}t - k) = 2^{-\frac{j}{2}}\phi\left(\frac{t - 2^j k}{2^j}\right) \tag{19}$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi(2^{-j}t - k) = 2^{-\frac{j}{2}}\psi\left(\frac{t - 2^j k}{2^j}\right) \tag{20}$$

$S_{j,k}$ are called the smooth coefficients and $d_{j,k}$ are called the detailed coefficients. Then define:

$$S_J(t) = \sum_k s_{J,k}\phi_{J,k}(t) \tag{21}$$

$$D_j(t) = \sum_k d_{j,k}\psi_{j,k}(t) \tag{22}$$

Then the signal $f(t)$ is equal to the sum of the following signals:

$$f(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_1(t) \tag{23}$$

There are two main types of Wavelet Transform: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). If $W(a,b)$ is the CWT of $f(x)$, then

$$W(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(x)\psi\left(\frac{x-b}{a}\right)dx = \int_{-\infty}^{+\infty} f(x)\psi_{a,b}(x)dx \tag{24}$$

If $w(p,q)$ is the DWT of $f(x)$, then

$$w(p,q) = 2^{-\left(\frac{p}{2}\right)}\sum_{t=0}^{T-1} f(t)\psi\left(\frac{t - q \cdot 2^p}{2^p}\right) \tag{25}$$

where T is the length of $f(x)$. For more information about wavelet analysis, refer to Chui (1992), Daubechies (1992), and Percival & Walden, 2000.

4. The proposed method

This article has proposed a novel method for forecasting financial time series. In the first instance, an ANFIS-wavelet tuned with QPSO is used as a one-step-ahead forecasting system. Also a novel Dynamic Time Warping (DTW)-wavelet hybrid method is proposed for automatic pattern extraction. Finally, dependent upon the outputs of the proposed method, the system makes some trading decisions, like 'buy', 'sell' or 'neutral'. In this article we tried to create a decision support system that emulates the behavior of real traders in financial markets.

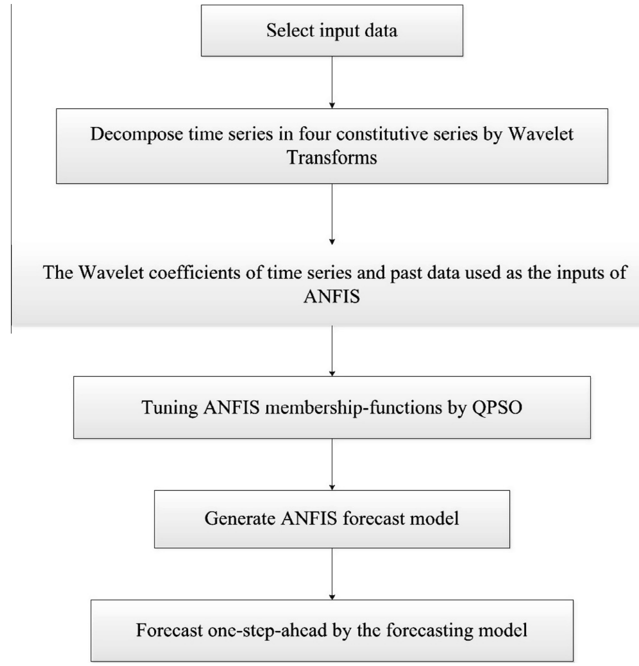

Fig. 5. Flowchart of the forecasting model.

4.1. Wavelet-ANFIS-QPSO system

ANFIS has a good performance in forecasting systems and is also widely used. The main differences between the methods reviewed in the literature are the ways of selecting input data and tuning the ANFIS parameters. Most of the proposed methods used technical analysis indicators as the input data. Technical indicators describe the behavior of the main time series. Technical indicators are also easy to implement, because they are based on a statistical formula. This article describes how the wavelet coefficients of time series can be used as the input values of the ANFIS. Wavelet Transform is used to decompose the main time series into its constitutive series. These constitutive series can reflect the behavior of the main time series. We used Daubechies 4 (db4) with three decomposition levels as the mother wavelet. For tuning the membership function parameters and improving the ANFIS performance, the Quantum-behaved Particle Swarm Optimization (QPSO) has been used. The proposed model is shown in Fig. 5.

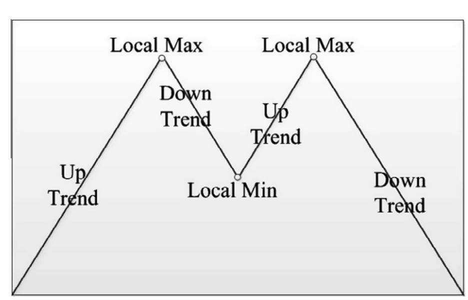

Fig. 6. The important features of the double tops pattern.

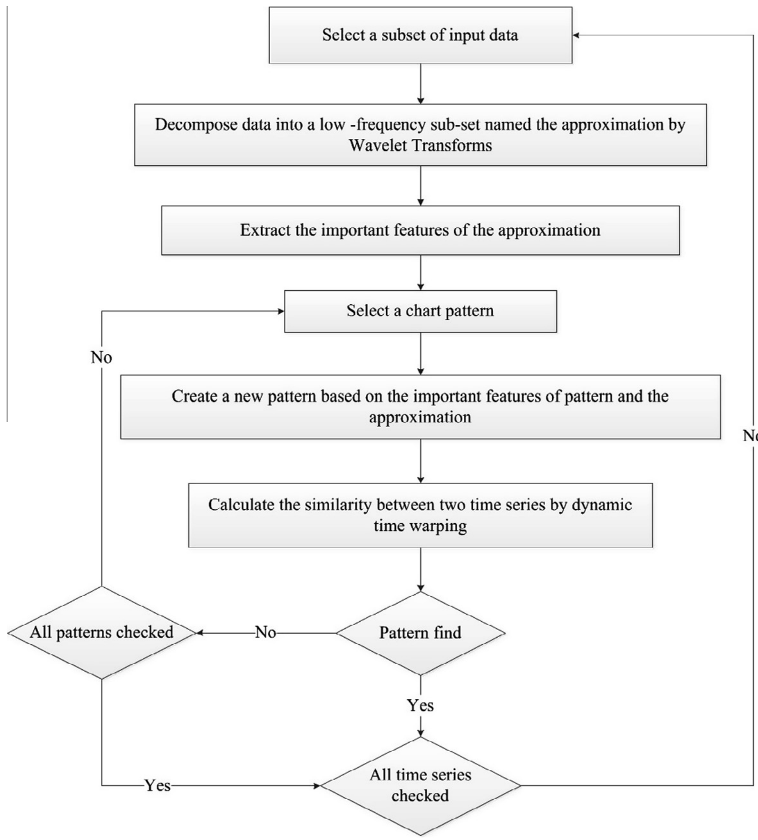

Fig. 7. The proposed hybrid WT-DTW method.

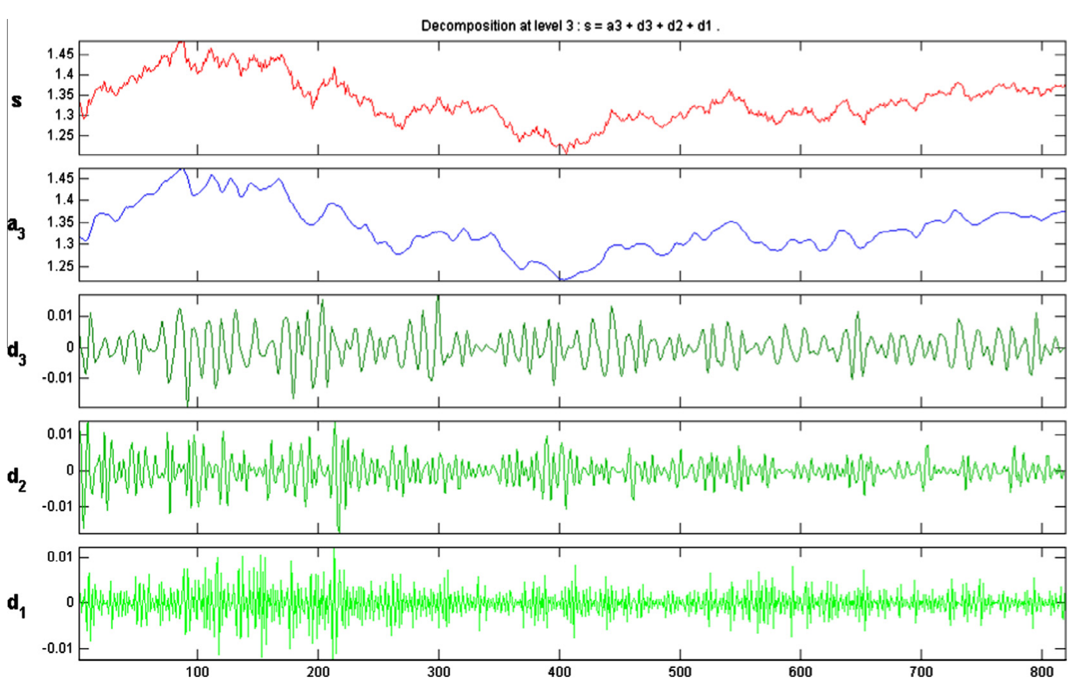

Fig. 8. s is the EUR/USD exchange rate (red), a_3 is the wavelet approximation at level three (blue), and d_1,d_2 *and* d_3 are details at levels one, two and three (green). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

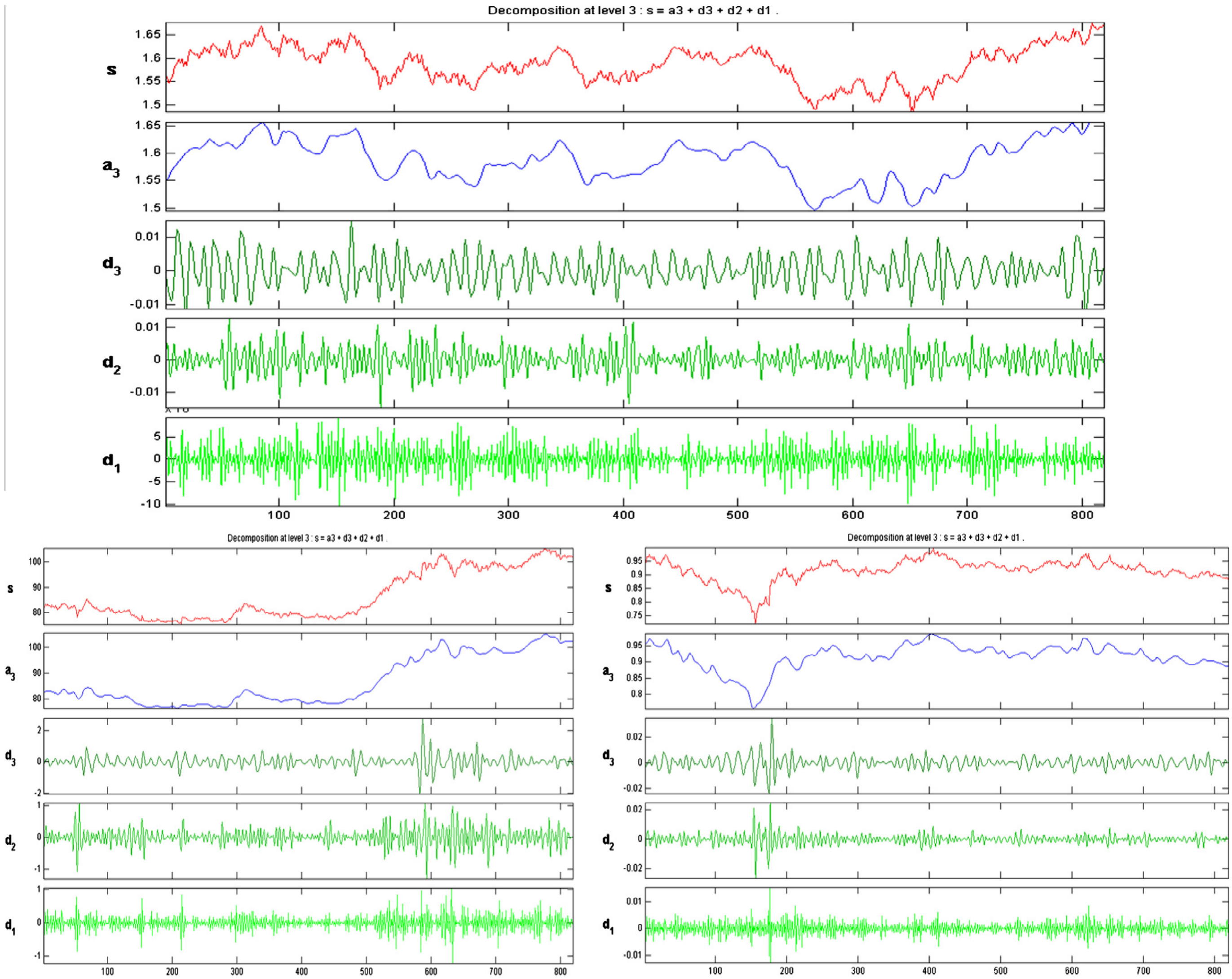

Fig. 9. The full decomposition for GBP/USD (top), USD/JPY (bottom left) and USD/CHF (bottom right).

Table 1
ANFIS input data set.

Date	App. L.3	Detail L.1	Detail L.2	Detail L.3	App. L.3	Detail L.1	Detail L.2	Detail L.3
	EUR/USD				*GBP/USD*			
2011.01.03	1.336649	−0.00111	−0.00034	-0.0001	1.552652	−0.0036	-0.00081	−0.00033
2011.01.04	1.328624	0.001852	0.00043	6.41E-05	1.552318	0.006056	0.000958	0.000218
2011.01.05	1.315162	−0.00032	0.000122	4.94E-05	1.551143	−0.00132	0.000306	0.000242
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2014.02.26	1.371393	−0.0015	−0.00085	−0.00046	1.668198	−0.0007	−0.00033	−0.00013
2014.02.27	1.373517	−0.00194	−0.00048	−0.00016	1.670377	−0.00121	−0.00035	−9.77E-05
2014.02.28	1.376792	0.001855	0.001058	0.000425	1.672253	0.00102	0.000502	0.000155
	USD/JPY				*USD/CHF*			
2011.01.03	81.75182	0.050147	−0.03378	−0.03419	0.936877	−0.00111	−0.0012	−0.00081
2011.01.04	82.2901	−0.19594	−0.01079	0.005636	0.947296	−0.00049	0.000589	0.000373
2011.01.05	82.91832	0.200788	0.054791	0.043099	0.959709	0.003663	0.00135	0.000918
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2014.02.26	102.252	0.083128	0.016537	0.009328	0.888484	0.001087	0.000653	0.000356
2014.02.27	102.0544	0.051117	0.016478	−4.35E-05	0.885875	0.001825	0.000392	9.78E-05
2014.02.28	101.8831	−0.05649	−0.0345	−0.0131	0.882701	−0.00163	−0.00089	−0.00036

Table 2
Evaluating the forecast model.

	EUR/USD	GBP/USD	USD/JPY	USD/CHF
RMSE	0.003472	0.004781	0.454605	0.002898
SEM	0.000245	0.000290	0.032818	0.000210
MAPE	0.196349	0.243643	0.335298	0.243298
MAE	0.002674	0.003995	0.344018	0.002190

4.2. Dynamic Time Warping (DTW)-Wavelet Transform Hybrid Method

Before the occurrence of some market events, price trends in financial market charts begin to show some patterns. Identifying these patterns is a very important part of financial trading but, unfortunately, they are not obvious and easy to find. This article introduces a novel hybrid method for financial patterns extraction by Wavelet Transform (WT) and Dynamic Time Warping (DTW). By using WT we can decompose input time series into a low-frequency subset, named 'the approximation', and a high-frequency subset, named 'the detail'. The approximation of the input time series indicates the general trend without allowing for small fluctuations. This approximation is used instead of the input time series. Also, Dynamic Time Warping (DTW) is used as a measure of distance in the pattern matching process. The method presented is based on two main steps: adaptive pattern creation and comparing two time series.

4.2.1. Adaptive pattern creation

The main idea in this step is to create a specific pattern for any particular subsets of the input time series. Firstly, the important features of selected patterns are extracted; for example, double tops. Based on the primary form of the pattern, there are some local minima and maxima points that appear in the specific sequence. The local minimum and two local maxima for a double tops pattern are shown in Fig. 6. Next, whilst keeping the structure of the original pattern, and depending on the length of minimum and maximum values of selected subset input time series, a new pattern has been made by combining the extracted features for the selected subset input time series.

4.2.2. Comparing Pattern and Time Series

It is the nature of the financial market to be indistinctive and variable. It is nearly impossible for a specific pattern to appear in its exact form without any fluctuation. The human brain can find patterns in time series containing many irregularities. To simulate the behavior of the human brain, we used Dynamic Time Warping as a method to measure distance. If the shape of a specific pattern is shown in the input time series, then DTW can be used for the automatic

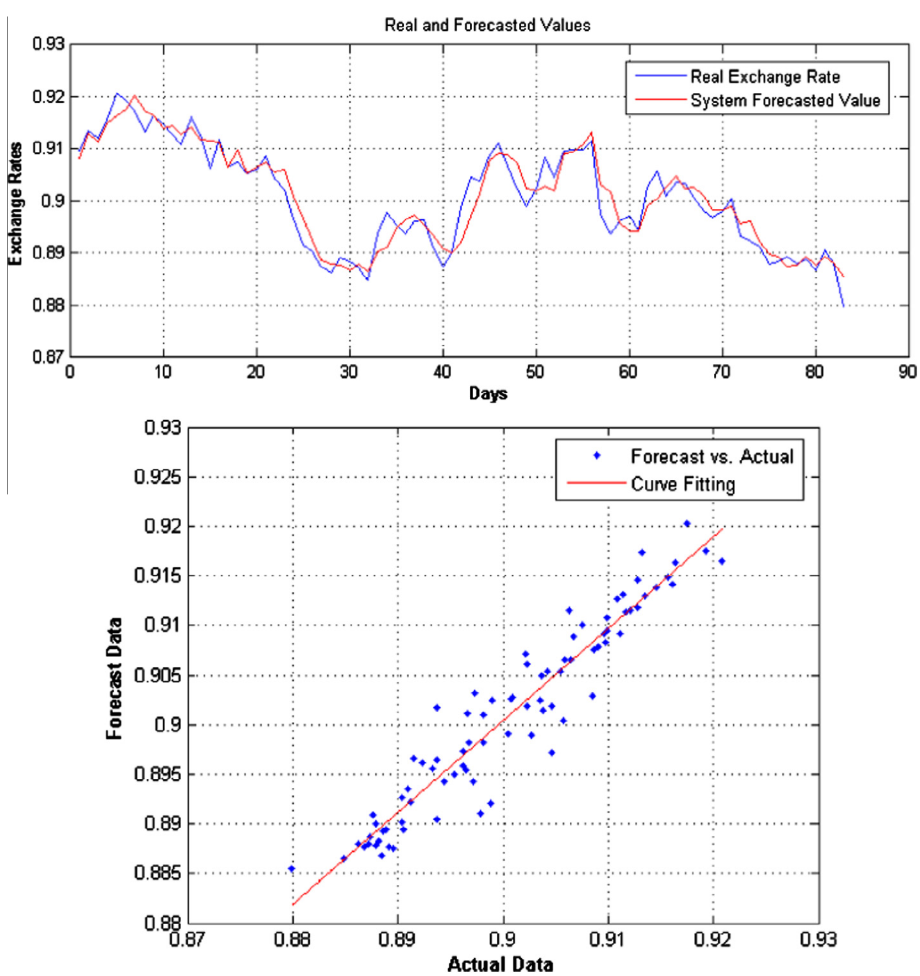

Fig. 10. EUR/USD results – forecast (red), actual (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

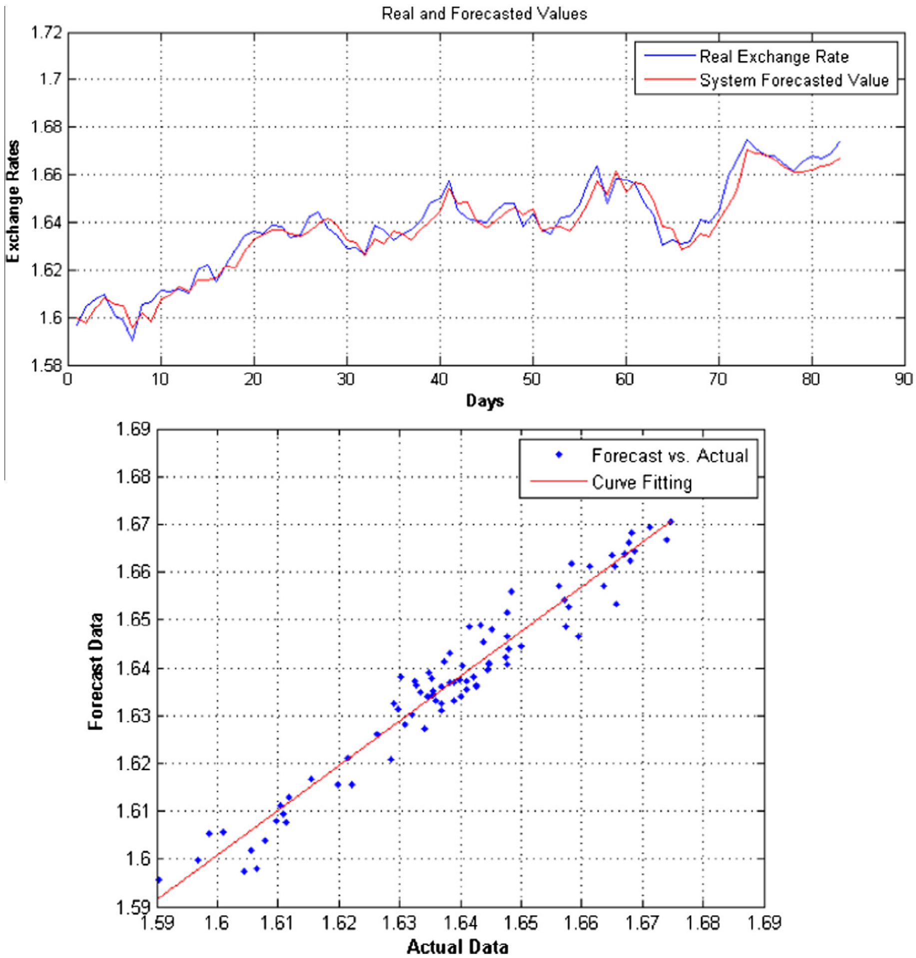

Fig. 11. GBP/USD results – forecast (red), actual (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

pattern extraction process. The presented method is shown in Fig. 7.

4.3. Trading advisory section

Most of the proposed methods in the literature just tried to forecast market price one step ahead. It is obvious that, by relying on current human knowledge, forecasting the exact value is impossible. Therefore, researchers used complicated methods to minimize the forecasting error. The proposed method gives some trading advice, such as 'buy', 'sell' or 'neutral', instead of predicting an exact value. We know which patterns appear in time series, and we can also forecast the next time series data value based on the outputs of the two previous steps. In the final step, depending on the extracted patterns and the forecasted price, this method creates a decision support system that emulates the behavior of real traders in financial markets.

5. Experiments and comparisons

In this section, to demonstrate the proposed model and to introduce the proposed method step-by-step, the daily exchange rates of four major currency pairs from January 2011 to December 2013 are used as the experimental dataset. The four major currency pairs used are EUR/USD, USD/JPY, GBP/USD and USD/CHF. The first part describes the machine learning model. The second part presents the pattern recognition method. The third part generates some trading advice from the system.

5.1. Part 1: One-step-ahead forecasting

Part 1 Step1: Collect datasets

As an example to illustrate the proposed model, we collected the exchange rates of four major FX currency pairs. There were 819 trading days from January 1, 2011 to February 28, 2014. We used the first 735 days, from January 3, 2011 to October 31, 2013 inclusive as training data, and the remaining 84 days, from November 1, 2013 to February 28, 2014, for testing the model.

Part 1 Step2: Decomposition by Wavelet Transform

In this step, we decomposed the training data by using Daubechies 4 (db4) with three decomposition levels. The full decomposition of the EUR/USD exchange rate vs. days is shown in Fig. 8.

The full decomposition of other currency pairs is shown in Fig. 9.

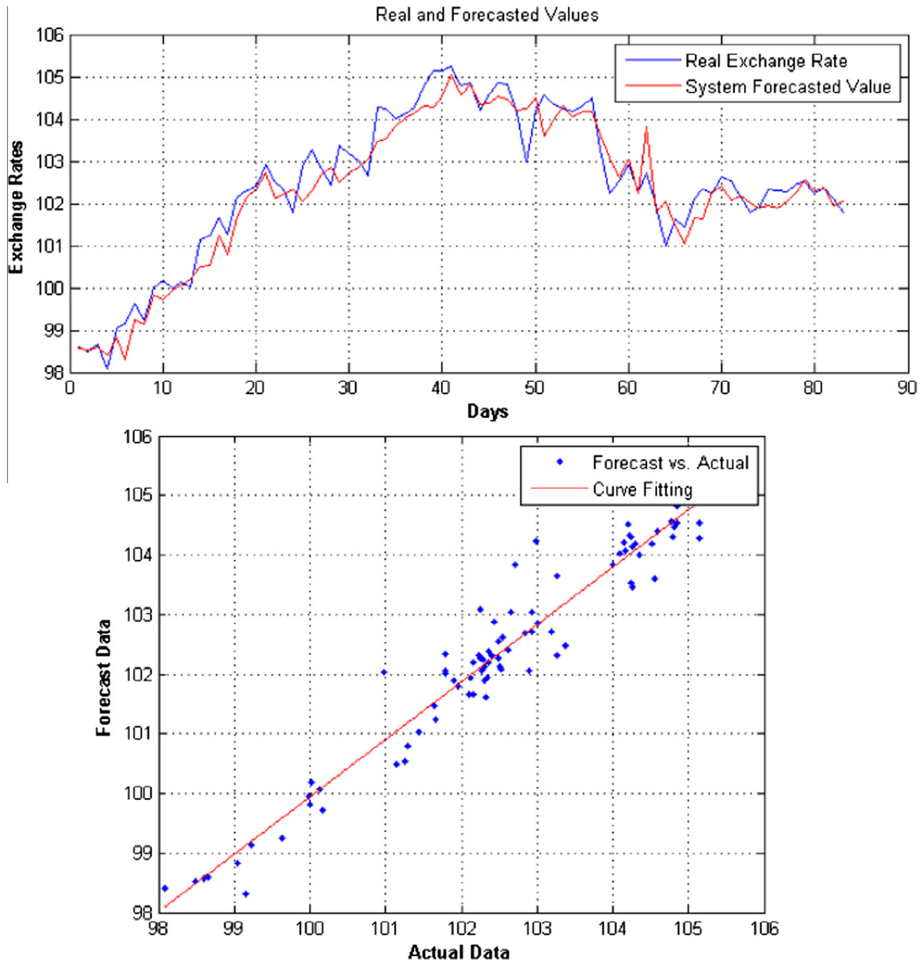

Fig. 12. USD/JPY results – forecast (red), actual (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Part1 Step3: Creating the ANFIS input set

We used the wavelet full decomposition of training time series as the inputs of ANFIS. The input data is shown in Table 1.

Part1 Step4: Setting membership function parameters

For tuning the membership function parameters and improving the ANFIS performance, we used the Quantum-behaved Particle Swarm Optimization (QPSO) method. In MATLAB the 'genfis' function is used for creating a fuzzy inference system. In 'genfis' code there is another important function named 'genparam'. Output of the 'genparam' function,named 'mf_param', contains the membership function parameters and depends on the type of membership function. In the proposed method, to improve the performance of the forecasting model, QPSO is used for optimizing the membership function parameters in 'mf_param'.

Part1 Step5: Training ANFIS and evaluating the forecast model

In the final step of part1 we trained ANFIS with training data and tested the model with the last 83 days that remained as test data. For evaluating the forecast model, the Root Mean Squared Error (RMSE), the Standard Error of the Mean (SEM), the Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE) were calculated using Eqs. (26)–(29) and Table 2. Also the curve fitting plots for forecast vs. actual data are shown in Figs. 10–13.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Actual_i - Forecast_i)^2} \tag{26}$$

$$SEM = \frac{\sigma}{\sqrt{N}} = \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{27}$$

$$MAPE = \left(\frac{1}{N}\sum_{i=1}^{N}\left|\frac{Actual_i - Forecast_i}{Actual_i}\right|\right) * 100 \tag{28}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Actual_i - Forecast_i| \tag{29}$$

5.2. Part 2: pattern extraction

Part2 Step1: Creating subsets from input time series

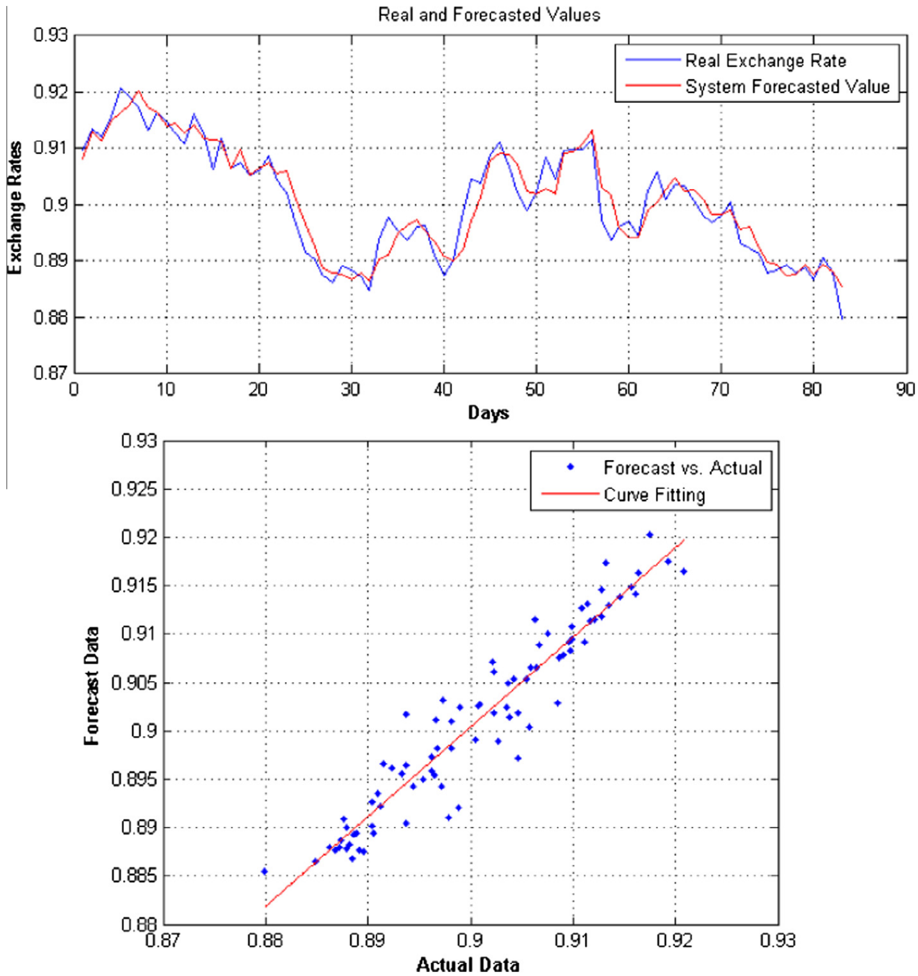

Fig. 13. USD/CHF results – forecast (red), actual (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

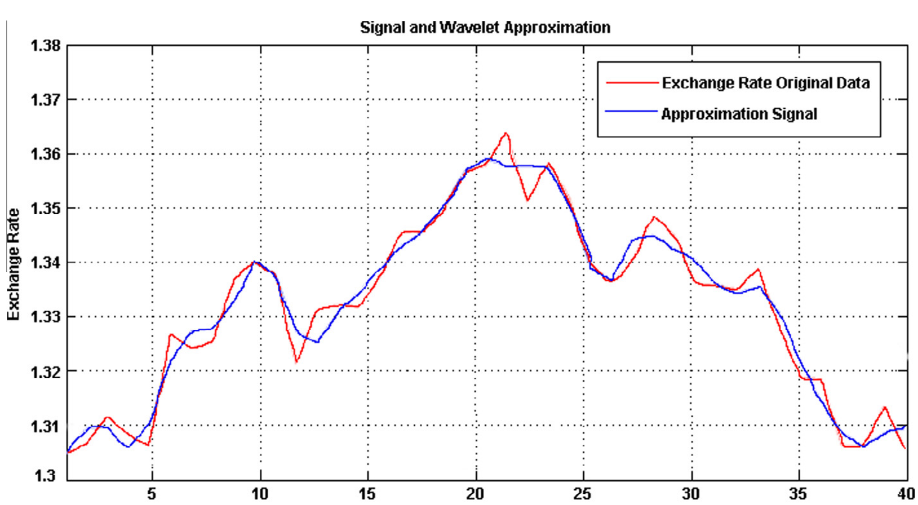

Fig. 14. Original time series (red) and level1 approximation (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Extracted features from the approximation.

Subset length	Overall min	Overall max
40	1.3049	1.3639
Index	Local min	Local max
1 to 10	1.3049	1.3400
11 to 20	1.3213	1.3564
21 to 30	1.3362	1.3639
31 to 40	1.3055	1.3388

The second part is to extract patterns that were shaped in the selected time series. The input time series is divided into subsets.

Part2 Step2: Smoothing data fluctuation

In this step, subsets are decomposed into a low-frequency subset named 'the approximation' by Wavelet Transform using Daubechies 4 (db4) with one decomposition level as the mother wavelet. This makes the subsets' data smoother, and omits some unnecessary fluctuations. The approximation and original subsets are shown in Fig. 14.

Part2 Step3: Feature extraction from the approximation

The important features are length and the local minima and maxima points in the approximate time series. These features are shown in Table 3.

Part2 Step4: Selection of a chart pattern and adaptive pattern creation

In this step, we selected a chart pattern, created a new pattern dependent on the approximation and pattern extracted features, and examined the occurrence of a new pattern in the approximation. The created pattern and selected subset from the EUR/USD exchange rate case and the approximations are shown in Fig. 15. Also another sample from the USD/CHF case is shown in Fig. 16.

Part2 Step5: Evaluating the similarities between the new pattern and the approximate time series

Dynamic Time Warping (DTW) was used as a method for measuring distance. If the DTW distance is near zero, it means that the two time series are similar. The calculated distances are shown in Table 4.

5.3. Part 3: making decisions

In the final part of the experiment, a decision support system was created based on extracted patterns and the next-day forecasted prices. The final recommendations of the system are shown in Table 5.

5.4. Proposed method evaluation

To determine the accuracy of the proposed method, we used hit rate as an evaluation function. The hit rate is calculated by Eq. (30):

$$Hit\ Rate\ (\%) = \frac{Correct\ Predictions}{Number\ of\ Test\ Data} * 100 \tag{30}$$

The overall hit rate of the proposed method is shown in Table 6.

The calculated hit rate is compared with three other methods. The comparison results are shown in Table 7.

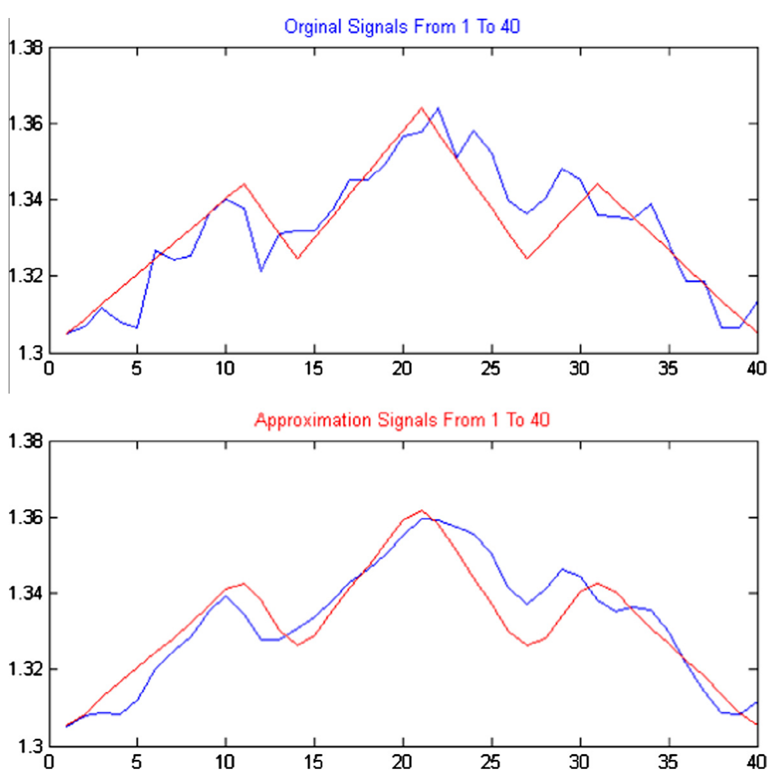

Fig. 15. Head and Shoulders pattern – original signal (blue) and adaptive pattern (red) – for EUR/USD. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

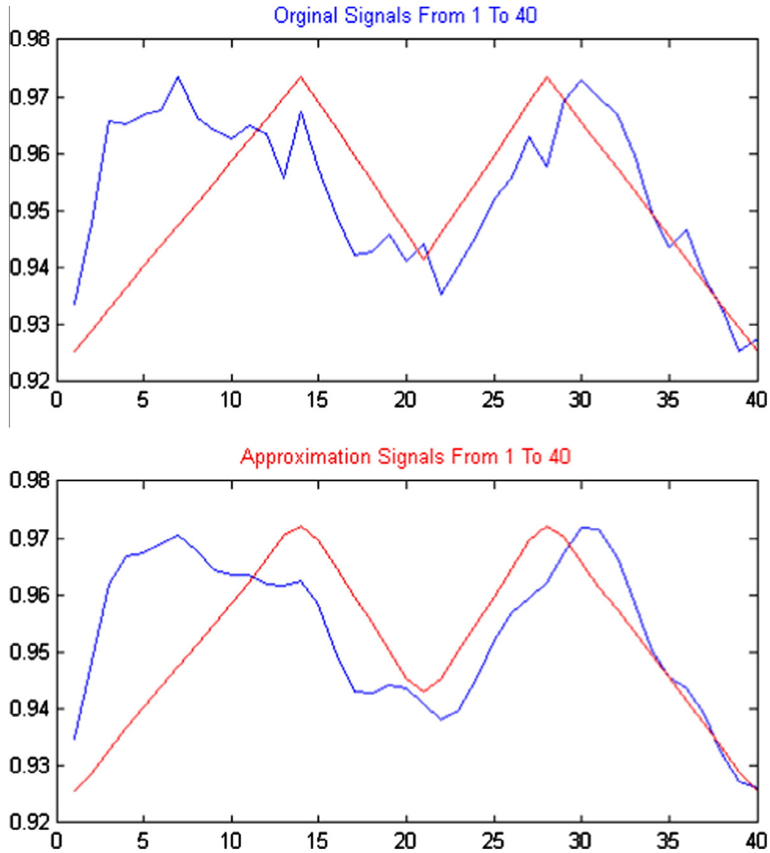

Fig. 16. Double Tops pattern – original signal (blue) and adaptive pattern (red) – for USD/CHF. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
DTW distances.

Distance between the pattern and approximation by DTW	
EUR/USD Sample subset (Fig. 12)	0.101933
USD/CHF Sample subset (Fig. 13)	0.187829

Table 5
Final system recommendation.

Sample subset	Forecasted price recommendation	Extracted pattern recommendation	Final system recommendation
EUR/USD	Buy	Neutral	Buy
GBP/USD	Buy	Buy	Buy
USD/JPY	Sell	Sell	Sell

Table 6
Comparing the hit rate of the method reviewed.

Currency pairs	Hit rate (%)
EUR/USD	68.68
GBP/USD	74.70
USD/JPY	61.45
USD/CHF	71.08
Overall Hit Rate	68.98

Table 7
Comparing the hit rate of the method reviewed with other methods.

Author	Model	Hit rate
Doeksen, Thomas, and Paprzycki (2005)	M-FIS	53.31
	TS-FIS	56.00
Atsalakis and Valavanis (2009)	Neuro-Fuzzy	68.33
Proposed method	ANFIS-QPSO Wavelet-DTW	68.98

6. Conclusions

The main purpose of this paper was to create a Forex trading advisory system that used both chart patterns and past exchange rate values in the decision making process and that would perform like a real trader. We proposed a state-of-the-art method that forecast one-step-ahead market values by using a hybrid of ANFIS, QPSO and WT, and also extracted chart patterns by using WT and DTW at the same time. In addition, unlike most methods in the literature review, the proposed system generates trading advice instead of predicting the exact exchange rate values.

We observed that, by implementing and testing the proposed method on real FX data, we could forecast the market direction and make correct trading decisions with approximately 69% accuracy. The proposed method covers the areas of both machine learning and pattern recognition. Also, just like a real trader would do, the forecasting method used both the historical data and the chart patterns. The experimental results demonstrate that the proposed method performs well in financial forecasting, especially in the Forex market.

Many economic and political factors influence financial market values, so forecasting them is very difficult. Soft computing techniques perform well in financial forecasting, but naturally there are many complications in their implementation. As Sir William Golding said, "The greatest ideas are the simplest." The greatest potential limitation to the proposed method is its complexity. We used a combination of ANFIS, QPSO, DTW and WT, and obviously that is not the greatest idea.

An interesting direction for future work would be to apply the proposed method to shorter time-frames, such as six hours, one hour, or even one minute, in order to create a real time advisory system. Decreasing the size of the time-frame would present more opportunities for making a profit. Furthermore, the proposed method could be used in other financial markets, like the stock exchange market.

Acknowledgements

The authors gratefully acknowledge anonymous reviewers for their valuable comments and suggestions. Also we would like to appreciate the help and support rendered by Mr. James Morrison from JamesEdits for editing this paper.

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