A new modular neural network approach for exchange rate prediction

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Abbas Ahmadi
Amirkabir University of Technology

A new modular neural network approach for exchange rate prediction

Ebtesam Zargany and Abbas Ahmadi*

Department of Industrial Engineering and Management Systems,
Amirkabir University of Technology,
424 Hafez Ave., Tehran, Iran
Email: Ebtesam.Zargany@gmail.com
Email: Abbas.Ahmadi@aut.ac.ir
*Corresponding author

Abstract: A novel approach using modular neural networks to forecast exchange rates based on harmonic patterns in Forex market is introduced. The proposed approach employs three algorithms to predict price, validate its prediction and update the system. The model is trained by historical data using major currencies in Forex market. The proposed system's predictions were evaluated by comparing its results with a non-modular neural network. Results showed that the infrastructure market data consist of significant accurate relations that a single network cannot detect these relations and separate trained networks in specific tasks are needed. Comparison of modular and non-modular systems showed that modular neural network outperforms the other one.

Keywords: ANNs; artificial neural networks; modular neural networks; exchange rate prediction; harmonic patterns.

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Biographical notes: Ebtesam Zargany received the BSc in Applied Mathematics in 2004 at Sheikh Bahaei University of Isfahan, MSc in Industrial Engineering and Management Systems in 2012 at Amirkabir University of Technology in Tehran. She joined Payamnour University in Khorramshahr as a University teacher at the Department of Industrial Engineering. Her research interests are in operation research, data mining, artificial neural networks and electronic financial markets.

Abbas Ahmadi received the BSc in Industrial Engineering in 2000 at Amirkabir University of Technology, MSc in Industrial Engineering in 2002 at Iran University of Science and Technology, and PhD in Systems Design Engineering in 2008 at University of Waterloo. He joined the Amirkabir University of Technology, Iran in 2009 where he is at present Professor at the Department of Industrial Engineering and Management Systems. His research interests are in supply chain management, business intelligence, swarm intelligence, computational intelligence, data and information management, system analysis and design, and cooperative intelligent systems.

1 Introduction

Foreign exchange (FOREX) is the largest and most floating financial market in the world. It has been widely considered by investors, analysts and researchers. Investors and analysts benefit from price fluctuations and researchers try to find tools for predicting price and recognising factors that affect price oscillations (Zargany and Ahmadi, 2011). Several methods have been developed to forecast future price in financial markets. These methods consist of economical, statistical and artificial intelligence (AI) context (Chan and Teong, 1995; Haider Khan et al., 2011; Kimoto et al., 1990; Kamruzzaman and Sarker, 2004; Mizuno et al., 1998; Manjula et al., 2011; Ni and Yin, 2009). Due to dynamic behaviour of financial markets, many researchers concluded that AI methods have better results in price prediction (Gholizadeh et al., 2008; Guresen et al., 2011; Ince and Trafalis, 2006; Lawrence, 1997; Mostafa, 2010; Sinaei et al., 2005; Yao and Tan, 2000). Artificial neural network (ANN) is one of the most popular branches of AI in price prediction of financial markets.

Few scientific studeis have been conducted about FOREX market relative to stock market area. As FOREX market is the largest market in the world with average daily turnover $5.3 trillion,[1] serious studies on price forecasting using modern sciences can be done in this area. It was an incentive for us to do research in this field.

With a smart look to price forecasting by using new sciences and the efficiency of neural networks in dealing with nonlinear objects and specially the ability of modular neural networks in the market segmentation to evaluate price movements and the results of its specific movements motivated us to consider that the combination of modular neural networks and harmonic patterns is a wonderful and is efficient method to predict price reverses in FOREX market.

The study was conducted in order to answer the following questions; the patterns formed in FOREX market that used in traditional prediction methods can make better results considering neural networks? Do neural networks have the ability of resolve defects of traditional prediction methods in finding exact price reverse points? Can they find these points with high accuracy? Can we find neural networks that are useful for any time in prediction of reverse points? Do not they expire over time?

The popularity of neural networks was established since they have the ability to work with nonlinear models, while statistical methods only deal with linear models. Since the dynamic nature of financial markets has non-linear behaviour, our objective at this research is to convert traditional methods to scientific methods in finding reverse price by using neural networks with high accuracy.

In the following, we first review the literature of forecasting financial markets using scientific methods. Once the literature reviewed, we start to introduce the context used in our proposed model. This section consists of two parts. The first part is general introduction to the traditional method of reverse price prediction, Harmonic Patterns. The second part is an introduction to neural networks and the specific form we use, modular neural networks. After that we start to introduce our proposed model that uses the traditional method harmonic patterns into modular neural networks. The proposed system contains three algorithms to increase its accuracy and efficiency in forecasting price reverses in FOREX market. After introducing the system, we implement the proposed model and evaluate the obtained results using real data in FOREX market. The conclusion section comes at the end along with our suggestions for future researches.

2 Literature review

We have conducted extensive studies to propose our system. A summary of these studies is as follows. This summary contains different parts with a specific process that shows our goal of referring such subjects. The first part contains traditional studies in technical analysis context and price prediction in financial markets with traditional methods. The next part is about task decomposition especially with modular neural networks. After that the main part is devoted to the usage of neural networks along with the other price prediction tools in financial markets.

Academic researchers along with financial analysts are trying to extract underlying law of price movement in financial markets. Analysing financial markets is based on technical analysis, fundamental analysis or the combined approach (Nazari Nejad and Nazari Nejad, 2008). Some methods of technical analysis are formulated by special ratios of Fibonacci sequence (Carney, 1999; Duddella, 2007; Fischer and Fischer, 2003). Harmonic patterns, first introduced by Carney (1999), are formed by these special ratios. Next, five well-known harmonic patterns were introduced by other analysts and potential reversal zone (PRZ) for calculating best point of price reverse was developed (Carney, 1999; Duddella, 2007).

Auda and Kamel (1998), used modular neural networks for distinguishing high overlapping classes. They concluded that in addition to reduce complexity, task decomposition into appropriate modules, exhibits more accurate results (Auda and Kamel, 1998). Different neural networks are used for different goals (Karray and De Silva, 2004). This includes a wide range from linear separation of patterns by a simple single layer neural network to nonlinear separation by multi-layer perceptron (MLP) (Karray and De Silva, 2004). Modular neural networks also were used for phoneme recognition(Ahmadi et al., 2006). Different neural networks were used and high level and low level classification for phoneme recognition was created. The proposed model showed satisfactory results in phoneme recognition (Ahmadi et al., 2006). A MLP neural network with back propagation learning algorithm was used to predict Tehran Stock Exchange Index (Sinaei et al., 2005). In this research, the proposed network inputs were various intervals of the stock index and macroeconomic factors. The results for the next seven days showed better estimations than that of ARIMA linear model. In another research Euro against US Dollar was studied (Gholizadeh et al., 2008). In this study a supervised learning with Levenberg-Marquardt algorithm caused a great improvement in the network performance. Modular neural networks also were used to predict Tokyo Stock Exchange Price Index (TOPIX) for the next 30 days (Kimoto et al., 1990). This proposed system was composed of several neural networks. These networks learned the relationship between technical and economical indices, and determined the proper time for buying and selling stocks. By developing 'Supplementary Learning' concept and task decomposition between distinguished modules, accurate results in price prediction were achieved (Kimoto et al., 1990). In a study of Forex market price prediction, high, low and close price of the last five days were used to predict high, low and close price of the next three days. The system used an MLP with single hidden layer network. Results showed that using network outputs with trading indicators lead to better predictions than using trading indicators only (Chan and Teong, 1995). Lawrence (1997) investigated the results of common prediction tools such as technical, economical and regression analysis with performance of neural network on IBM stock. He also compared *Efficient Market Hypothesis* with *Chaos Theory* and neural network. Results rejected the use of efficient market hypothesis in ANNs. Moreover, he concluded that although neural network prediction is not completely accurate, but gives better results than statistical methods and regression analysis (Lawrence, 1997). Mizuno et al. (1998) used ANN to predict the right time to buy and sell for TOPIX. In their proposed system, even by heterogeneous input data, the network acted correctly (Mizuno et al., 1998). Yao and Tan (2000) used time series data and technical indicators such as *moving average* (*MA*) as input to neural network so that the network learns the underlying structure of price fluctuations of US dollar against five other major currencies. The results indicated that using data only from market prices without employing analytical data returns good price predictions. Accordingly, considerable profits through the use of technical analysis and neural network parameters can be acquired (Yao and Tan, 2000). Kamruzzaman and Sarker (2004) used three neural network algorithms to predict exchange rate. They used five technical indicators and historical data to feed the networks. ANN performance for Australian dollar against five major currencies was compared with the usual statistical methods. Results indicated that neural networks using technical analysis indicators, and historical market data present very accurate predictions for the future rate of exchange (Kamruzzaman and Sarker, 2004). Ince and Trafalis (2006) proposed a two-step model for exchange rate prediction. The model included parametric techniques such as ARIMA, VAR[2] and integration techniques as well as nonparametric techniques such as SVR[3] and ANN (Ince and Trafalis B, 2006). Ni and Yin (2009) combined technical indicators (MACD[4], RSI[5]) with self organising map (SOM) and SVR neural networks to predict price in Forex market. They used neural networks alone and also by a combination of technical indicators. The results showed the superiority of the combined model (Ni and Yin, 2009). In a recent research, a new system was developed that included MLP, DAN2[6] and a hybrid neural network GARCH[7] for price prediction in NASDAQ market. The results were evaluated by statistical methods and the predictions obtained from the proposed system were very satisfactory (Guresen et al., 2011). In a research for Bombay stock index prediction, a proposed MLP network, learned with MLR[8] (Manjula et al., 2011). In a study, for ACI stock prediction, a two-module algorithm was developed. In the first module by back propagation learning, the network was trained and in the second module by a multi-layer feed forward network, stock price was predicted (Haider Khan et al., 2011). In a recent study, in order to predict financial time series, researchers fed technical indicator results to their proposed system. Providing a prediction system with new features different from the conventional features of ANNs led them to an optimised system with accurate results in financial time series prediction (Chang et al., 2012). In order to forecast Kuwait stock exchange (KSE), a researcher used an MLP neural network and generalised regression neural networks. He successfully achieved better results than statistical methods such as regression and ARIMA in KSE price prediction (Mostafa, 2010). Some researchers used Wilcoxon norm in their proposed system to show the superiority of neural networks in exchange rate prediction than conventional squared error based models (Majhi et al., 2012). In order to predict the stock of the National Bank of Greece some researchers proposed a system based on *Elliot Wave Theory* and neuro-fuzzy architecture. Their proposed system showed better results than Buy and Hold strategy. In a 400 period test, their system by using nine Anfis systems, showed significant results in buying and selling signals based on Elliot wave counting. They found that using nerou-fuzzy systems along with Elliot wave theory makes an effective system in stock market forecasting (Atsalakis et al., 2011).

Results of all studies above show the superiority of neural networks and also modular neural networks in different financial markets.

In all studies reviewed, the price behaviour in financial markets has historically been studied. The special relationship between price fluctuations in specific intervals has not been considered. Hence special patterns that arise as a result of this specific relationship are ignored. Therefore, reaction of the price against these patterns has never been investigated.

Innovation of this study consists of three items. First of all, none of the studies cited speak about the price patterns' form in the market and they just look at the market history as a whole. Hence, our first innovation is to use the historical price patterns in order to investigate the price behaviour in future with scientific methods. Our second innovation is to estimate price trend milestones in which the trend starts inverse movement. This case never has been pointed before in scientific studies. The last innovation is to create a system which updates itself.

3 Research methodology

One of the most frequent patterns formed in financial markets is *harmonic pattern*. In this paper we propose a method based on harmonic patterns formed in Forex market. In this method, exact relations existing in the infrastructure of the price are considered. So we can investigate the respond of the price vs. these patterns and make exact predictions of future price behaviour. Using this approach in provided systems of the literature reviewed does not provide satisfactory results. Hence we proposed a new modular system for price prediction based on harmonic patterns. Each module is responsible for one pattern and predicts the price behaviour after this pattern taking place. The system also has confirmatory algorithms to provide accurate results.

In order to show the road path in our research and to keep the readers in the main stream, in this section we express a summary of the research methodology. The proposed method is combined of two famous methods of predicting price in financial markets. These two methods have never seen together in a unique system in order to forecast the future price. One has been used traditionally by traders to predict the reverse points in financial markets. This method calls harmonic trading and based on specific patterns shaped in the market on the base of Fibonacci numbers. The other method is ANNs that wildly used by researchers. In the following we provide a summery about these two methods for the readers to get familiar with them in general. After that it is time to use them in a combination in our proposed method. So the proposed system will be introduced completely. It has three different parts that are specialised for different tasks. After that by using real data from FOREX market, we implement our system to predict future reverse prices. The results are provided in tables and figures. Finally the conclusion part will provide the research results.

4 Fibonacci levels and Harmonic patterns

In this section we discuss theoretical basis of the model. We will introduce Fibonacci levels and the way they are used in financial markets analysis. Five well-known harmonic patterns based on special Fibonacci levels also will be introduced.

4.1 Fibonacci levels in financial markets

Fibonacci sequence for the first time introduced by Italian mathematician Leonardo Fibonacci (1200 AD) in response to the breeding of rabbits after N months. The sequence is 1, 1, 2, 3, 5, 8, 13, 21, … in which after the third number, each number obtained from the sum of two previous numbers. By dividing each number to the previous one, we will have a new sequence that is convergent to 1.6180339 that called *Golden Ratio* (Φ). Except for the first few sentences, each sequence number is approximately 1.618 times the number before and 0.618 times the number after (Carney, 1999; Duddella, 2007; Fischer and Fischer, 2003). In financial markets such as stocks and Forex, Fibonacci ratios are largely used for transaction targets. In fact Fibonacci ratios used as support and resistant levels that price moves between them. These levels are based on the Golden Ratio and by using them we can predict future price trend. Main Fibonacci ratios in financial markets are 38.2%, 50%, 61.8%, 78.6% that are retrace levels and 127.2%, 161.8%, 261.8% that are extension levels (Carney, 1999; Duddella, 2007; Fischer and Fischer, 2003).

4.2 Fibonacci tools principles

Several types of Fibonacci tools in financial markets are used to analyse price trend return or continuation (Carney, 1999; Duddella, 2007; Fischer and Fischer, 2003).To set Fibonacci levels, we need to find major high and low points in the chart. This may require getting back in the chart for a few days or even weeks. There are several types of Fibonacci levels including, but not limited to, Fibonacci retracement (Ret), Fibonacci extension (Ext), and Fibonacci projection (Pro). Typically the price after a strong move will enter a resting area and return a part of its movement. This return may be internal or external. For internal returns, we use Fibonacci retracement (Ret) with retrace levels, and for external returns, we use Fibonacci extension (Ext) with extension levels. Fibonacci projection is similar to Fibonacci Ext and displays points of return over 100% per wave. In Fibonacci projection, price corrections over 100% per wave are important. Therefore, it is also called the price target (Fischer and Fischer, 2003).

4.3 Harmonic patterns

Harmonic Trading is a method that uses specific price patterns and Fibonacci ratios, to identify probable places where there is price reverse. Fibonacci ratios are very important in identifying harmonic patterns. Specific combinations of these ratios form harmonic patterns and the points of entry and exit transactions. By identifying *Market patterns*, many profitable trades can be achieved (Carney, 1999). Harmonic patterns are consisting of four patterns of five points and one pattern of four points. In the following, we introduce five main harmonic patterns used in Forex market.

ABCD (*AB* = *CD*) pattern is the most common harmonic pattern frequently seen in the market and it is easier to detect than other patterns. This pattern first introduced by Gartley in his book entitled '*Profits in Stock Market*' in 1935. In this pattern, the first move (*AB*) in a direction of the market takes place. At point *B*, a reversal move starts and stops at point *C*. the main movement starts from *C* with the same size and direction with *AB* to end at *D* in the Goledn ratio where *AB* = *CD* (Carney, 1999). Depending on the first move direction, we have Bullish or Bearish ABCD pattern. When the pattern is completed, we will have a reverse in the trend price with certain targets. For an ideal ABCD pattern we should have ideal Fibonacci levels.

Take profit (*TP*) *and stop loss* (*SL*): By selling or buying in point *D*, depending on bearish or bullish pattern, first TP can be in 61.8% Fibo Ret *CD* and second TP can be in point *C* (Carney, 1999). Stop loss can be considered as much as 10% of average daily movement.

Take profit and stop loss for all five harmonic patterns are the same.

Gartley also in his book, described five point *Gartley pattern*. Gartley pattern is a multi-dimensional and very powerful market pattern composed of five basic points *X*, *A*, *B*, *C*, *D*. *XA* is the greatest arm in this pattern that followed by a reverse from *A* to *B*. After a reverse from *B* to *C*, point *D* can be formed according to the harmonic calculations. This point determines the reversal zone (Duddella, 2007; Fischer and Fischer, 2003).

As well as Gartley pattern, *Butterfly pattern* is a multi-dimensional and very powerful market pattern that comprises five basic points *X*, *A*, *B*, *C*, *D*. In this pattern, unlike the Gartley pattern, point *D* is situated outside *XA* (Carney, 1999; Duddella, 2007).

Bat pattern is another harmonic pattern that has been discovered by Scott Carney in 2001. Apparent structure of this pattern is the same as Gartley pattern with five basic points *X*, *A*, *B*, *C*, *D*. Like Gartley pattern, the end point of this model should complete inside *XA* (Duddella, 2007).

Crab pattern also discovered by Scott Carney in 2000. Apparent structure of this pattern is the same as Butterfly pattern with five basic points *X*, *A*, *B*, *C*, *D*. Like Butterfly pattern the end point of this pattern should complete outside *XA* (Duddella, 2007).

Table 1 shows ideal ratios that form each pattern and their associated figures in bullish form. In five point patterns *XA* is formed in one side of the market. Then *B*, *C* and *D* take place in specific Fibonacci rations. For ABCD pattern, *AB* forms in one direction then *C* and *D* complete in specific Fibonacci ratios.

Table 1 Harmonic patterns with ideal ratios (see online version for colours)

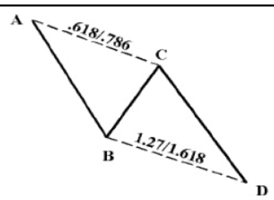
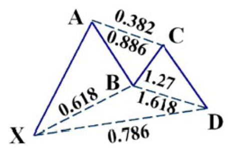
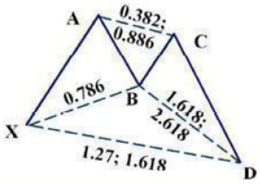
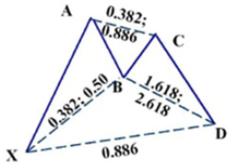
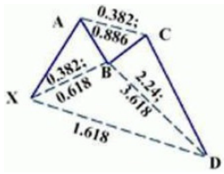
Pattern	*Description*	*Figure*
ABCD	*B*: – *C*: 0.618–0.786% *AB* *D*:127.2–161.8% *BC*	
Gartley	*B*: 0.618% *XA* *C*: 0.382–0.886% *AB* *D*:0.786% *XA*	

Table 1 Harmonic patterns with ideal ratios (see online version for colours) (continued)

Pattern	*Description*	*Figure*
Butterfly	*B*: 0.786% *XA* *C*: 0.382–0.886% *AB* *D*:127.2–161.8% *XA*	
Bat	*B*: 0.50% *XA* *C*: 0.382–0.886% *AB* *D*:0.886% *XA*	
Crab	*B*: 0.618% *XA* *C*: 0.382–0.886% *AB* *D*:161.8% *XA*	

4.4 Relative strength index (RSI)

Relative strength index (RSI) is a rate of change oscillator that ranges between zero and 100. This index measures the price change rate. When Wilder[9] introduced the index in 1978, he recommended using its 14 period mode.

The most common method of using RSI is the mode by which *Divergence* occurs. Divergence refers to the condition that price touches a new high, but RSI fails to register a new high and confirms the price pick. This definition also applies to new lows in the price. This divergence refers to an upcoming reverse in price trend (Wilder, 1978).

$$\text{Wilder stated RSI calculation as: } RSI = 100 - \left(\frac{100}{1+(U/D)}\right), \tag{1}$$

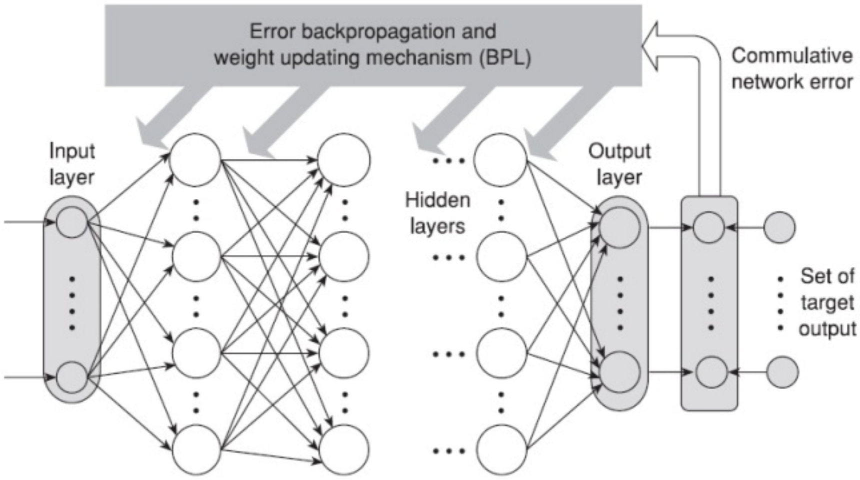
in which, U is the average number of positive price changes and D is the average number of negative price changes (Wilder, 1978).

5 Artificial neural networks

ANNs are physical cellular systems capable of acquiring, storing and using their experiential knowledge. An ANN consists of a large number of nodes and directional connections to link nodes together. A typical neural network in its input layer has sensory nodes and in the output layer has respondent nodes. Hidden layer is between input and output layer (Karray and De Silva, 2004).

MLP is one of the types that used for nonlinear separation in classes. To do this, an MLP uses Back Propagation Learning algorithm in which, weights of different layer connections are tuned in a way that minimises error between network outputs and the model targets (Figure 1) (Karray and De Silva, 2004).

Figure 1 Multi-layer perceptron with back propagation algorithm



5.1 Modular systems

In modular approaches a problem is divided into sub problems and each module can manage a part of the problem (Auda and Kamel, 1999). In this approach the principle 'divide and conquer' prevails (Haykin, 2008). Some reasons for using modular systems are as follows: improving performance, reducing the complexity of the model, simplifying the problem, and recombining important information (Amanda and Sharkey, 1999). A neural network is called modular if network calculations can be decomposed into some modules that each one works on certain inputs without any relationship to other modules. By an integrator system, modules' outputs come together to make total output of the system (Haykin, 2008).

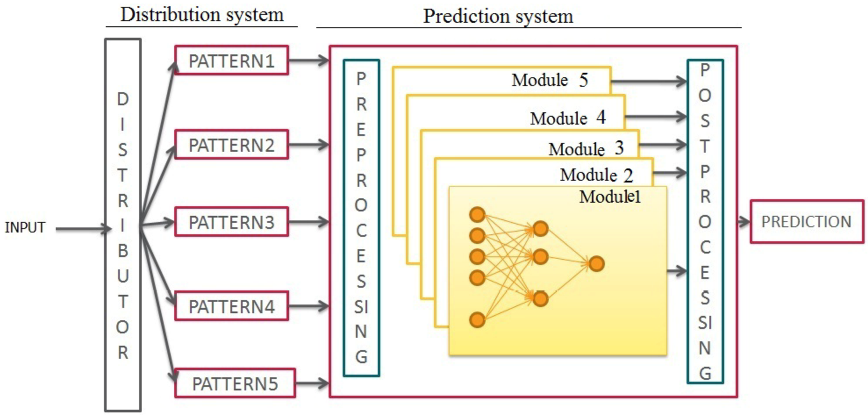
6 Proposed modular-based system (FPUMN)

Before introducing the proposed system, considering three tips is required. First, although Harmonic trading is a very powerful method to predict price in financial markets, but is not used widely. This is due to one reason; the price resists reversing and does not do it rapidly after pattern accomplishment. This causes delayed and uncertain condition for starting a new transaction. This problem reduces pattern validity. Second, harmonic patterns without a divergence at the end, does not considered as valid patterns that cause a main reverse. Third, most forecasting systems in financial markets do not have the market dynamic nature in them; because their data is based on the past history of the market. So they cannot be used in long term and lose their validity over time. Considering these three important points led us to provide a prediction system with three algorithms.

Forex prediction using modular network (FPUMN) system consists of three phases with three different algorithms to predict, evaluate the results and maintain system dynamics.

Prediction modular system is composed of several neural networks. Each module of the system has a MLP neural network that specially deals with one harmonic pattern. The main goal of the system is to predict the best price for starting a transaction after completing a harmonic pattern with confirmation of RSI indicator. Figure 2 illustrates an overview of the proposed modular system. FPUMN system gets a harmonic pattern points as input and recognises the pattern type and its validity. A distribution system distributes input patterns to the specific module. In this module a well-learned neural network predicts the best point for price reverse and provides modular system output.

Figure 2 Proposed modular system (see online version for colours)



This modular system consists of two parts: distribution and prediction. We defined five different patterns in distribution part.

An unknown input pattern X which consists of four or five points of a harmonic pattern, first fed into the distribution system. The distribution system recognises the unknown pattern X as pattern k^* as follows:

$$k^* = \arg\max_k \sum_{l=1}^{l} DM_{\text{dist}}(l,k); \quad k = 1, 2, ..., K, \tag{2}$$

where

$$DM_{\text{dist}}(l,k) = \begin{cases} 1 & \text{if} \quad k = \arg\max_k p(f_l \mid CL_k) \\ 0 & \text{otherwise} \end{cases}, \frac{n!}{r!(n-r)!} \tag{3}$$

where $p(f_l \mid CL_k)$ denotes the posterior probability of the lth point of pattern data given pattern type CL_k. Also, l denotes the number points of a pattern. Posterior probability of each point of pattern data given all patterns is obtained through distribution system. Then, label of the pattern is estimated by aggregating the responses over all points using distribution system. Distribution system is shown in Figure 3.

For each pattern, we designate a specific module to predict the future price based on the pattern. Suppose that the output of the distribution system for input pattern X is denoted by CL_k. Hence, the corresponding distribution module classifies X as member $j*$ of CL_k if

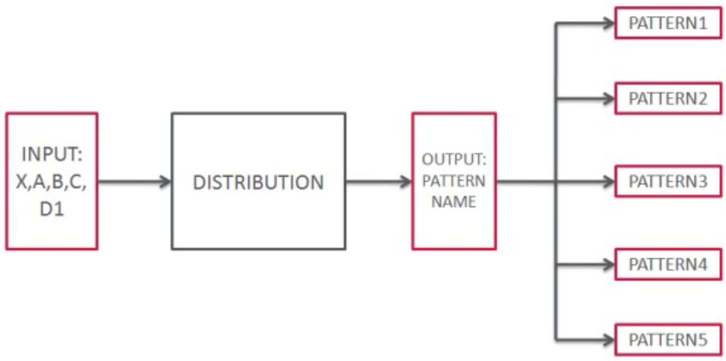
$$j^* = \arg\max_j \sum_{l=1}^{l} DM_{\text{predict}}(l, j); \quad j = 1, 2, ..., m_k, \tag{4}$$

where

$$DM^k_{\text{predict}}(l, j) = \begin{cases} 1 & \text{if } k = \arg\max_j p(f_l \mid CL_{k,j}) \\ 0 & \text{otherwise} \end{cases}, \tag{5}$$

where, p (f_l | $CL_{k;j}$) denotes the probability of the lth point of pattern data given member j of pattern type CL_k. In other words, pattern data is fed to the kth prediction module point by point. Posterior probability of each pattern given all points of the pattern type is obtained through the corresponding prediction module. Then, predicted point of the input pattern determined by the related module.

Figure 3 Distribution system in FPUMN (see online version for colours)



6.1 FPUMN's algorithms

We have provided a new modular approach to predict the exchange rate. This method is implemented in three phases. In other words, the proposed approach requires three different algorithms to predict, verify the accuracy of the pattern and maintain the system dynamics. First algorithm is prediction algorithm in which each module of the system trains one specific harmonic pattern. Second algorithm confirms divergence between RSI indicator and the completed harmonic pattern. Third algorithm, maintains the system dynamics based on its last prediction. Performance of FPUMN algorithms will be introduced next.

6.1.1 Prediction algorithm

Prediction algorithm in FPUMN system recognises the input pattern type by a distributor. It also, checks the pattern's adaption to ideal forms of harmonic patterns. After that the system distributes the pattern to the responsible module. The related module produces the system output. The output is a future price for starting a transaction. Different steps of the algorithm are as follows:

1 Provide a set of training data to each harmonic pattern.

2 **for** pattern $k = 1$ to 5 **do**

3 **If** the training data don't match ideal harmonic patterns **then** go to 9 **else**

4 Represent the identified harmonic pattern's name.

5 Send the indentified pattern to the responsible module by the distributor system.

6 Use MLP network in the responsible module to predict the reverse price.

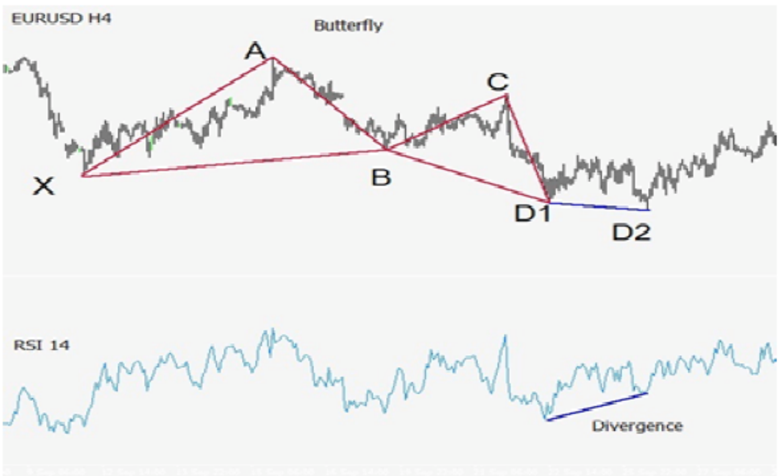
7 Denote the predicted price of reverse as the system output.

8 **end for**

9 Exit.

Figure 4 shows prediction and verification algorithms performance. In this figure a harmonic pattern formed in Forex market is shown by *X*, *A*, *B*, *C*, *D1*. FPUMN system recognises the pattern type and sends it to the related module by the distributor system then the module predicts *D2* point as the real reverse price.

Figure 4 Prediction and verification algorithm performance (see online version for colours)



6.1.2 Verification algorithm

Modular system output in the previous phase was *D2* point that is the real trend reverse point in the market. Validity of harmonic patterns in financial markets is confirmed by creating divergence between *D1* and *D2* and the related points in RSI. Transactions that are based on harmonic patterns without a valid divergence between *D2* and RSI, may lead to trades with higher risk that cause losses in traders balances. Essentially, traders prefer to ignore harmonic patterns without divergences and not to look at them as trading opportunities.

Verification algorithm steps are as follows:

1. Provide the prediction algorithm's output, *D2* point.
2. Provide *D1* point.
3. Provide price vector from beginning to end of the pattern.
4. Compute RSI corresponding *D1* and *D2*.
5. Compute the slope of the connection between *D1*and *D2* in the price vector.
6. Compute the slope corresponding to *D1*and *D2* in RSI.
7. Compare slopes in 5 and 6.
8. **If** the slopes have opposite directions **then** represent "the pattern has divergence", **else**
9. Represent "the pattern doesn't have divergence".

At the end of this algorithm by the approval of divergence, the harmonic pattern is confirmed as a valid pattern. Hence a new transaction can be started based on the first algorithm's prediction. If the verification algorithm result does not approve divergence between the pattern and RSI, it is better to avoid starting a new trade based on this harmonic pattern.

Figure 4 shows a divergence between the pattern and RSI; thus, the pattern validity is confirmed in this algorithm.

6.1.3 Maintaining system dynamics algorithm

In the previous algorithms, after predicting *D2* point as output of the modular system, and verifying divergence in RSI by verification algorithm, now the best way to maintain the system dynamics is to add the last harmonic pattern to the system database. Most forecasting systems in financial markets, due to lack of market dynamics are not usable in the long run, and lose their credibility over time. Therefore, one of the advantages of FPUMN system is maintaining market dynamics that makes it possible to use the system in long-term with its basic validity. When a new pattern enters the system, *D2* is predicted by prediction algorithm. Then verification algorithm proves its validity by checking the divergence. Now the third algorithm maintains the system dynamics. The new pattern would be added to the modular system database as a valid harmonic pattern. This valid pattern has the ability to make reverse in price trend. While the database is updated, neural network in the related module, re-learns the updated database in order to achieve a minimum system error. Next time when a new pattern enters the system, updated neural network is used.

Maintaining system dynamics algorithm steps are as follows:

1. Provide prediction algorithm's output
2. Provide verification algorithm's output
3. **If** (1) and (2) are Null **then** go to 10, **else**
4. Find the appropriate module responsible for the pattern

5 Replace i+1 for the database number

6 Add X, A, B, C, D2(A, B, C, D2) to the network database

7 Re-train the network in responsible module to find lower mean square error

8 Use the new trained network in the next prediction algorithm's run

9 End if

10 Exit

In the next section, we will implement the proposed system and analyse the experimental results.

7 Model implementation and experimental results

In this section we implement the system described in the previous section step by step. In order to construct the system modules, we need to train separate networks in the best topology to work as the mastermind of each module. The appropriate topology of the best trained networks is used to simulate the future price in the modular system. Once the system implementation completes, we need to measure the system reliability. In order to validate the proposed modular system results, a non-modular neural network will be introduced. The two system results in future price prediction will be compared and their performance analysis will be presented.

At first we describe neural networks topologies employed in the modular system.

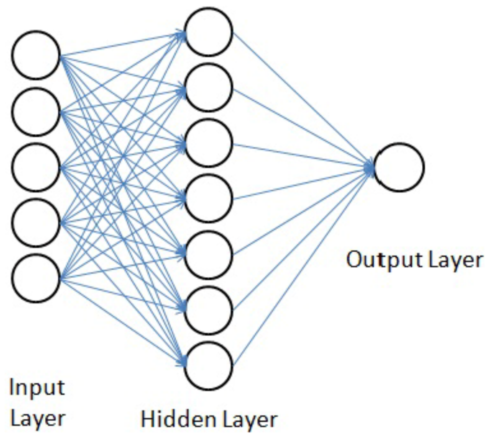
7.1 Modular system structure

Modular system that includes the first phase of FPUMN system is composed of two parts. The first part is a distributor and the second part is a modular system that composed of five separate modules. The distribution system inputs are points forming a harmonic pattern. Outputs of this system are the name and ideality of identified harmonic pattern. Failure to comply with any of harmonic patterns defined in the system, lead to exit the system. Distributor system's output is sent to the related module in the second part of modular system. In the second part of the modular system, each module includes a neural network which has learned one of the harmonic patterns. Implementing the modular system requires training each neural network composed of the modules. In the following section we talk about networks training, their required training data, data pre-processing and performance of trained networks.

7.1.1 Modules' networks architecture

Forecasting system is composed of several neural networks. Each network learns one harmonic pattern. A feed-forward multilayer neural network with sigmoid function in hidden layer and linear function in output layer and an advanced Levenberg-Marquardt algorithm for error back propagation, prepared in each module of the system. Optimal number of hidden layer neurons after multiple tries, reached seven neurons. Figure 5 shows the network architecture for a five point pattern. In four point pattern we have four neurons in input layer.

Figure 5 Module's network architecture (see online version for colours)



7.1.2 Training data

Network input data are points forming a harmonic pattern. Depending on the type of the pattern we have 4 or 5 input points. 500 real data of harmonic patterns formed in Forex market in different currency pairs-100 data per pattern- for their bullish form were collected. Only ideal form of patterns was gathered.

7.1.3 Data selection

Training data was gathered from real data of Forex market in 4 h time frame. After completing bullish ideal form of each pattern, its basic data enters the network and the desired output is the real turning point of the price to reverse the trend. Currency pairs for choosing input data were: *EURUSD*, *GBPUSD*, *USDCHF*, *USDJPY*, *EURGBP*, *AUDUSD* and *NZDUSD*.

7.1.4 Data pre-processing

In order to increase the accuracy of neural network computation, input data in each module were removed from the floating-point mode and then entered the network. Although this causes the error come to a large number, but since each input is multiplied by 10^4, the error values should be divided into this number to determine its real value.

7.2 Modular system implementation

Prediction algorithm in modular system has these tasks; recognises input pattern type, investigates pattern ideality, sends the pattern to the related module and receives output of the system.

To predict the future price with prediction algorithm, we provided a set of training data separately for each pattern. The number of input layer neurons depending on the harmonic pattern type, are 4 or 5 neurons. The number of hidden layer neurons after multiple repetitions in different patterns reached the optimum number of seven neurons that causes the lowest error in the system. Now it is time to find best division for data to divide them into training, test and validation sets. Studies led us to allocate 90% of the data for train, 5% for test and 5% for validation. This division caused minimum error of the system.

Training data fed to each neural network with four/five neurons in input layer, seven neurons in hidden layer and one neuron in output layer. A feed-forward multilayer neural network with sigmoid function in hidden layer and linear function in output layer and an advanced Levenberg-Marquardt algorithm for error back propagation used to train each neural network in modules. Then we started to train networks in multiple iterations to achieve the lowest error for the entire network.

Five neural networks with a training set of 100 elements for each network trained separately. Training five networks for five harmonic patterns is repeated to achieve minimum error for the system. Table 2 shows the results of training five networks.

Table 2 Harmonic patterns training results in modular system

Network	*Mean square error*	*Iterations*	*Regression*
ABCD	37×10^{-4}	13	0.98407
Butterfly	115×10^{-4}	73	0.9999
BAT	9×10^{-4}	15	0.9999
Gartley	232×10^{-4}	193	0.99902
Crab	25×10^{-4}	12	0.9998

Now training networks to predict the future price is completed. Simulated networks are used in FPUMN system modules. So we have a modular system that takes a harmonic pattern as input, sends it to the relevant module and gives the best point of price reverse as output of the system. All these tasks are held in the first phase of the system. Two other phases of FPUMN system (verification and dynamism maintaining algorithms) are only used to improve the quality of the system predictions. Verification algorithm increases validity of system predictions by verifying divergence between price and RSI. On the other hand, when a new valid harmonic pattern is added to the system database, its updating is always guaranteed. It is a great advantage of FPUMN system.

In order to investigate the proposed system reliability in price reverse predictions, we used a non-modular neural network. After training the non-modular neural network, we will compare price reverse predictions in proposed modular system and non-modular system.

7.3 Proposed system validation check

As we read in the literature review, using neural networks to predict price in financial markets is a known and valid method. In many studies, the superiority of neural networks in forecasting price vs. classical methods and statistical techniques in financial markets is clearly proven. A key point about these studies is that they predict future price generally and do not pay special attention to price reverses and this is the main difference between our proposed system and previous researches.

In order to check the validity of the proposed modular system, a non-modular neural network is used. The non-modular neural network trained with a relatively long term market data. Then simulation of network performance in an interval where a harmonic pattern took place is done and its ability to forecast price reverse is examined. The results of the proposed modular neural network with the non-modular network are compared to the real price trend in Forex market.

7.3.1 Validation system structure

To have a system with a non-modular neural network we provided training data from market history. Data needed to validate the proposed system, are taken from EURUSD currency in 4-h time frame from 2006 to 2011. This set of 5272 elements divided to three parts. Training data used 90% of input data and for test and validate of the network performance, we used the two 5% of the rest. This division caused minimum error in the network performance. Training data fed to a neural network with three neurons in input layer, seven neurons in hidden layer and one neuron in output layer. The input set was from open, high and low price and target data was close price of a 4-h candle. A feed-forward multilayer neural network with sigmoid function in hidden layer and linear function in output layer and an advanced Levenberg-Marquardt algorithm for error back propagation used to train the non-modular neural network. Then we started to train the network in multiple iterations to achieve the lowest error for the entire network. Table 3 shows the results of training non-modular network.

Table 3 Training results in non-modular system

Network	*Mean square error*	*Iterations*	*Regression*
Non-modular	10^{-5}	50	0.9997

As Table 3 shows, non-modular network provided satisfactory results in its performance. Now we have two well-trained systems. One works in a modular system and the other works in a non-modular system. In the following section we are going to study performance of these two systems after completion a harmonic pattern to analyse FPUMN system validation performance.

7.3.2 Validation system implementation

In order to compare the non-modular network and FPUMN system performance we selected intervals of EURUSD price in 4-h time frame where a harmonic pattern took place at the end. Four/five points forming a harmonic pattern are fed into the proposed modular system. At the same time continues data matrix of this pattern is fed to the non-modular system. Then simulation to forecast future price by non-modular neural network and FPUMN system will be started. Since both networks are well trained, it is expected to have satisfactory results in future price prediction.

We start with a Butterfly pattern. So we select a price trend in which a Butterfly pattern is occurred at the end of it. The whole interval is inserted to the non-modular system and five points of the Butterfly pattern are fed to the modular system. Figure 6 shows input data for non-modular system which consist a matrix of 98 rows and 3 columns of open, high and low price in 4-h time frame.

Well trained non-modular system started to predict the future results. Figure 7 shows the results of non-modular system prediction vs. real price. Both system predictions start right after the end of the simulation point.

Figure 6 Input data to non-modular system for Butterfly pattern (see online version for colours)

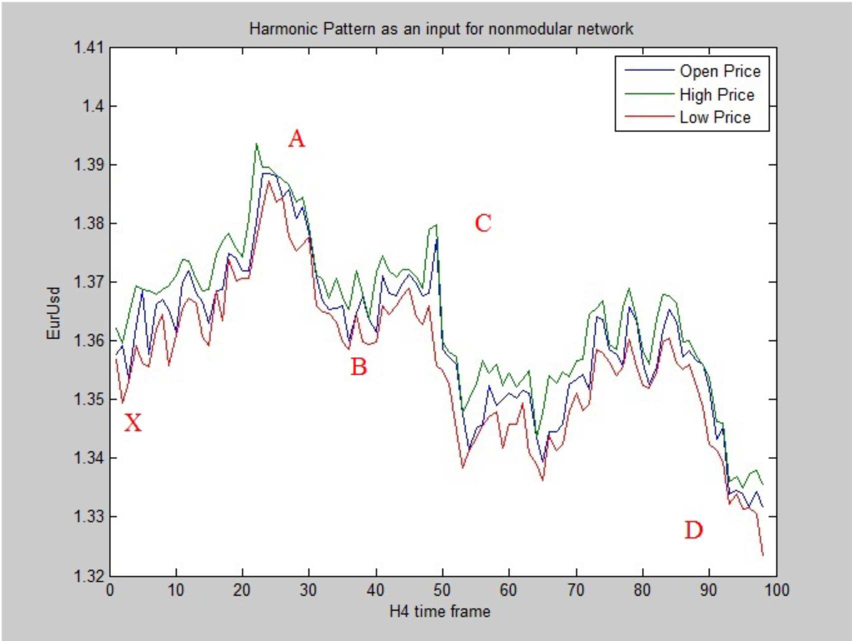
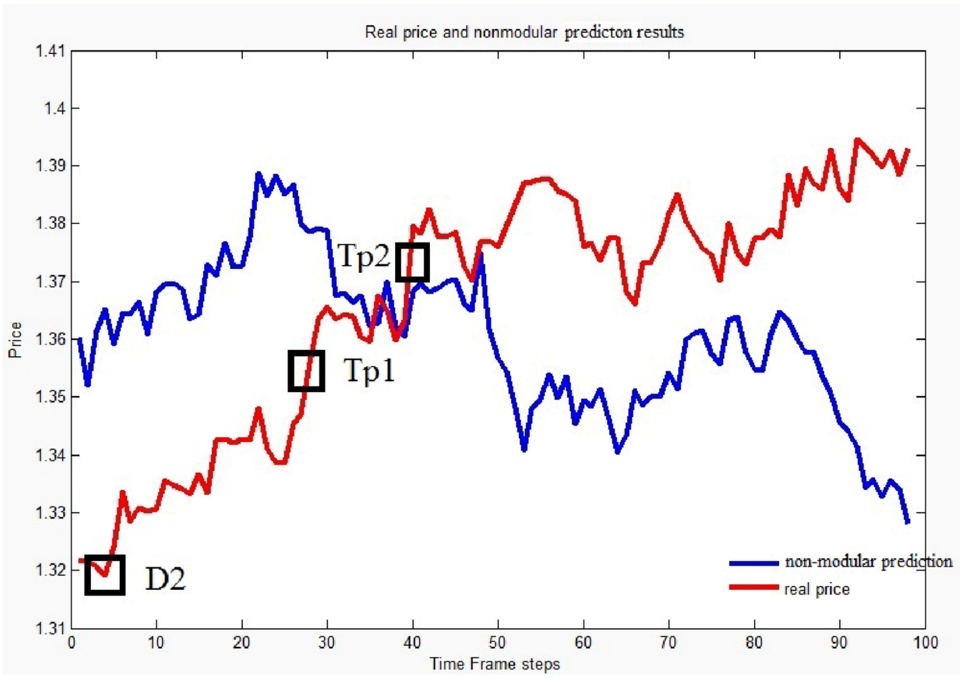


Figure 7 Comparison modular and non-modular prediction results with real price for Butterfly pattern (see online version for colours)



Non-modular neural network predicted results in trend reverse shows clearly high error in comparison with real trend price. In a part of its prediction the trend is clearly contrary to the real price. FPUMN system with five points forming the Butterfly pattern and the price vector to calculate RSI shows accurate results both in price reverse point and the targets. This pattern is a valid one in FPUMN system due to divergence conformation between price and RSI that leads to reverse in price trend. This pattern is also added to the database of the modular system to maintain dynamics of the system. FPUMN system performance results are shown in Table 4. This table consists of five harmonic points (*X*, *A*, *B*, *C*, *D1*), prediction result of FPUMN system (*D2*) and price targets that calculated by harmonic pattern rules (*Tp1*, *Tp2*).

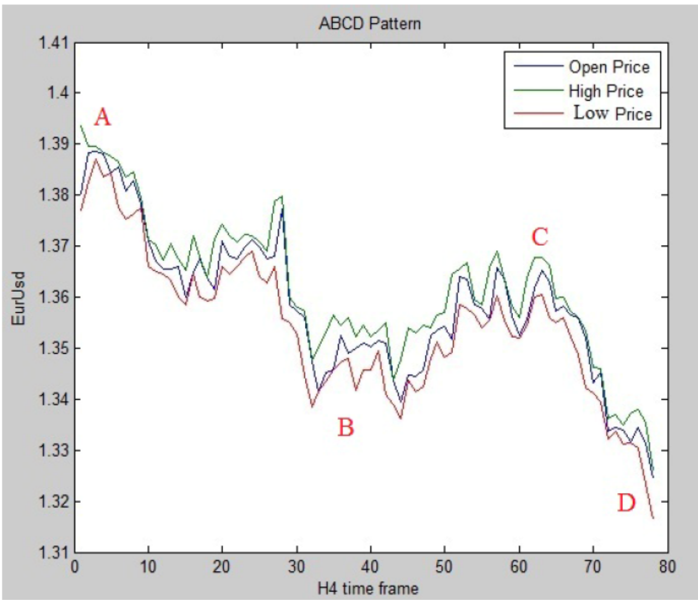
Table 4 Butterfly pattern points, FPUMN prediction point, pattern target price

Butterfly	*X*	*A*	*B*	*C*	*D1*	*D2*	*Tp1*	*Tp2*
Price	1.3492	1.3936	1.3587	1.3720	1.3217	1.3191	1.3559	1.3720

Predictions of FPUMN system in trend reverse clearly match real price in its new trend and show superiority of the proposed modular system.

A same work is done for ABCD pattern. A price trend where an ABCD pattern is occurred at the end is selected. The whole interval is inserted to the non-modular system and four points of the ABCD pattern are fed to the modular system. Figure 8 shows input data for non-modular system which consist a matrix of 78 rows and 3 columns of open, high and low price in 4-h time frame.

Figure 8 Input data to non-modular system for ABCD pattern (see online version for colours)



Well trained non-modular system started to predict the future results. Figure 9 shows the results of non-modular system prediction verses real price. Both system predictions start right after the end of the simulation point.

Non-modular neural network predicted results in trend reverse shows clearly high error as well as Butterfly network, in comparison with real trend price. The same steps are done like Butterfly pattern and FPUMN system performance results are shown in Table 5.

As well as the previous example, predictions of FPUMN system in trend reverse clearly match real price in its new trend and show superiority of the proposed modular system.

The next example is for Bat pattern. A price trend where a Bat pattern is occurred at the end is selected. The whole interval is inserted to the non-modular system and five points of the Bat pattern are fed to the modular system. Figure 10 shows input data for non-modular system which consist a matrix of 211 rows and 3 columns of open, high and low price in 4-h time frame.

Figure 9 Comparison modular and non-modular prediction results with real price for ABCD pattern (see online version for colours)

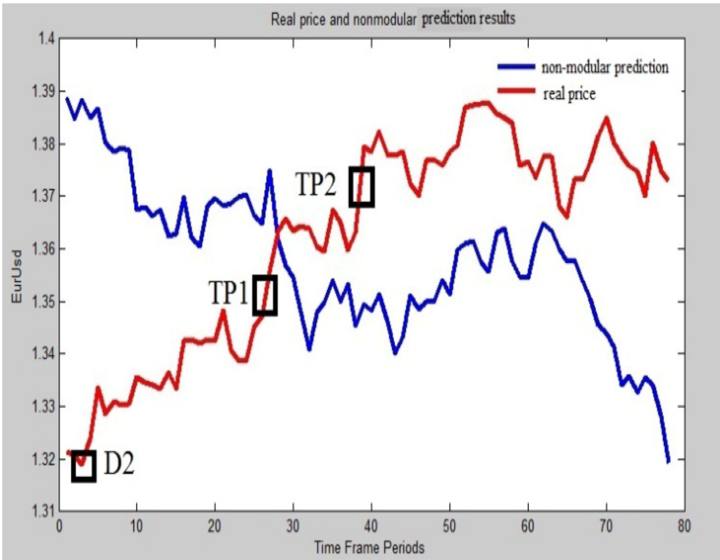


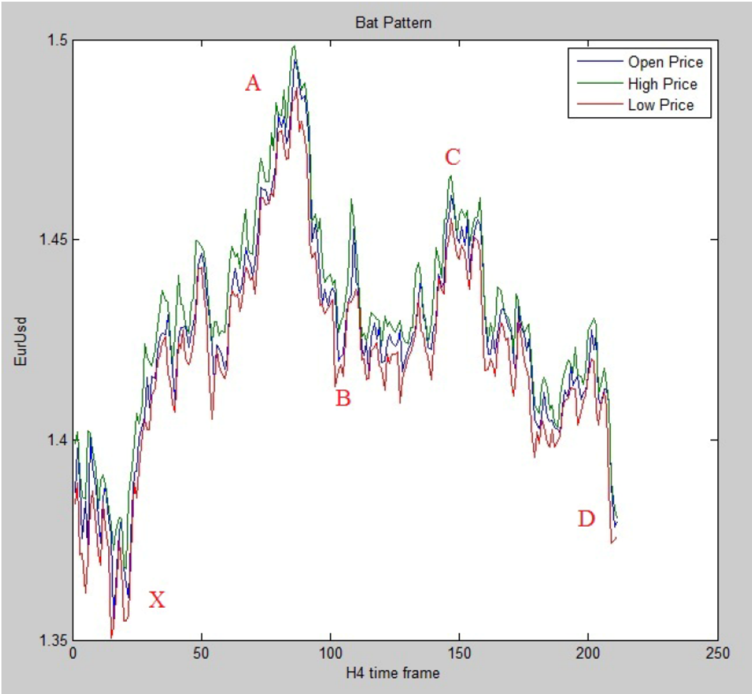
Table 5 ABCD pattern points, FPUMN prediction point, pattern target price

ABCD	*A*	*B*	*C*	*D1*	*D2*	*Tp1*	*Tp2*
Price	1.3932	1.3416	1.3734	1.3218	1.3183	1.3537	1.3734

Well trained non-modular system started to predict the future results. Figure 11 shows the results of non-modular system prediction verses real price. Both system predictions start right after the end of the simulation point.

Non-modular neural network predicted results in trend reverse shows clearly high error as well as two previous networks, in comparison with real trend price. The same steps are done like before and FPUMN system performance results are shown in Table 6.

Figure 10 Input data to non-modular system for Bat pattern (see online version for colours)



Predictions of FPUMN system in trend reverse clearly match real price in its new trend and show superiority of the proposed modular system.

The next example is for Crab pattern. A price trend where a Crab pattern is occurred at the end is selected. The whole interval is inserted to the non-modular system and five points of the Crab pattern are fed to the modular system. Figure 12 shows input data for non-modular system which consist a matrix of 223 rows and 3 columns of open, high and low price in 4-h time frame.

Table 6 Bat pattern points, FPUMN prediction point, pattern target price

Bat	*X*	*A*	*B*	*C*	*D1*	*D2*	*Tp1*	*Tp2*
Price	1.3532	1.4830	1.4181	1.4427	1.3687	1.3673	1.4144	1.4427

Well trained non-modular system started to predict the future results. Figure 13 shows the results of non-modular system prediction verses real price. Both system predictions start right after the end of the simulation point.

Non-modular neural network predicted results in trend reverse shows clearly high error as well as previous results, in comparison with real trend price. The same steps are done like Butterfly pattern and FPUMN system performance results are shown in Table 7.

Figure 11 Comparison modular and non-modular prediction results with real price for Bat pattern (see online version for colours)

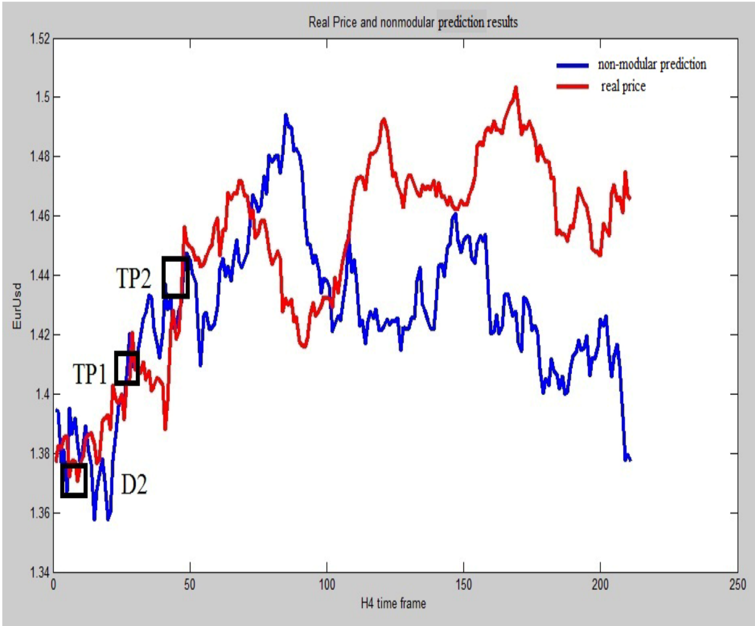
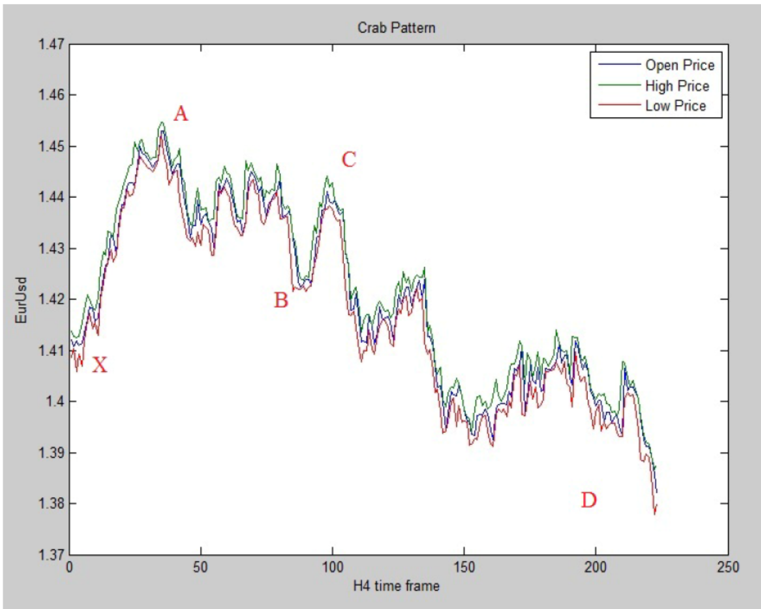


Figure 12 Input data to non-modular system for Crab pattern (see online version for colours)



Predictions of FPUMN system in trend reverse clearly match real price in its new trend and shows superiority of the proposed modular system.

The last example is for Gatrley pattern. A price trend where a Gatrley pattern is occurred at the end is selected. The whole interval is inserted to the non-modular system and five points of the Gatrley pattern are fed to the modular system. Figure 14 shows input data for non-modular system which consist a matrix of 29 rows and 3 columns of open, high and low price in 4-h time frame.

Figure 13 Comparison modular and non-modular prediction results with real price for Crab pattern (see online version for colours)

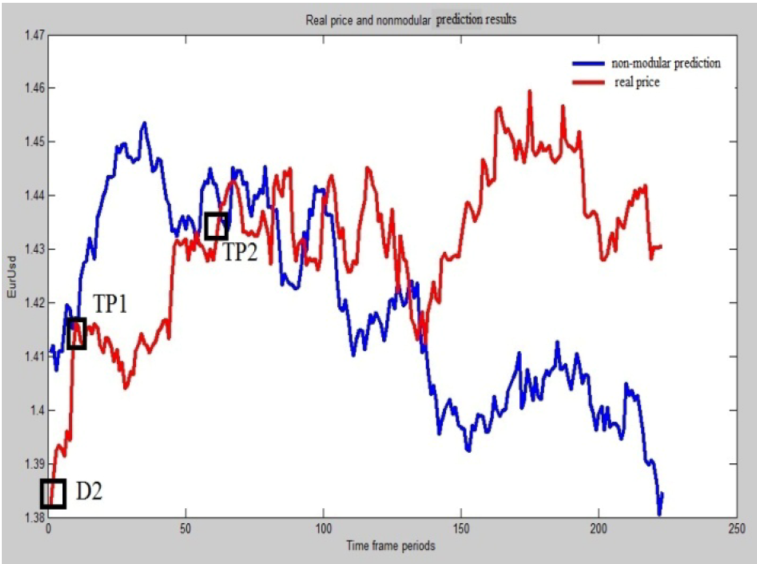


Table 7 Crab pattern points, FPUMN prediction point, pattern target price

Crab	*X*	*A*	*B*	*C*	*D1*	*D2*	*Tp1*	*Tp2*
Price	1.4087	1.4479	1.4236	1.4329	1.3844	1.3830	1.4144	1.4329

Well trained non-modular system started to predict the future results. Figure 15 shows the results of non-modular system prediction verses real price. Both system predictions start right after the end of the simulation point.

Non-modular neural network predicted results in trend reverse shows clearly high error as well as previous results, in comparison with real trend price. The same steps are done like Butterfly pattern and FPUMN system performance results are shown in Table 8.

Predictions of FPUMN system in trend reverse clearly match real price in its new trend and shows superiority of the proposed modular system.

Table 8 Gartley pattern points, FPUMN prediction point, pattern target price

Gartley	*X*	*A*	*B*	*C*	*D1*	*D2*	*Tp1*	*Tp2*
Price	1.2390	1.2787	1.2541	1.2635	1.2474	1.2461	1.2574	1.2635

Figure 14 Input data to non-modular system for Gartley pattern (see online version for colours)

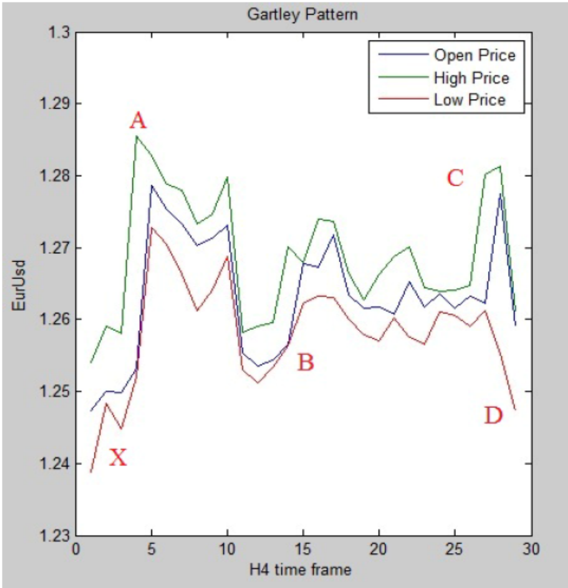
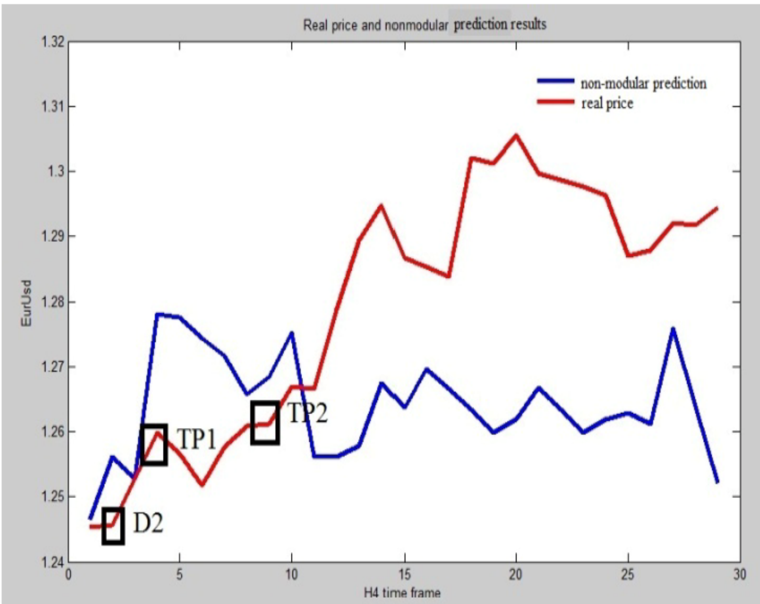


Figure 15 Comparison modular and non-modular prediction results with real price for Gartley pattern (see online version for colours)



7.4 Results analysis

The main reason of using modular neural networks to predict price reverses in financial markets is their modularity property. A non-modular neural network on its own is not able to recognise infrastructure relationships between patterns. This requires separate networks that are specialised for each pattern. A single non-modular neural network only is able to predict trends similar to what it had learned. Thus, in cases where the price is quite the opposite with non-modular network training trend, the performance of these networks will be very weak. We proved this claim by comparing prediction results in proposed modular and non-modular systems in previous section.

8 Conclusion

Although technical analysis is a very useful method for managing an investment portfolio in financial markets, some other factors must be considered. Financial markets are influenced by various social, political and economical factors such that nothing clearly is predictable in these markets. Hence, with all-round pressure on the price in these markets, finding repeatable patterns in price movements may in somewhat guide traders to have profitable trades.

Traditional technical analysis using harmonic patterns is one of the most widely used methods of technical analysis, in Forex market. By using harmonic patterns traders can find reverse points in price movements. They use the end point of the pattern to start an inverted trend transaction. Not knowing the related divergence between price movement and RSI indicator points cause failure in predicting reverse price.

Hence, in this study, we proposed a prediction system for future reverse price in FOREX market. Its goal is to find reverse points in price trends by the ability of neural networks and modular systems by inspiration of harmonic patterns. Hence, we reviewed previous studies about price prediction in financial markets. We found a common view that neural networks, work better than statistical methods. Related concepts such as Fibonacci sequence and its application in financial markets, RSI oscillator and modular systems also were reviewed.

Our proposed FPUMN system, consist of three different algorithms, is a modular system that each module is an expert of a specific harmonic pattern in Forex market. Since FPUMN is a system with specialised modules for specific behaviours, it does not need a wide range of data input to predict specific movements. This system uses key points of forming special patterns and releases specific results of them. So having only four/five key points per pattern is enough to predict exact results that matches future real price. In the same situation a non-modular prediction system requires at least ten times more data to predict non satisfactory results in price reverses. Results have emphasised that specialised infrastructure of data in financial markets is complex enough that needs separated expert systems to recognise its principal relations.

Our limitations in this study were about finding patterns for training neural networks in the related modules. Some of harmonic patterns are very frequent but others rarely occur. To gather enough data for rare patterns, we needed to search a large range of data history in FOREX market for network training.

To find exact relationships in data infrastructure, future researches can be based on fuzzy neural networks to recognise trend price direction. Combination of technical indicators such as MACD and Stochastic oscillator with modular networks can lead to more accurate results in finding price reverses. In addition to harmonic patterns, using Elliot wave analysis in modular neural networks can be a new way in finding future price behaviour.

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Notes

[1] *Source*: The Economist.

[2] Vector autoregressive.

[3] Support vector regression.

[4] Moving average convergence divergence.

[5] Relative strength index.

[6] Dynamic artificial neural network.

[7] Generalised autoregressive conditional heteroscedasticity.

[8] Multiple linear regression.

[9] J.Welles Wilder.