achievements that have been done in the Turkish stock market. [Şenol and Özturan] [3] applied advanced seven different prediction models combined in one system to predict the direction of the stock market index in Turkey. The study used a data set consists of more than 2000 records represents the daily closing prices of each stock in Istanbul Stock Index (ISE-30). The findings of this research showed that ANN model outperformed the other six used prediction models. The study claimed that ANN model can be a useful technique for prediction of the stock market direction, because it is capable of capturing unrealized relationships among the represented data even when it is hard to explain or describe it.

[Ajith, Baikunth and Mahanti] [4] introduced a Hybrid Intelligent Systems for Stock Market Analysis. The model applied a hybridized soft computing technique for automated stock market forecasting and trend analysis. The model used a neural network for one day ahead stock forecasting combined with a neuro-fuzzy model for analyzing the trend direction. The data set represented 24 months stock data for Nasdaq-100 main index as well as six of the companies listed in the Nasdaq100 index. The forecasting accuracy could have been improved if the model used individual neural networks customized for each stock instead of using a single generic network.

[Hepin, Chandima, and John] [5] presented a computational approach for predicting the Australian stock market index – AORD using multi-layer feed-forward neural networks from the time series data of AORD and various interrelated markets. A basic neural network with limited optimality was developed and achieved a correctness in directional prediction of 80%. The paper concludes that probability ensemble of neural networks is one of the most reliable directions for predicting stock markets direction.

Overall, these researches conclude that neural networks are suitable for use within trading systems, and that trading systems developed using neural networks can be used to provide economically significant profits.

3 A Kohonen's Self-organizing Maps Trading Model

The suggested model used Kohonen self-organizing map as part of its trading system. The Dataset contained 31 Stock Symbol continuous day trade. The period represented was over the past 9 years (January 2009-July 2018). Training set was 2/3 of the data set, and the remaining set was used for testing.

The total number of data points were 83700 values. Daily updates provided by a local data feed company were recorded for the period from March 1, 2009 till March 31, 2018. The statistics of the data is described as follows:

Mean = 0.309647
Standard deviation = .1553885
Maximum = .9201
Minimum = .1436

Figure.1. shows the graphical representation of the data set

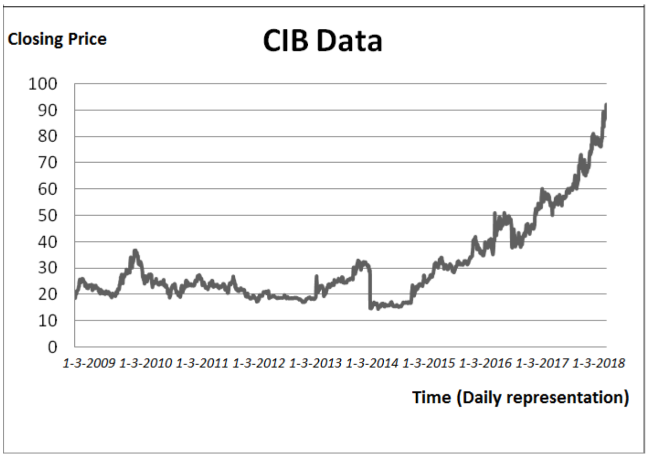

Fig. 1: Data set: CIB stock prices on daily up-dates (March 1, 2009 till March 31, 2018).

Data set analysis showed that the majority of the changes of the daily stock closing price occur to vary in the spectrum from 1% to 4%.(without taking to account the sign of the change). Therefore the model suggested 7 classes or intervals: (- ; -4.5%), (-4.5%; -2.5%), (-2.5%; -0.5%), (-0.5%; 0.5%), (0.5%; 2.5%), (2.5%; 4.5%), (4.5%; -).

This number of classes found to be large enough to contain the trading strategy.

The first dataset sliding window technique used in the model was set to 20 (4 weeks). The used input vector includes 27 items = 20 (day) + 7 selected Technical Analysis Indicators values (14 days EMA, Momentum, Stochastic, MACD, RSI, CCI, and OBV).

In the second dataset the input vector was the set of closing prices of the stock. In another data set, the window represented a set of the opening, closing, highest and lowest price of three or more trading days. The model examined both of these approaches and the better results were found to be that of the first one. The applied system consists of a number of sub models each of which has its own predictive power in a certain direction.

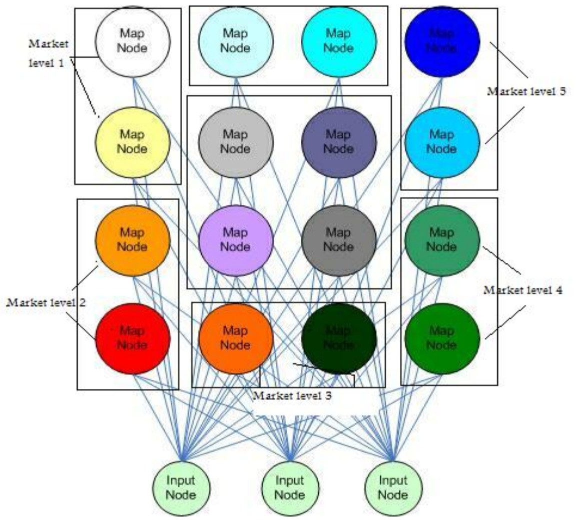

Fig. 2: Market 7 levels in Kohonen's network

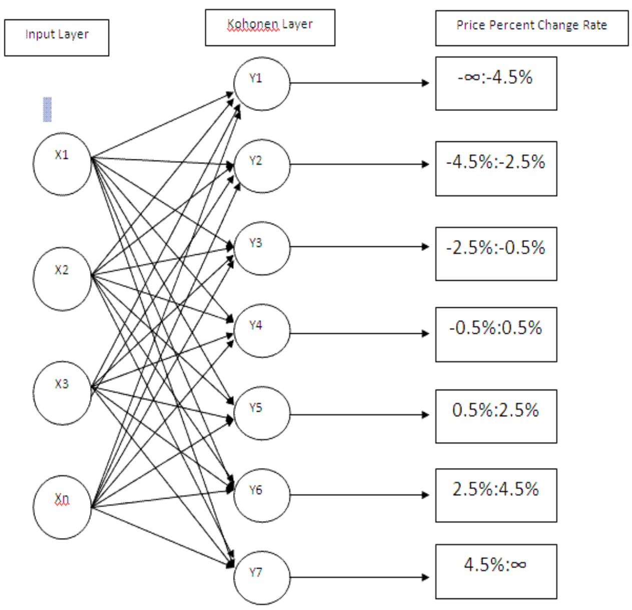

Fig.3: Kohonen's network architecture for price prediction

Kohonen networks was used to split data into predefined classes. Each class with pre-determined intervals as shown in Figure.3.

The window size is relative to the number of input units (there are 20 units).

Number of clusters in the Kohonen layer is already determined (seven clusters). Each unit represents a cluster of neurons. Supervised learning approach was used for training as each cluster is trained individually. This is done by freezing all other neuron clusters while the inputs with the desired response identical to the given cluster are processed. Seven stages are needed to train this network accordingly to the number of classes we used for the CIB stock. After the learning is completed, all clusters are de-frozen (all neurons may be active), and the network works in a normal manner.

The Kohonen SOM network model experiments is shown in Table1. The Kohonen SOM output vector produces one trading result:
1= Major Downtrend,
2 = Secondary Downtrend,
3 = Minor Downtrend,
4 = Sideways,
5 = minor Uptrend,
6 = Secondary Uptrend,
7 = Major Uptrend.

Table.1: Kohonen SOM Network Model Experiments

Networks	**RMSE Data**				
Input-Neurons-Output	**Training (Tr)**	**Testing (Te)**	**Tr - Te**	**Learning Rate**	**Epochs**
27-8	**0.1789**	**0.1887**	**- 0.0098**	**0.8**	**32,000**
27-49	**0.1325**	**0.1372**	**- 0.0047**	**0.9**	**20,000**
27-64	**0.1113**	**0.1332**	**-0.0219**	**0.7**	**20,000**
27-81	**0.1505**	**0.1934**	**-0.0429**	**0.9**	**40,000**
27-100	**0.0912**	**0.1624**	**-0.0712**	**0.7**	**30,000**

The model used a simple back propagation network as well. It consists of 20 input neurons, 10 hidden neurons and 7 output neurons. The model used a set of last closing prices of the stock as input vector, to predict the market future direction. As shown in table 1 the best results were achieved with the look-ahead horizon of 4 weeks or 20 trading days.

Table.2: Back Propagation Neural Network Model Experiments:

Networks	**RMSE Data**				
Input-Neurons-Output	**Training (Tr)**	**Testing (Te)**	**Tr - Te**	**Learning Rate**	**Epochs**
27-3-1	**0.0298**	**0.0559**	**-0.0261**	**0.3**	**50.000**
27-8-1	**0.0156**	**0.0226**	**-0.0070**	**0.3**	**50.000**
27-16-1	**0.0173**	**0.0374**	**-0.0201**	**0.3**	**50.000**
27-20-1	**0.0169**	**0.0405**	**-0.0236**	**0.3**	**50.000**
27-27-1	**0.0184**	**0.0174**	**-0.0010**	**0.3**	**50.000**
27-100-1	**0.0168**	**0.0574**	**-0.0406**	**0.3**	**50.000**
27-27-1	**0.0163**	**0.0575**	**-0.0575**	**0.5**	**50.000**
27-27-1	**0.0188**	**0.0359**	**-0.0171**	**0.1**	**50.000**

The back-propagation network model produced also one trading result:
1= Uptrend.
0 = Sideways.
-1 = Downtrend.

3.1 Trading Rules

The system processed a simple crossover method using the Moving Average (MA) technical indicator as a threshold:
Sample of the MA trading rules:
IF price crosses the MA from the upside to the downside THEN sell
IF price crosses the MA from the downside to the upside THEN buy
If signal correction chosen on using support or resistance levels, track the support and resistance value. Check for breaks out to fire signal.
Sample of the RSI trading rules:
B3:
RSI: Crossed 30 up.
B2:
RSI is moving up 50 < RSI < 70
B1:
RSI is moving up 30 < RSI < 50
RSI is moving up RSI < 30
RSI is moving up RSI > 70
S3:
RSI: Crossed 70 down
S2:
RSI is moving down 30 < RSI < 50
S1:
RSI is moving down 50 < RSI < 70
RSI is moving down RSI > 70
RSI is moving down RSI < 30
RSI horizontal same as previous signal
A snapshot of the system generated Buy/Sell signals using M.A. crossover is illustrated in Figure 4.

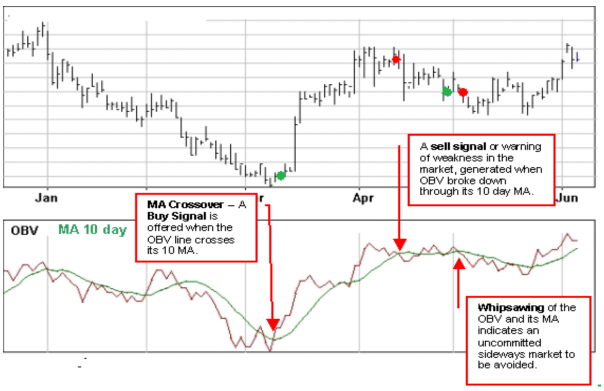

Fig.4: Snapshot of system generated Buy/Sell signals using M.A. crossover

3.2 The Voting System

A voting system generated the trading signal. A committee of networks with different time horizon generated:
Buy signal, when the majority of networks classify the input pattern as a rising case.
Sell signal, when networks predict price decrease.
Do nothing (untradeable day), when the committee have no or unambiguous answer.
Sample of the RSI trading rules:
If the BPN = 1 "Uptrend", and the SOM = 7 "Major Uptrend", and the pattern detection = Ascending Triangle "Continuation Bullish Pattern", and the 20-day EMA crosses above the 50-day EMA = Buy Signal.
If the BPN = -1 "Downtrend", and the SOM = 5 "Minor Uptrend", and the pattern detection = Rectangle "Continuation Pattern", and the 20-day EMA crosses the 50-day EMA to the downside = Sell Signal.

3.2 Fuzzy Logic Module

The system used candlesticks as a way to represent the daily stock prices, because it is the most widely used technique among stock market investors. It is also the most appropriate representation technique to detect the patters used in the prediction process. Figure. 5 shows an example of the daily candlestick chart for the stock market. Daily open, close, high, and low prices are recorded in the candlestick lines from day number1 till day number 10.

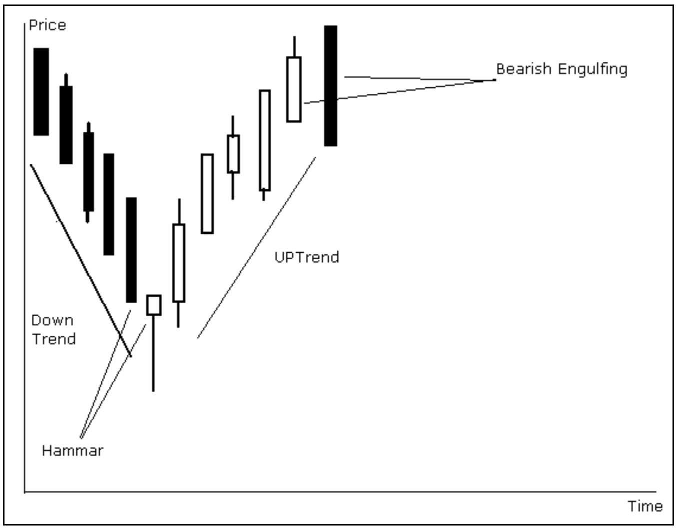

Fig.5: Candlestick pattern examples

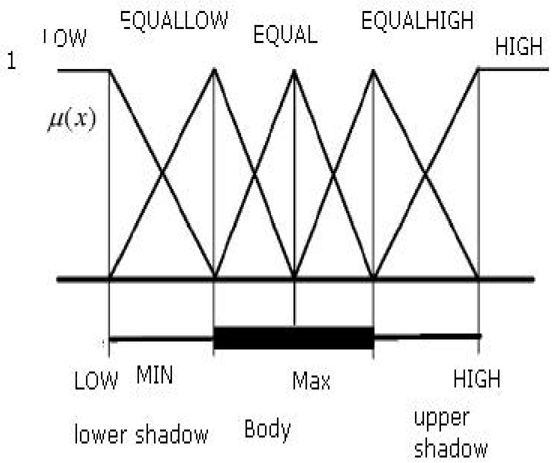

Fig.6: Fuzzy sets of the open style and close style

Figure.6. shows the membership function of the linguistic variables of the open style and close style. The candlestick line in the bottom of Figure 5 is the candlestick line of previous trading time. The unit of X axis is the trading prices of previous day and the unit of Y axis is the possibility values of the membership function. The Open, Close, High, and Low values are provided to the system, and five linguistic variables are defined to represent the open style relationships: OPEN LOW, OPEN EQUAL_LOW, OPEN EQUAL, OPEN EQUAL_HIGH, and OPEN HIGH, and five linguistic variables are defined to represent the close style relationships: CLOSE LOW, CLOSE EQUAL_LOW, CLOSE EQUAL, CLOSE EQUAL_HIGH, and CLOSE HIGH.

The following example demonstrates pattern representation
Pattern description part- Pattern information part
Pattern name: Bearish Engulfing
Confirmation suggest: Suggest
Previous trend: Uptrend Confirmation information:
The open price after the pattern should not be higher than the Open price of candle line 0.
Recognition rule:
1. A definite downtrend must be underway.
2. The second day's body must completely engulf the prior day's body.
3. The first day's color should reflect the trend: black for a downtrend and white for an uptrend.
Candle lines:
Candle line 0:
Open style: OPEN HIGH
Close style: CLOSE LOW
Upper shadow: null
Body: ABOVE MIDDLE
Body color: BLACK
Lower shadow: null
Candle line 1:
Open style: ABOVE OPEN EQUAL_LOW
Close style: CLOSE HIGH
Upper shadow: null
Body: ABOVE SHORT
Body color: WHITE
Lower shadow: null
Interested time period: DAY
Pattern explanation:
The first day of the Engulfing pattern has a small Body and the second day has a long real body.
Another example is the Hammer
Pattern description part Pattern information part
Pattern name: Hammer
Confirmation suggest: Suggest
Previous trend: Downtrend

Recognition rule:
Uptrend must be identified before the pattern
Candle lines:
Candle line 0:
Open style: OPEN HIGH
Close style: CLOSE LOW
Upper shadow: null
Body: ABOVE EQUAL
Body color: BLACK
Lower shadow: double body n
Candle line 1:
Open style: HIGH
Close style: CLOSE LOW
Upper shadow: yes
Body: ABOVE SHORT | EQUAL
Body color: BLACK
Lower shadow: yes
Interested time period: DAY
Pattern explanation:
Hammer is a potentially bullish pattern which occurs during a downtrend. It indicates that the market is hammering out a bottom.
The applied system generates alerts during the construction of any candlestick pattern when its success probability exceeds 40%. For example, alerts for Hanging man or Doji pattern detection would be generated when their success probability exceeds 40%. However, at the end only a single pattern would be suggested at the end of the process.

4 Experimental Results

For the Kohonen NN the model findings are that to have a clear signal one Kohonen layer cluster should noticeably be higher than all the rest. With two or more neuron clusters are active, additional interpretation is needed. Signals that are not occurring in contiguous neurons (clusters) should be ignored. If, for example, neurons 3 and 7 are active, the network is not able to classify the pattern. A simple buy signal is generated when neurons in the positive ranges are active, sell when neurons in the negative ranges are active and stand aside when neutral or conflicting activation occur.

Table.3. shows the back propagation and the Kohonen network prediction results on the training and on the test sets.

Training set was for the period from 1-3-2009 till 31-3-2016 (2/3 of the data set), and the remaining set was used for testing (1/3 of the data set).

Table.3: Training and testing results

Data	**Back Propagation**	**Kohonen**
Training Set: Correctly classified cases	79%	85%
Test Set: Correctly classified cases	60%	72%

Here is a sample output to the applied model results. The samples are divided by symbols, and for each symbol a sample of two years was represented, i.e.2016/2017 & 2017/2018. The applied model gave the best results when using window size of 10 sticks up to 50. Table.4 describes an example of the test samples.

Table.4: Pattern detection results

No.	**Input dataset**	**Operation**	**Actual Output**	**Detected output**
1	hrho1.csv[1]	Downtrend pattern recognition	9.downtrend patterns	8.downtrend patterns
2	hrho1.csv	Uptrend pattern recognition	7.Uptrend patterns	6.uptrend patterns
3	hrho1.csv	Downtrend pattern recognition Uptrend pattern recognition	7.Uptrend 3.downtrend patterns	7.Uptrend 3.downtrend patterns
4	hrho2.csv[2]	Downtrend pattern recognition	2.downtrend patterns	2.downtrend patterns

A sample of the pattern detection results for the data files of Egyptian Financial Group EFG/Hermes Holding "hrho" were presented in Figure 7, 8, and 9. Egyptian Mobile Service "EMOB" in Figure 10, 11, and Orascom Telecom in figure 12.

[1]hrho1.csv: The trading data of the symbol hrho during the period 2014-2015
[2]hrho2.csv: The trading data of the symbol hrho during the period 2016-2017

Fig.7: Pattern detection results for hrho data file (2014/2015), with window size (10-50)

Fig.8: Pattern detection results for hrho data file (2016/2017), with window size (10-50)

Fig.9: Pattern detection results for hrho data file (2018), with window size (10-50)

Fig.10: Pattern detection results for EMOB data file (2014/2015), with window size (10-50)

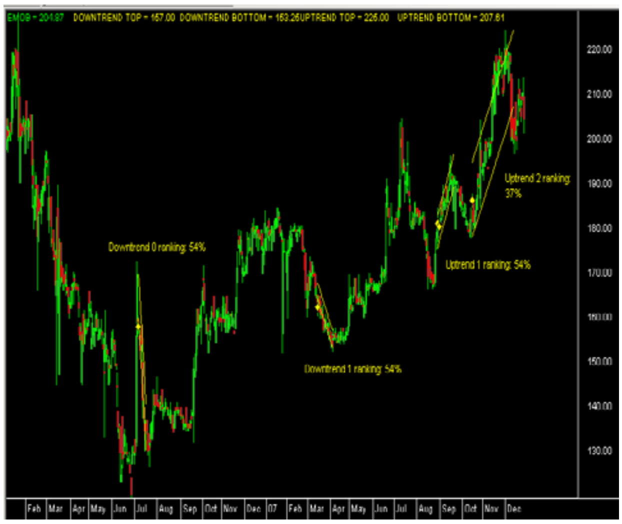

Fig.11: Pattern detection results for EMOB data file (2016/2017), with window size (10-50)

Fig.12: Pattern detection results for ORTE data file (2014/2015), with window size (10-50)

5 Conclusion

The model proposed a Kohonen self-organizing map to split data into predefined classes representing seven different market levels. In the multilayer model the back-propagation network was used to generate a final trading signal.

The proposed hybrid fuzzy-neural multi-layer model can enhance the performance of online trading by using ANNs voting system.

Using Fuzzy logic techniques in detecting candlesticks patterns in a multilayer soft computing model successfully predicted the change in the market direction.

6 Future Work

One of the limitations of using ANN in forecasting is the local maximum problem. Using genetic algorithms (GA) will be very useful to overcome this situation for nonlinear optimization problems.

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