A Synergistic Forecasting Model for High-Frequency Foreign Exchange Data: Statistical Significance, Economic Significance and Trading Strategies

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Submitted to the
Institute of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Finance

Eastern Mediterranean University
July 2018
Gazimağusa, North Cyprus

Approval of the Institute of Graduate Studies and Research

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ABSTRACT

In this thesis, we develop a synergistic forecasting model using the information fusion approach. By using high frequency (one-minute) foreign exchange (FX) data, the model fuses two standalone models, namely the technical analysis structural model and the intra-market model. Subsequently, the outputs are fed into a unique modified extended Kalman filter whose functional parameters are estimated dynamically by using an artificial neural network. The synergistic model is tested on four currency pairs (EURUSD, EURGBP, NDZUSD, and USDJPY) that dominate the FX market. In terms of forecasting performance, both root mean squared error and correct directional change performance results show that the synergistic model statistically outperforms and is superior to each of the both standalone models as well as to the benchmark random walk model.

This thesis also presents the economic significance of trading system based on the synergistic forecasting model by developing automated simple trend-following and adaptive trading systems strategies, considering the market microstructures of transaction costs. The results for economic significance support the possibility of profiting from these predictions which are positive for both trading strategies, but the adaptive trading system gain higher return than simple trend following trading.

Keywords: foreign exchange, Kalman filter, forecasting, high-frequency data, technical analysis indicators, automated trading, statistical significance, economic significance.

ÖZ

Bu çalışmada bilgi füzyon yaklaşımını kullanarak yüksek frekanslı verilerin gelecek değerlerini tahmin etmeye yönelik sinerjik bir model geliştirdik. Bu model tahmin sürecinin ilk aşamasında teknik analiz yapısal modeli ve piyasa içi modeli birleştirerek yüksek frekanslı (bir dakikalık) döviz piyasası verilerini analiz etmektedir. Bu süreçten elde edilen çıktılar fonksiyonel parametreleri yapay bir sinir ağı kullanılarak dinamik olarak tahmin edebilen genişletilmiş Kalman filtresine aktarılmaktadır. Oluşturulan model, küresel piyasalarda en çok işlem gören dört döviz çiftinin (EURUSD, EURGBP, NDZUSD, ve USDJPY) gelecek değerlerinin tahmin edilmesinde kullanılmıştır. Tahmin performansı açısından, gerek hata kareleri toplamı gerekse yön değişimlerini tahmin edebilme yüzdesi olarak, modelin karşılaştırıldığı diğer tahmin modellerine göre daha üstün olduğu görülmektedir. Çalışma aynı zamanda piyasa mikro yapılarını, işlem maliyetlerini ve komisyon ücretlerini de göz önünde bulundurarak, sinerjik tahmin modelinin kullanıldığı çeşitli alım-satım stratejilerinin ekonomik olarak anlamlılığını da ortaya koymaktadır. Modelin istatistiksel üstünlüğünün yanında ekonomik olarak da anlamlılığının gösterilmesi modelimizin piyasa işlemlerinde kullanılabilir olduğunu ifade etmektedir.

Anahtar Kelimeler: döviz kuru, Kalman filtresi, tahmin, yüksek frekanslı veri, teknik analiz göstergeleri, otomatik işlem, istatistiksel önem, ekonomik önem.

DEDICATION

To My Lovely Mom

ACKNOWLEDGMENT

I would like to express my unlimited thanks to my supervisor Prof. Dr. Cahit Adaoglu who has always guided me in the right path and never let me to deviate in my journey. Supporting me in my academic life and talking to him makes everything easier for me. I have learned from him the lesson of morality, humanity and honesty besides finance.

Meanwhile, I would like to thank my co-supervisor, Assoc. Prof. Dr. Korhan Gokmenoglu for his great support and accompany like a brother. Whenever he talks to me, he opens a new door in my life and knowledge, motivate me to move forward without fear.

I would like to thank the previous department chair Prof. Dr Salih Katircioglu, and current department chair, Assoc. Prof. Dr. Nesrin Ozatac who have given me the opportunity to have a nice experience of teaching as an instructor in an international university during my student life.

I have to thank my sisters, family members and on top, to my lovely and great mother for all of her support during my life. My dear and devotee mom has always been awake and smart at every stage of my life. I am sorry for all distressing and troublesome circumstances you have endured because of my distractions.

I am always grateful to have these angles in my life.

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LIST OF ABREVIATIONS

ANN	Artificial Neural Networks
AR	Auto Regressive
ATR	Average True Range
CDCP	Correct Direction Prediction
CF	Commission Fee
DQ	Directional Quality
EKF	Extended Kalman Filter
FX	FOREX Market
GRNN	Generalized Regression Neural Network
IRLS	Iteratively Reweighted Least Square
K	Stochastic Indicator
MA	Moving Average
MFI	Money Flow Indicator
MQL	Meta Quotes Language
OBV	On Balanced Volume
PIP	Percentage in Point
RAC	Return after Commission Fee
RAT	Return after Transaction Cost
RBF	Radial Base Function
RMSE	Root Mean Square Error
RSE	Robust Sequential Estimator
RSI	Relative Strength Indicator
SD	Standard Deviation

TC	Transaction Cost

Chapter 1

INTRODUCTION

1.1 The Synergistic Forecasting Model and its Statistical Significance

The foreign exchange market is the largest global financial market, in which trillions of currency units change hands each day. As of April 2016, the average total daily value of transactions in the FX market is $5.1 trillion (BIS, 2016). Understanding the behavior of the exchange market and forecasting the price of currencies have been ongoing challenges for all market participants, professional investors, researchers, and policy makers.

A vast amount of literature is dedicated to models that attempt to forecast exchange rates. The models differ in goals, and mathematical methods employed and the nature of available information. Two types of information sets can be used for FX forecasting, namely macroeconomic fundamental data and technical data. FX market participants use both types of information sets (Gehrig & Menkhoff, 2004). Researchers and practitioners argue that for short-term forecasting, the performance of technical data is relatively better (Neely & Weller, 1999; Menkhoff & Taylor, 2007; Vasilakis et al., 2013). Moreover, as the forecasting horizon becomes shorter, the relative importance of technical analysis data in forecasting becomes larger (De Zwart et al., 2009). Relying on infrequent typical macroeconomic models of fundamental variables relevant to exchange rate determinations such as purchasing power parity perform poorly and are not useful in explaining the dynamics of exchange rate movements at frequencies of less than one year (e.g., Meese & Rogoff, 1983; Frankel & Rose, 1995; Cheung et al., 2005; Gradocevic & Yang, 2007; Engel et al., 2007; Korol, 2014).

Taking into account the discussion in the literature, we develop a code that captures tick-by-tick one-minute interval FX data from the popular Metatrader FX trading platform. We use high frequency (one-minute) data, which necessitates the use of technical analysis indicators. We do not incorporate macroeconomic fundamental data due to its low frequency.

In this study, we follow the "information fusion" approach. This approach is a process of combining data from several sources by different methods into a single, consistent and accurate whole (Dasarathy, 2011). Traditionally, several disciplines such as defense, aerospace, and robotics use information fusion. However, information fusion also has potential uses in forecasting (Dasarathy, 2013). Application of the information fusion approach, especially in finance, can lead to better forecasting of both stock and currency prices (Dasarathy, 2013). We apply the information fusion approach in the FX market which has more uncertain dynamics in high-frequency trading strategies (i.e., less fundamental changes) and data characteristics (i.e., non-Gaussian distribution) (Agrawal et al., 2010; Bekiros, 2015).

In terms of modeling, we use a novel fusion approach, which we refer to as "the synergistic model for short-run FX forecasting". In financial forecasting, we define the synergistic model as the simultaneous combination of two standalone models, namely the technical analysis structural model (regressed by panel data method) and the intra-market model (Auto regressive Time series model). We combine these two standalone models in a way that creates an information fusion synergy in order to predict the behavior of the whole system. The advantage of the proposed model eliminates the need for processing large amounts of data very frequently, which simplifies and speeds up the forecasting process by fewer computational operations in the Kalman filter model.

The synergistic outputs of the two combined standalone models are then fed into a modified extended Kalman filter. In stock price forecasting, the Kalman filter is one of the most effective forecasting methods, and it fuses information derived from technical and fundamental data (Haleh et al., 2011). Unlike having constant parameters in typical Kalman filter applications, we uniquely use an artificial neural network that allows us to vary the parameters in the filter. Especially for high-frequency financial data, conditional variances are not constant over time (Aldridge, 2010), and these parameters should be treated as time varying due to the nature of the data used.

The empirical results of forecasting accuracy show that our synergistic model provides better forecasting accuracy in comparison to the two standalone models, the technical analysis structural model and the intra-market model. The information fusion approach is effective and the resulting model has statistically significant better forecasting accuracy results model in terms of both correct direction prediction (%CDCP) and root mean squared error (RMSE). We also compare our forecasting accuracy performance to the random walk model as the benchmark in the literature (Cai & Zhang, 2016; Hong et al., 2007). The synergistic model also beats the random walk model.

1.2 The Synergistic Forecasting Model and its Economic Significance

Since the early 2000s, the availability of high-frequency financial data assists market analyzers to use more sophisticated models in their predictions (Brogaard, 2010). Effective utilization of publicly available intra-day FX data and different modeling techniques might be a more effective means to explain the behavior of exchange rates in the short to medium term (Shen et al., 2015).

Recently, the world of high-frequency trading has been reshaping the dynamics of financial markets by creating new opportunities and challenges for traders (Hendershott & Moulton, 2011). Research has shown that, in most cases, slow traders (e.g., human traders) are strictly worse off when algorithmic trading is widespread (Hoffmann, 2014).

The battle of trading robots has therefore become the most challenging field for financial institutions and markets. A new generation of algorithms, such as genetic algorithms (Kim et al., 2017; Sermpinis et al., 2015), fuzzy trading systems (Bekiros, 2010; Korol, 2014; Thirunavukarasu & Maheswari, 2013), and artificial neural networks (Kablan, 2009), has been applied to develop automated and intelligent trading systems based on forecasting models.

Although many forecasting techniques pass the statistical significance tests, they are not practical in real markets or they vary in different market conditions. This means that applying the statistical forecasting model may improve the accuracy of prediction, but this may not necessarily translate to economic benefits. This is because of the relevant costs of trades, such as transaction costs and commission fees, where the costs and benefits may offset each other. However, some studies still neglect the transaction cost and economic significance analysis so as to keep the computations tractable (Morales Arias & Moura, 2013; Araujo et al., 2015). The aim of an economic significance study is to investigate whether the investor can benefit from the anticipation of the future market movement by considering the relevant costs.

This study describes the empirical results and proof of economic significance analysis of an automated simple trend following trading and adaptive trading robot built to generate profitable buy and sell signals for the foreign exchange market in high frequency through the use of a synergistic forecasting model.

The following chapter explains the literature review, data, and methodology of synergistic forecasting model by applying the modified extended Kalman filter and its statistical significance analysis. Chapter 3 discusses the economic significance analysis of the synergistic forecasting model and the trading strategies followed by Chapter 4 as the conclusion.

Chapter 2

STATISTICAL SIGNIFICANCE ANALYSIS OF THE SYNERGISTIC FORECASTING MODEL

2.1 Literature Review

Many researchers argue that, for short term prediction, technical data exhibit relatively better performance. The weight of technical analysis has therefore increased (De Zewart et al., 2009; Neely & Weller, 1999; Yao & Tan, 2000; Menkhoff & Taylor, 2007; Vasilakis et al., 2013; Kim & Shin, 2007; Ye et al., 2016; Zhang et al., 2015). Studies show the statistical significance of excess returns obtained from technical analysis trading rules in one-minute high-frequency forecasting of FX rates (Manahov et al., 2014; Thinyane & Millin, 2011).

Even though time series models have demonstrated better performance than theoretical traditional models in forecasting exchange rates in the short to medium term (Evans, 2002; Evans et al., 2012; Cai & Zang, 2016), not taking into account the nonlinear nature of the exchange rate process might limit the prediction power of these models (Mark, 1995). Therefore, a variety of sophisticated non-linear time series models have been developed to explain the behavior of exchange rates and forecast short-term exchange rate movements (Strozzi & Zaldívar, 2005). These models have made important contribution to our understanding of the distinctive behaviors of financial time series such as volatility clustering (Kumar, 2014), leptokurtosis (Bollerslev, 1987), long swings (Engel & Hamilton, 1990), and jumps and discontinuities (Bates, 1996). However, their contribution to forecasting accuracy is marginal (Hong et al., 2007).

2.2 The Synergistic Model

Synergy is widely defined as the interaction of multiple interdependent elements in a system that generates an effect greater than the sum of the individual element effects (Corning, 1998). The term “synergy” is used in studies for investigating the hybridization effect between classical and soft-computing techniques for time series forecasting (Lai et al., 2006; Rojas et al., 2004; Araujo et al., 2015; Deng et Al., 2015). We combine the two standalone forecasting models, namely the technical indicators structural model and the intra-market model. The predicted return of exchange rates obtained from the combination of the preceding two models is then passed through the modified extended Kalman filter. With the consequent information fusion, we aim to offer superior forecasting of the next step return.

Figure 1 shows the synergistic model. There are two types of inputs. The first block of inputs are technical analysis indicators which are used in two different models. The first model is the artificial neural network (ANN), which is trained to dynamically and adaptively model the functional parameter (Q) of Kalman filter. Additionally, in the second model, these technical indicators are the endogenous variables of structural regression model. The structural panel data regression estimates the next rate of return based on lags of technical analysis indicators. The next inputs are the lags of exchange rates of returns for the specific pairs ($L^i\varphi\ \mathrm{r_t}$). Those are the endogenous variables of the intra-market model (i.e., an AR time series model). This model is used as the state model of Kalman filter. Then, we feed the outputs of the models into the Kaman filter block to predict the next exchange rate of return. There is also a lag operator (Z^{-1})

which returns the predicted rate of return for further use in the Kalman filter model. To the best of our knowledge, the fusion approach and, the resulting model have not been applied before in the FX forecasting literature. In the following sections, we explain the components of the model in Figure 1.

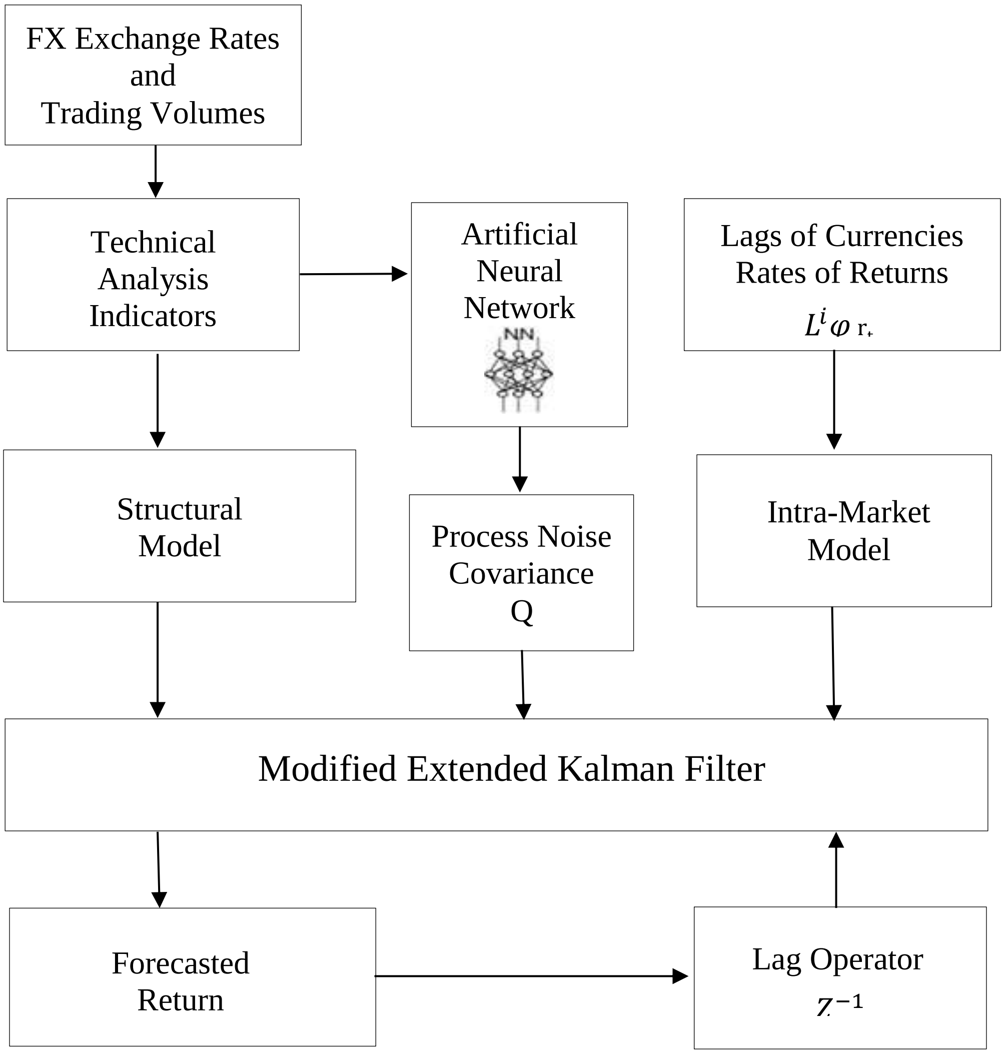


Figure 1. Synergistic model flow chart

2.2.1 The Structural Model

Studies have shown technical analysis can be most useful at high-frequency time intervals during which the macroeconomic (fundamentals) change rarely and the least (Bekiros, 2015; Lyons, 2001). Technical analysis indicators play an important role in forecasting the fluctuations and turning points of price trends (Ni & Yin, 2009). There are hundreds of technical analysis indicators. However, we use the indicators that are supported by principal component analysis in the FX market, such as the relative strength indicator (RSI), the standard deviation (SD), the stochastic indicator (%K), and the moving average (MA). These indicators contain rich information about price trends and show the market dynamics and trend reversion (Neely & Weller, 2012; Zhang et al., 2015).

In the structural model, different lags of technical analysis indicators of volume, price, and volatility are used as the exogenous variables of a structural regression model, to investigate the impact of past market dynamics on future return (Brock & Lebaron, 1996; Pathirawasam, 2011). Following the previously developed FX forecasting models (e.g., Yao & Tan, 2000), as the first indicator, we use the RSI, which is a rate of changing momentum oscillator. RSI (see equation (1)) is used as a criterion for measuring the velocity and the magnitude of directional price changes (Wilder, 1978). In equation (1) $\overline{\Delta P}_i^+$ and $\overline{\Delta P}_i^-$ are average positive (+) and negative (-) price change respectively during the last n minutes ago. According to Wilder (1978), the best assigned n is 14.

$$RSI(n) = 100 - \frac{100}{1+\frac{\sum_{i=1}^{n}\overline{\Delta P}_i^+}{\sum_{i=1}^{n}\overline{\Delta P}_i^-}} \tag{1}$$

The second indicator in the structural model is the average true range (ATR; see equations (2) and (3)), which is a volatility index showing the commitment or enthusiasm of traders in a specific commodity (Wilder, 1978).

$$ATR_t = \frac{1}{n}\sum_{i=1}^{n} TR_i \qquad (2)$$

$$TR = \max[(price_{high} - price_{low}), \left|price_{high} - price^{previous}_{close}\right|, \left|price_{low} - price^{previous}_{close}\right|] \qquad (3)$$

The third indicator, on balanced volume (OBV; see equation (4)), shows the movement of volume resulting from the closing price ($price_t^{close}$) changes (Blume et al., 1994). OBV measures demand and supply volumes by assessing the trading volumes (V_t) and the change in OBV. The change in OBV is considered as a factor in the decision making process by the market analysts (Granville, 1976).

$$OBV_t = OBV_{t-1} + \begin{cases} V_t & if \;\; price_t^{close} > price_{t-1}^{close} \\ 0 & if \;\; price_t^{close} = price_{t-1}^{close} \\ -V_t & if \;\; price_t^{close} < price_{t-1}^{close} \end{cases} \qquad (4)$$

The fourth indicator, the money flow indicator (MFI; see equations (5) and (6)), is an indicator of money flowing “into” or “out of” an asset; however, the expression only refers to the forecasting reliability of the buyer enthusiasm trend. Obviously, there is never any net money in or out; for every buyer, there is a seller of the same amount (Kirkpatrick & Dahlquist, 2010).

$$MFI_t = 100 - \frac{100}{1+\frac{Positive\ money\ flow_t}{Negative\ money\ flow_t}} \qquad (5)$$

$$Money\ flow_t = \frac{price_t^{high}+price_t^{low}+price_t^{close}}{3} \times volume_t \qquad (6)$$

For the structural model component in Figure 1, we use panel data analysis to investigate the total impact of the market dynamics for whole sample of pairs of exchanges in a specific period, which can be explored from the regression of the lags of technical analysis indicators on the next market return. The regression model in equation (7) estimates the FX market return using the random effects general least square (GLS) panel data method. Panel data regression predicts the FX rates more accurately than the time series models because the model parameters are heterogeneous and are explored from currency prices and trading volumes or the combination of those market elements. We can also use the full sample of all pairs of exchanges together in order to have tests that are more powerful as long as the model parameters are uncorrelated with the regression errors (Mark & Sul, 2012). Especially in the adaptive forecasting models of FX rates, a wide-ranging information set decreases the ex-ante uncertainty and improves the prediction precision in a panel data setting (Morales-Arias & Mura, 2013).

As shown in equation (7), we estimate the regression model for the structural model component in order to capture the effects of the preceding technical indicators on FX returns r.

$$\hat{r}_{m,t} = \Phi_0 + \sum_{m=1}^{4}\sum_{i=1}^{14} L^{i}\Phi_1 D(\mathrm{RSI}_{m,t}) + \sum_{m=1}^{4}\sum_{j=1}^{14} L^{j}\Phi_2 D(\mathrm{ATR}_{m,t}) + \sum_{m=1}^{4}\sum_{k=1}^{14} L^{k}\Phi_3 D(\mathrm{OBV}_{m,t}) + \sum_{m=1}^{4}\sum_{l=1}^{14} L^{l}\Phi_4 D(\mathrm{MFI}_{m,t}) \tag{7}$$

In equation (7), all the variables are considered in the first difference because the indicators' one-minute change is of interest. D is the difference operator and the Lφ's are the lag operators of the independent variables. m stands for cross-sectional pairs of exchanges and t stands for time series. i, j, k, l are set from 1 to 14, because as mentioned before, those indicators are calculated for the last 14 minutes.

2.2.2 The Intra-Market Model

The following state space model f, defines the intra-market model. The time series autoregressive approach (AR) including lags of exchange rates of returns estimates f, as shown in equation (8) (Serpeka, 2012). The intra-market model estimates the relationship between the lags of FX returns and the future return, and it is specifically estimated for every pairs of currencies.

$$f_t = \sum_{i=1}^{m} \sum_{j=1}^{n} L^i \, \Phi_j(r_t) \tag{8}$$

In equation (8), the Lφ's are the lag operators of the independent variables. f is the forecasted rate of return. r_t is the currencies pairs' rates of returns. i stands for the number of lags and j stands for the coefficients indices.

2.2.3 The Kalman Filter

The Kalman filter presents a recursive solution to filter the linear discrete data (Kalman, 1961). The process centers on finding the best estimate from noisy data through the filtering process. It is a set of mathematical equations with optimal estimator, predictor, and corrector phases, which sensibly minimize the estimation error covariance (Maybeck, 1979).

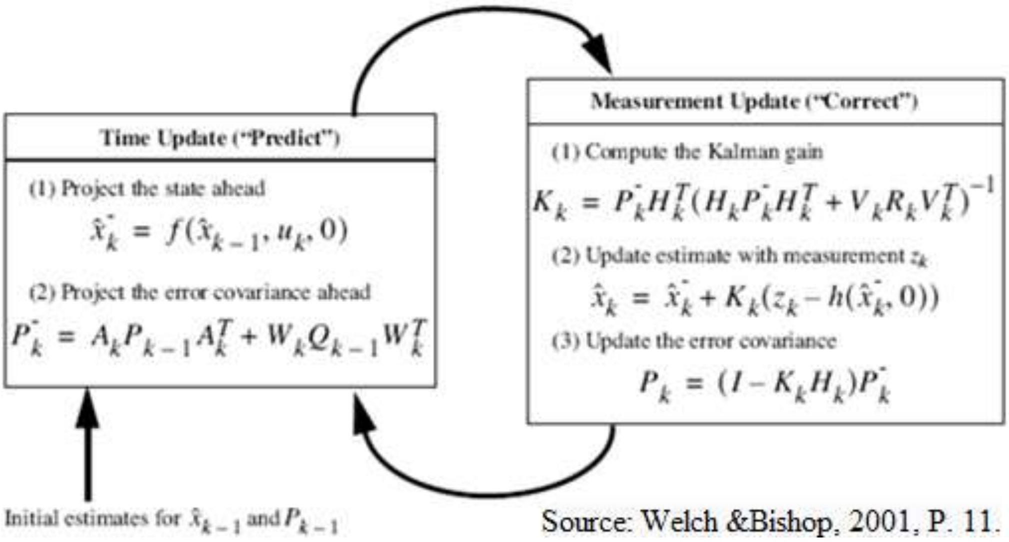


Figure 2. Kalman filter recursive equations

This filter is effective for Gaussian distribution (Welch & Bishop, 2001). However, empirical studies show that the distributions of intraday fluctuations of FX returns are non-Gaussian and contain fat tails (Seemann et al., 2011). Thus, the problem is how to apply the Kalman filter to such data.

We solve this empirical challenge problem by modifying the Kalman filter algorithm for non-Gaussian heavy-tailed distributions through a robust sequential estimator (RSE) method. The RSE method detects the outliers by using a weighting mechanism. As shown in equation (9), these weights are calculated repetitively by the maximum likelihood error technique for non-normal distributions, and a weight is assigned to each observation (Mirza, 2011). Equation (9) is a linear regressing model of z on the independent variable X. X is the previous lags of exchange rates of returns. z is the exchange rates of return observations; θ represents regression coefficients to be estimated, ϵ is the disturbance term, and k is the time.

$$z_k = \theta . X_k + \epsilon_k \tag{9}$$

The maximum likelihood error solution of the nonlinear equation is

$$s^2 = \hat{\sigma}^2 = \frac{\sum_k w_k (z_k - \sum_j \hat{\theta}_j x_{jk})^2}{k} \tag{10}$$

where

$$w_k = w_k(\theta, \sigma^2) = -2 \left[\frac{\partial lng\{(\epsilon_k/\sigma)^2\}}{\partial (\epsilon_k/\sigma)^2} \right] \tag{11}$$

$$g\left\{\left(\frac{\epsilon_k}{\sigma}\right)^2\right\} = \left\{1 + \frac{\epsilon_k{}^2}{f\sigma^2}\right\}^{\left(-\frac{1}{2}\right)(1+f)} \tag{12}$$

g has t-distribution having degrees of freedom f and is scaled by a parameter σ. Then, substituting the g value in equation (11) gives the weights for each observation, as shown in equation (13):

$$w_k = \frac{1+f}{f + (\frac{r_k}{s})^2} \tag{13}$$

$r_k = z_k - z_{robust}$ and z_{robust} are the location parameters of exchange rate returns obtained for a sample of data using an iteratively reweighted least square (IRLS) (Daubechies, 2010). This scale parameter s_k^2 is consecutively updated by equation (14) (Mirza, 2011):

$$s_k^2 = \frac{(t-1)s_{k-1}^2 + w_k r_k^2}{k} \tag{14}$$

The calculated scale parameters (s_k^2) are used to distinguish normally distributed data from outliers, which corrupt the normal distribution of sample data. This prevents the addition of the innovation term ($K_k(z_k - \hat{z}_k)$) to the outliers in equation (21).

In order to have a better insight to computational origin of the Kalman filter, the equations (15 and 16) and Figure 3 can simply explain the way how the fusion of two variables happens.

$$\mu = [\sigma_{z_2}^2 / (\sigma_{z_1}^2 + \sigma_{z_2}^2)]z_1 + [\sigma_{z_1}^2 / (\sigma_{z_1}^2 + \sigma_{z_2}^2)]z_2 \tag{15}$$

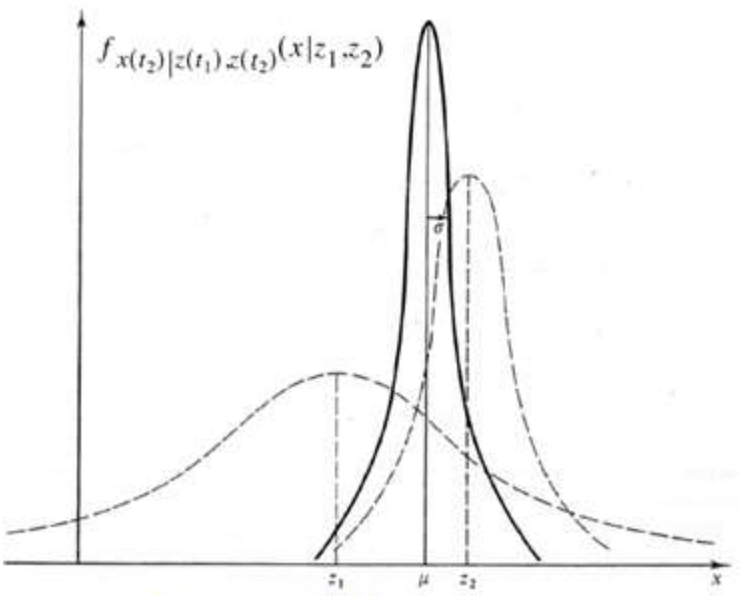
$$\hat{X}(t_2) = \mu \tag{16}$$

Here, μ is weighted average of two measuring systems and $\sigma_{z_n}^2$ is the variance of the measurement errors for each measuring tools.

$$\begin{aligned} \hat{x}(t_2) &= [\sigma_{z_2}^2 / (\sigma_{z_1}^2 + \sigma_{z_2}^2)]z_1 + [\sigma_{z_1}^2 / (\sigma_{z_1}^2 + \sigma_{z_2}^2)]z_2 \\ &= z_1 + [\sigma_{z_1}^2 / (\sigma_{z_1}^2 + \sigma_{z_2}^2)][z_2 - z_1] \end{aligned} \tag{17}$$

So, the equation 21 is explored from the above equation and,

$$1/\sigma^2 = (1/\sigma_{z_1}^2) + (1/\sigma_{z_2}^2) \tag{18}$$



Source: Maybeck, 1979, P. 11.

Figure 3. Conditional density location based on Z1 and Z2 measurements.

The Kalman filter estimates the state of the $X \in R^n$ discrete-time control process, which has a linear differential function. The next challenge is discovering what happens if the relationship with the measurement process is nonlinear. There are many interesting applications of the Kalman filter in these nonlinear cases. The extended Kalman filter (EKF) is the nonlinear extension of the Kalman filter (Haykin, 2001). In the equation 19, f is the time update (prediction) phase function that relates the state parameters in the previous time steps to the current time k.

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, w_{k-1}) \tag{19}$$

$$P_k^- = A_k P_{k-1} A_k^T + Q_{k-1} \tag{20}$$

In our study, the state model f is substituted by an autoregressive model (AR), which is the intra-market model in Section 2.2 (equation (8)). $\hat{x}_k^-$ is the prior estimate of $\hat{x}_k$, and $\hat{x}_{k-1}$ is the lagged term of the past FX return. u_{k-1} is the another control variable, which affects the future return estimation, and w_{k-1} is the random variable of process noise. P_k is the estimation covariance, which is expected to reduce during the repetition of the algorithm. Q_k is the covariance of process noise. A_k is the Jacobian matrix of partial derivatives of f with respect to x.

$$A_{[i,j]} = \frac{\partial f_{[i]}}{\partial x_{[j]}}(\hat{x}_{k-1}, u_k, 0) \tag{21}$$

In this study, through the measurement equation $z \in R^m$, we relate and approximate the state of x_k to the measurement z_k. We substitute function h by our structural regression equation (7) on one-minute ahead forecasting return of the FX that is known as z_k:

$$\hat{z}_k = h(x_k, v_k) \tag{22}$$

The random variable, v_k, represents the process and measurement noises. These also include the function parameters (u_k) and the zero mean noise process (w_k).

The next phase is "the measurement update", which corrects the prediction according to all functional and environmental conditions. This step is accomplished through equations (23) and (24).

$$K_k = P_k^- H_k^T (H_k P_K^- H_k^T + R)^{-1} \tag{23}$$

$$\boldsymbol{P_k = (I - K_k H_k) P_k^-} \tag{24}$$

The Kalman filter modified by robust sequential estimator (RSE) is incorporated at this stage by assigning the appropriate $\hat{x}_k^-$ to obtain the conditional *a posteriori* estimate (Mirza, 2011). By computing the mean value of the observations' weights in a sliding window and by comparing this mean value with a threshold that is assumed to be one-third of the mean value, it can be determined whether a given data point is an outlier. Then, we estimate the *posterior* value in equation (25). The weighted innovation term $K_k(z_k - \hat{z}_k)$ is added to *a priori* state estimates ($\hat{x}_k^-$) if the observation at time k is not an outlier. The detection of the outlier data prevents the addition of the innovation term $K_k(z_k - \hat{z}_k)$ to the outliers in following equation:

$$\begin{cases} \hat{x}_k^- & if \quad y_k is \quad an \quad outlier \\ \hat{x}_k = \hat{x}_k^- + K_k(z_k - \hat{z}_k) & otherwise \end{cases} \tag{25}$$

In equation (25), the term $\widehat{x}_k$, which is *a posteriori* estimate of the rate of the return, $(z_k - \hat{z}_k)$ is known as the innovation measurement or the residual, which reflects the discrepancy between the predicted measurements from the structural regression model and the realized measurement value. K_k is the Kalman filter coefficient. H is the Jacobian matrix of partial derivatives of h with respect to x.

$$H_{[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[j]}}(\tilde{x}_k, 0) \tag{26}$$

2.2.4 Artificial Neural Network for Filter Parameters and Tuning

As mentioned previously, the Kalman filter requires the use of preprocessed operational parameters such as Q_k, R_k, W_k, and V_k, which are typically used as static parameters during the process. In order to calculate Q, known as the covariance of process noise, the change in asset price returns is calculated for a time interval. For this purpose, in a specified period such as in a day and in a week, the change in asset price returns is calculated by equations (27) and (28), and it remains as a fixed number during the forecasting period.

$$e_k = r_k - \tilde{r}_k \tag{27}$$

$$Q = Var(e_k) \tag{28}$$

where r_k is the actual rate of return of pairs of exchanges, and $\tilde{r}_k$ is the approximate average value of the rates of return.

There is a dynamic structure in the high-frequency FX market (Sazuka et al., 2003). Consequently, we adopt a dynamic approach for the estimation of these parameters. For the FX market with high-frequency data, the magnitude of process noise covariance Q should dynamically vary depending on the market conditions. Due to the problem of estimating good noise covariance matrices ($\hat{Q}_k$), it is difficult to practically implement the Kalman filter. There are various approaches to estimating these matrices (Rajamani & Rawlings, 2009). In order to have a reliable extended Kalman filter (EKF) for all financial market conditions, we need to modify the (Q_k) parameter dynamically by using an artificial neural network that can predict the fluctuations of the prices in the next period. This is our distinctive approach in using the EKF process for the FX market.

As noted before, technical indicators such as RSI, ATR, and SD; some market microstructure parameters, such as bid and ask spread; and trading volume have significant impact on the short-term future volatility of the market, which is measured by Q_k (Roll, 1984). However, there is no linear relationship among these variables and the statistical measure of Q_k. Due to the non-linear characteristics of the model, a type of artificial neural network, which is called the generalized regression neural network (GRNN), is designed to predict Q_k. GRNN does not need any predetermined equation form. There are several studies use neural networks as one of the most popular components of the fusion models (Kim & Shin, 2007; Guresen & Kayakutlu, 2008; Araujo et al., 2015). The GRNN is designed with the MATLAB neural network toolbox (MATLAB, 2007; Tabrizi & Panahian, 2011), and it can approximate any function between inputs and outputs.

GRNN consists of four layers, namely the input layer, the pattern layer, the summation layer, and the output layer. These layers are shown in Figure 4. The neurons of the first and last layers are decided by the number of input and output variables. The summation layer has two neurons, and the hidden layer uses a Gaussian transfer function in the radial basis function (RBF) in order to approximate the given function (Broomhead & Lowe, 1988). For each pair of currencies, we train the GRNN through the supervised method of learning using the results of equations (27) and (28).

In Figure 4, lags of the RSI, SD, $Spread$, and $Volume$ are the inputs, and $\widehat{Q}_k$ represents the outputs of the neural network. IW is the input weights matrix, LW is the hidden layer neuron weights matrix, and b are the biases. Subsequent to the supervised learning period, $\widehat{Q}_k$ is generated for each market situation in line with the technical indicators and market microstructure parameters at the prediction time.

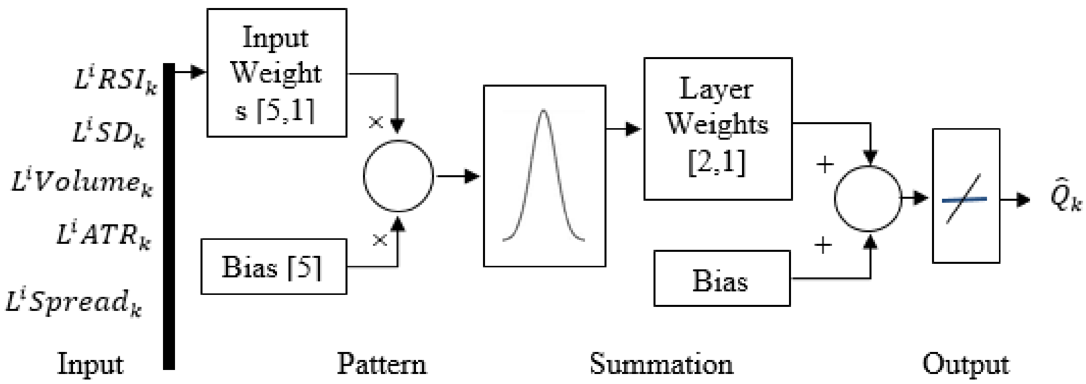


Figure 4. GRNN artificial neural network for estimating adaptive dynamic Q

Then, $\hat{Q}_k$ is fed into the EKF model in order to forecast the FX return in the next step. Subsequently, the Q_{k-1} in equation (16) is replaced by $\hat{Q}_k$ in equation (29).

$$P_k^- = A_k P_{k-1} A_k^T + \hat{Q}_k \tag{29}$$

2.3 Data and Forecasting Performance Measures

2.3.1 Data

We use five dominant currencies that are widely traded in the FX market. In terms of descending trading volume, these five dominant currencies are the US dollar (USD), the New Zealand dollar (NZD), the Euro (EUR), the Japanese Yen (JPY), and the British Pound (GBP) (BIS, 2014). Our samples are one-minute high-frequency, tick by tick FX market price data. Each "tick" is one logical unit of information such as a quote or a transaction price.

We develop the Meta Quotes Language (MQL) code that captures the required data from the popular electronic platform of the Metatrader FX trading platform (Metatrader, 2010). Our data consists of the FX spot price rates of return and the technical analysis indicators of four dominant pairs of currencies: EUR/USD, EUR/GBP, NZD/USD, and USD/JPY. We randomly picked the sample period and the MQL code collects data for five working days of the week from 12/8/2013 to 16/8/2013. Each daily data set contains the trading data between 00:00 and 23:59.

Table 1 presents descriptive statistics of the sample data. Table 1 (Panel A) shows the statistics for one day (1,440 observations) on 12/8/2013, and Table 1 (Panel B) shows the statistics for one week (7,200 observations) for the period from 12/8/2013 to 16/8/2013. In both panels, according to the Jarque-Bera result, our data are not normally distributed. As emphasized in Section 2.3, the non-normality of our data is in line with the data characteristics found in previous empirical studies. The modified extended Kalman filter, which we develop in this study, is applied for this non-normally distributed data.

Additionally, data from randomly chosen bullish/bearish days and week are used to check the robustness of our model. A bearish day is a trading day with an overall downward trend, during which the prices drop off. A bullish day is a trading day with an overall upward trend, during which the prices rise up. A bearish week is a week with an overall downward trend, and a bullish week is a week with an overall upward trend. The randomly selected bearish and bullish days are on 20/6/2013 and 4/4/2013, respectively. The randomly selected bearish week is from 5/6/2013 to 9/6/2013, and the bullish week is from 27/3/2013 to 31/3/2013.

Table 1. Descriptive statistics of intraday (Panel A) and one-week (Panel B) observations

Panel A	EUR/USD	EUR/GBP	NZD/USD	USD/JPY
Mean	1.272303	0.794723	0.789609	97.61270
Median	1.269480	0.795030	0.788260	97.91800
Maximum	1.529850	0.804760	0.802410	98.43800
Minimum	1.262630	0.785520	0.781200	96.01900
Std. Dev.	0.010376	0.004895	0.004953	0.666217
Jarque-Bera	29209049	193.3967	395.6509	635.9929
J-B Prob.	0.000000	0.000000	0.000000	0.000000
Panel B	**EUR/USD**	**EUR/GBP**	**NZD/USD**	**USD/JPY**
Mean	1.318573	0.788830	0.854551	98.07065
Median	1.318510	0.788405	0.856790	98.04600
Maximum	1.324240	0.793480	0.858450	98.71700
Minimum	1.316180	0.785520	0.848320	97.70200
Std. Dev.	0.001878	0.001867	0.003678	0.204432
Jarque-Bera	109.8159	107.9919	220.0716	116.5810
J-B Prob.	0.000000	0.000000	0.000000	0.000000

2.3.2 Measuring Forecasting Performance

There are several forecasting performance measurement techniques. Researchers propose that if the model error term follows a normal distribution, root mean squared error (RMSE) may work better than other criteria, such as mean absolute error (MAE)

(Draxler, 2014). The RMSE is much more popular in high-frequency data studies (Chortareas et al., 2011; Lahmiri, 2014), and we use the RMSE in our study.

Predicting the direction of the changes is very important, especially for trend trackers (Bai et al., 2015). Many of trend-following trading techniques using the probability of trend direction in high-frequency timespans (Rechenthin & Street, 2013). As shown in equation (30), we use percentage of correct direction change prediction (%CDCP), which gives the proportion of correctly forecasted directional changes given lead time s (during whole forecasting period).

$$\%\, correct\ direction\ change\ prediction = \frac{1}{T-(T_1-1)} \sum_{t=T_1}^{T} Z_{t+s} \qquad (30)$$

Where Z_t's are binary expressions come from below equations, y_t and y_{t+s} are realized values and $f_{t,s}$ are the forecasted values.

$$Z_{t+s} = 1 \quad \text{if } (y_{t+s} - y_t)(f_{t,s} - y_t) > 0 \qquad (31)$$

$$Z_{t+s} = 0 \ \ otherwise$$

These two measures help us to evaluate the forecasting performance of the proposed synergistic model relative to the both standalone models, namely the technical analysis structural model and the intra-market model.

We also compare the forecasting performance to the random walk benchmark model. The random walk model implies that future price changes are not predictable. Historical memory is not useful; it is just a series of random numbers (Fama, 1965). The result of the percentage of correct direction change prediction (%CDCP) should be greater than 50% in order to validate the superior performance of the synergistic model in comparison with the random walk model (Hong et al., 2007).

The critical value at 1% statistical significance level can be approximated for the random walk model by the following equation (28) (Cai & Zhang, 2016):

$$\sigma_{0.01\%} = \frac{\sim 3.719016}{2\sqrt{n}} \qquad (32)$$

where n is the number of predictions, and ½ comes from the equal probability of having positive and negative change. In our case, due to the different number of observations, $\sigma_{0.01\%}$ would be 0.0490 and 0.0219 for 1,440 and 7,200 observations, respectively. The test statistic can be calculated by %CDCP - 50%. If its value is greater than the $\sigma_{0.01\%}$ critical value, we can conclude that the synergistic model outperforms the benchmark random walk model in forecasting directional changes.

2.4 Empirical Results

2.4.1 Forecasting Performance

Before reporting the synergistic model results, summaries of the estimations of the standalone models—namely the structural model and the intra-market model—are presented in Table 2.

Table 2. Panel data GLS estimation of structural model based on technical analysis indicators

Dependent variable: $\hat{r}_{m,t}$ (one-minute predictions of FX rates of returns)

Independent Variables	Coefficients	t-statistics
DRSI(6)	-1.61E-06***	-2.652456
DRSI(8)	1.88E-06***	3.082621
DRSI(9)	1.20E-06*	1.959445
DATR(2)	0.291679*	1.858444
DOBV(4)	-1.25E-07**	-1.964564
DMFI(6)	4.73E-07**	2.241022
DMFI(9)	-5.00E-07**	-2.315073
DMFI(12)	-3.36E-07*	-1.681412
R-squared	0.673850	
F-statistic	1.372523 (p: 0.03420)	

Notes: *, **, *** represent statistical significance at 10%, 5% and 1% respectively. The diagnostic tests show that the model is well specified. Heteroscedasticity and autocorrelation problems do not exist in the estimations.

The results of the estimated structural regression model (equation (7)) capturing the effects of the selected lagged technical indicators on FX returns $\hat{r}_t$ are shown there. All the endogenous and exogenous variables of the models are stationary by applying the ADF, PP and KPSS tests but the presentation of the results are ignored to shorten the writing. All technical indicators have some statistically significant values in their lags, and the two minutes lag of the ATR change has the largest impact (0.29) on the $\hat{r}_t$. This model is used as the measurement model in the Kalman filter algorithm.

Then, the AR model in equation (8) captures the impact of the intra-market data on FX returns r. Equation (8) is fed into the Kalman filter algorithm as a state model f_t.

Table 3. Autoregressive time series estimation of intra-market model.
Dependent variable: f_t (one-minute predictions of FX rates of returns)

Independent Variable (EUR/USD)	Coefficients	t-statistics
AR(1)	-0.095391***	-3.58965
AR(2)	-0.199751***	-7.50351
AR(3)	0.124287***	4.58159
AR(9)	-0.076193***	-2.86067
Independent Variable (EUR/GBP)	Coefficients	t-statistics
AR(1)	-0.053459***	-2.361333
Independent Variable (NZD/USD)	Coefficients	t-statistics
AR(1)	-0.066167***	-3.768015
AR(3)	-0.072380***	-3.103776
AR(20)	-0.057974**	-2.271774
Independent Variable (USD/JPY)	Coefficients	t-statistics
AR(16)	0.053879**	2.291329

Notes: *, **, *** represent statistical significance at 10%, 5% and 1% respectively. The diagnostic tests show that the model is well specified. Heteroscedasticity and autocorrelation problems do not exist in the estimations. We only present the statistically significant ARs.

Table 3 shows the statistically significant lags of FX rates of return for predicting the next one-minute for every pair of exchanges. For instance, in Table 3, the statistically significant lags of EUR/USD returns are lags one, two, three, and nine. The two minutes lag return ($AR(2)$) has the largest and most negative impact on the prediction of the next rate of return.

When the artificial neural network (ANN) is used for tuning the Kalman filter, the R-square of ANN is 0.82. In other words, the independent variables of technical analysis indicators as the inputs of ANN explain 82% of future market exchange rates returns variations ($\hat{Q}_k$). Subsequently, by using the synergistic forecasting model, out-of-sample predictions are tested for different pairs of foreign currencies.

The following empirical analysis examines the statistical performance of synergistic forecasting model. In a more comprehensive framework, we examine the one-step (i.e., one-minute ahead return) out-of-sample forecasting performances of the exchange rates of return for four major currency pairs in terms of RMSE. Tables 4 and 5 show the tests results of different methods at the one-minute frequency. Table 4 reports the forecasting accuracy simulation results of the two models, namely the synergistic model with static Q and the synergistic model with dynamic ANN Q. According to both RMSE (minimum) and %CDCP (maximum) criteria, the results show that the synergistic model with dynamic ANN Q has better forecasting accuracy than the synergistic model with static Q for all pairs of currencies. The corresponding RMSE values for the synergistic model with dynamic ANN Q are 4.16E-05, 2.58E-05, 3.83E-05, and 2.11E-05 for EUR/USD, EUR/GBP, NZD/USD, and USD/JPY, respectively. These results are much less than those achieved with the synergistic model with static Q, which are 9.72E-04, 8.24E-04, 9.86E-04, and 7.57E-04, for EUR/USD, EUR/GBP, NZD/USD, and USD/JPY, respectively. These findings provide strong support for the use of the dynamic ANN synergistic model.

Forecasting accuracy evaluations based on error measures such as RMSE is not useful for distinguishing between the best and the worst model (Shen et al., 2015). To this end, the correct direction change prediction (%CDCP) is calculated. The corresponding %CDCP numbers in Table 4 for the synergistic model with dynamic ANN Q are 74.26, 78.28, 74.63, and 75.77 for EUR/USD, EUR/GBP, NZD/USD, and USD/JPY, respectively. These results are greater than the %CDCP values for the synergistic model with static Q, which are 68.25, 70.63, 69.24, and 72.35 for EUR/USD, EUR/GBP, NZD/USD, and USD/JPY, respectively. We conclude that the synergistic model with dynamic ANN Q forecasts the directions more successfully.

Table 4. Comparison results of the synergistic model forecasting with static and ANN dynamic Q (Intraday (Panel A) 1,440 and one-week (Panel B) 7200 one-minute observations of FX rates of returns)

Models	RMSE				% Correct Direction Change Prediction (%CDCP)			
Panel A. One-day Period	EURUSD	EURGBP	NZDUSD	USDJPY	EURUSD	EURGBP	NZDUSD	USDJPY
Synergistic Model with Static Q	9.72E-04	8.24E-04	9.86E-04	7.57E-04	68.25	70.63	69.24	72.35
Synergistic Model with Dynamic ANN Q	4.16E-05	2.58E-05	3.83E-05	2.11E-05	74.26	78.28	74.63	75.77
Panel B. One-week Period	EURUSD	EURGBP	NZDUSD	USDJPY	EURUSD	EURGBP	NZDUSD	USDJPY
Synergistic Model with Static Q	6.70E-03	2.02E-04	5.77E-04	1.98E-04	64.48	64.69	70.90	66.06
Synergistic Model with Dynamic ANN Q	5.20E-03	1.84E-04	5.31E-04	1.79E-04	75.20	76.00	76.63	73.58

Table 5 shows the out-of-sample forecasting performance of one-minute frequency data for different pairs of currencies using the RMSE, %CDCP and the random walk model (%CDCP-50%) for one day and one week observations. The overall out-of-sample prediction performance of the synergistic model is superior. In all currency pairs in Table 5, the RMSEs of the dynamic ANN Q synergistic model (i.e., minimum values) are less than those of the two standalone models of the structural and the intra-market models. These results show the outperformance of the proposed synergistic model relative to traditional and novel models of forecasting used in other recent similar researches where the successful hit ratio (measure of correct sign prediction) of one-minute forecasting of currency pairs is maximum of 69.5% (Choudhry et al., 2012; Manahov et al., 2014; Cai & Zhang, 2016; Bekiros, 2015).

To test the robustness of our model, as mentioned in Section 3.1, some bullish and bearish days are randomly chosen, and both RMSE and %CDCP values are calculated. It is important to show the bearish and bullish overall data characteristics and patterns in a specific situation in the market. We select the EUR/USD pair for the robustness check in the bullish and bearish market because it is heavily traded and more liquid than the other exchange pairs. The results for the bullish day and bearish day are shown in the last two rows of Table 5. According to the RMSEs calculated for the 1,440 intraday observations in Table 5 (Panel A), the value for the synergistic model for the bearish day of EUR/USD is 1.66E-05, which is less than the intra-market and structural model values of 1.89E-05 and 2.10E-04, respectively. Moreover, for the bullish day of EUR/USD, the value is 7.31E-05, which is less than the other intra-market and structural model values of 1.23E-04 and 7.87E-05, respectively. For one-week observations in Table 5 (Panel B), the RMSE value of the synergistic model for the bearish day of EUR/USD is 1.4985e-04, which is less than the other intra-market model and structural model values of 1.6428E-04 and 1.7702E-04, respectively. Moreover, for the bullish day of EUR/USD, the value is 8.0364E-05, which is less than the other intra-market and structural model values of 9.9086E-05 and 1.3218E-04, respectively. In comparison to the values in Table 5 (Panel B), the lower RMSEs of Table 5 (Panel A) show that when the estimation window is extended from one day to five days, the performance of the model deteriorates. This result indicates that the one day pattern might offer beneficial information for better out-of-sample predictions in compare to the full week pattern in our model.

According to the percentage of correct direction of change prediction criterion, the %CDCP values in Tables 5 are all greater than 50% for all models. The %CDCP of the synergistic model is higher than those of all other models (i.e., its minimum value is 73.58). For the synergistic model, this means that the probability for forecasting the directional change is higher than those of the both standalone models are.

In comparison to the random walk model, the statistical values of the synergistic model are shown in the last columns of Table 5. These values are greater than the critical value $\sigma_{0.01\%}$ (i.e., 0.0490 and 0.0219 for 1,440 and 7,200 observations, respectively). Thus, we conclude that the proposed synergistic model also outperforms the random walk model. Overall, the results show that the out-of-sample forecasting power of the synergistic model are better than the forecasting powers of the two standalone models and the random walk model.

Table 5. Comparison results of the prediction error of different models one-step out-of-sample forecasting on an intraday sample data of 1,440 (Panel A) and one week sample data of 7,200 (Panel B) one-minute observations of FX rates of returns.

Panel A. One-day Period	RMSE			% Correct Direction Change Prediction (%CDCP)			
FX pairs	Int. Mrk. Model	Strc. Model	Syng. Model	Int. Mrk. model	Strc. Model	Syng. Model	%CDCP-50%
EUR/USD	1.59E-04	1.97E-04	4.16E-05	70.61	58.74	73.91	0.2391*
EUR/GBP	1.16E-04	1.33E-04	2.58E-05	73.84	59.30	78.28	0.2828*
NZD/USD	2.35E-04	2.58E-04	3.83E-05	68.19	72.93	74.63	0.2463*
USD/JPY	1.10E-04	2.28E-04	2.11E-05	71.77	66.36	75.77	0.2577*
Bearish EUR/USD	1.89E-05	2.10E-04	1.66E-05	73.59	56.40	76.87	0.2678*
Bullish EUR/USD	7.87E-05	1.23E-04	7.31E-05	74.29	54.15	75.32	0.2632*
Panel B. One-week Period	RMSE			% Correct Direction Change Prediction (%CDCP)			
FX pairs	Int. Mrk. Model	Strc. Model	Syng. Model	Int. Mrk. model	Strc. Model	Syng. Model	%CDCP-50%
EUR/USD	5.8000E-03	6.7000E-03	5.2000E-03	72.86	64.64	75.20	0.2520*
EUR/GBP	1.9938E-04	2.0371E-04	1.8415E-04	70.82	64.80	76.00	0.2600*
NZD/USD	5.6283E-04	5.3468E-04	5.3071E-04	74.14	72.78	76.63	0.2663*
USD/JPY	2.0197E-04	5.6455E-04	1.7927E-04	70.94	57.84	73.58	0.2358*
Bearish EUR/USD	1.6428E-04	1.7702E-04	1.4985E-04	72.14	60.86	75.48	0.2548*
Bullish EUR/USD	9.9086E-05	1.3218E-04	8.0364E-05	73.14	55.98	74.06	0.2406*

Note: * represents statistical significance at 1%.

Chapter 3

ECONOMIC SIGNIFICANCE ANALYSIS OF THE SYNERGISTIC FORECASTING MODEL

3.1 Literature Review

Zhang (2015, p. 2) stress that "…most of previous literature on intra-day exchange rate forecasting has focused on regular time intervals such as 30 minutes or one hour." Studies show that the excess returns are both statistically and economically significant in forecasting FX rates at the one-minute frequency (Manahov et al., 2014; Thinyane & Millin, 2011). Neely and Weller (2013) conducted intraday technical analysis trading strategies of foreign exchange market to investigate the forecasting performance and its applicability in the financial markets. Their proposed technique was profitable and economically significant even with two basis points transaction costs.

Cai and Zhang (2016) proposed a forecasting method called the autoregressive conditional multinomial autoregressive conditional duration, which enhances the prediction accuracy in high-frequency exchange rates and suggests a large return before costs to dealers, but the economic analysis shows that it is only profitable with very low per trade transaction costs. Manahov et al. (2014) investigated the impact of high-frequency trading on market efficiency by applying an algorithm based on strongly typed genetic programming for one-minute prediction of most traded currency pairs. Their results showed that the proposed method outperformed traditional econometrics models and that the generated profits were statistically and (even by presence of transaction costs) economically significant. Bekiros (2015) proposed a heuristic learning model to improve technical analysis forecasting in EUR/USD intraday high-frequency trading. The empirical results of the study validated the presence of technical trading rules predictability in terms of RMSE and directional quality (DQ), with a maximum percentage of 53.6 correct predictions when transaction costs exist (Bekiros, 2015).

3.2 Measuring Economic Performance

By determining the statistical significance of the model, we are interested in whether such accuracy can be translated into economic value. According to the theory of efficient market hypothesis, no abnormal profit can be obtained by any trading strategy based on the publicly available data and the existence of trading costs. However, according to research done by Neely and Weller (2012), the long-run profitability of technical analysis trading suggests that the adaptive market hypothesis is functioning well in exchange rate market and may permit profit opportunities over time. We examine the economic significance of the forecast model by considering the possibility of profiting from these predictions. This is implemented by reporting the out-of-sample economic findings.

3.2.1 Market Microstructure Impact

The costs associated with every trade are called transaction costs. These include bid and ask spread, exchange fees, commissions, and commodity-specific fees. Transaction cost is the very important in high-frequency trading. This is because large numbers of short horizon trades with a very small fraction of return in high volume may seem to be a risky gamble.

Bid and ask spread is a hidden cost of FX trading which can affect the profit size. It is the difference between bid price (to sell) and ask price (to buy). It is suggested to use pending (limit) orders rather than executive market orders to better off when spread exists in fast moving markets. The spread is considered in our automated trading system. All the buy and (short) sell orders are submitted based on ask and bid prices, respectively.

Commission fee in FX market are in three forms of relative commission fee, fixed commission fee, and per-trade percentage-based commission fee. The relative commission fee amount is based on the volume of the trading (trade size). For the fixed commission fee, the trades are charged a fixed amount regardless of the trading volume by the broker. The per-trade percentage-based commission fee is a small percentage that can be a fraction of a percentage in points (PIP). It allows a trader to pay a lower amount of transaction cost.

Considering that our trading system does not decide on the size of the trades, therefore, in our economic significance analysis it is assumed that the commission fee is calculated on the basis of the per-trade percentage-based commission fee which is a proportion of the realized profit from each trade as well as fixed commission fee.

Two scenarios of high and low transaction costs are considered in the study (Granger & Pesaran, 2000). The costs are described in four performance metrics, which are the percentage changes in the return values of trades. One basis point is the first metric that is equal to 0.01% (or 0.0001 in decimal form) of the traded value. Half basis point is the second metric, which is 0.005% or 0.00005 of the traded value. Four basis points is the third metric that is equal to 0.04% (or 0.0004 in decimal form) of the traded value and six basis points is the fourth metric that is equal to 0.06% (or 0.0006 in decimal form) of the traded value.

$$RAC = \sum_{i=0}^{k}(r_i - r_i .\ RCF_{base\ point}) \tag{33}$$

RAC is the total return after per-trade percentage-based commission fees which is a percentage of the obtained returns, r_i is the amount of returns, and $RCF_{base\ point}$ is the per-trade percentage-based commission fees basis points (0.005%, 0.01%, 0.04% or 0.06%) in k number of trades (Bekiros, 2015).

The trades are conducted based on two strategies of buy/sell and short-sell to benefit from both up and down trends of the market. This is legal execution according to the trading rules of Forex and currency markets (SEC Investor Bulletin, 2011).

In order to investigate the impact of fixed commission fee on both of trading algorithms, another analysis is conducted to test the possibility of making profit in terms of this type of payment.

$$DTC = \sum_{i=0}^{k}(n\ .\ FCF_{base\ point}) \tag{34}$$

DTC stands for daily total fixed commission fee, n is the number of daily trades and $FCF_{base\ point}$ are the fixed commission fee of 0.5, 1, 2, 4 and 6 basis points. Table 15 shows the empirical results to demonstrate whether there is an opportunity of making profit with the existence of these transaction costs.

3.3 Trading Robot Architecture

Figure 5 shows the trading robot architecture and the main properties of the system. The trading robot connects to the FX market via the electronic platform for data interchanges.

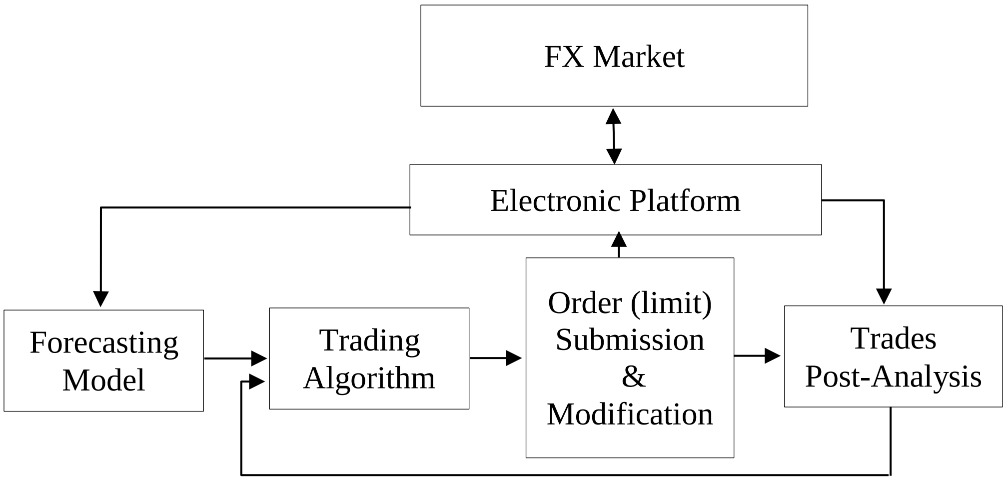


Figure 5. Trading robot architecture

The forecasting model predicts the one-step ahead exchange rate by analyzing the market data through the synergistic model. The predicted ER passes to the trading algorithm to generate the appropriate (limit buy/sell) order based on the trading strategy. The order is submitted to the market by electronic platform for execution. After execution of the order, the post-analysis section reviews the report of the filled trades for resetting the trading strategies parameters mentioned in equations (35 and 36).

3.4 Trading Strategies

The main performance measure is the amounts of return generated by two different trading strategies algorithms, namely simple trend following and adaptive trading. Therefore, the trigger for taking a position is the one-step-ahead prediction of the synergistic forecasting model. Then, the calculation of the transaction costs and commission fees are done on every closed position.

3.4.1 Simple Trend Following Trading Strategy

The approach is implementing an active trading system. A simple trend following strategy forecasts the turning points and sends the appropriate order accordingly. The trading rules of the investing system compare the predicted return with the threshold value. If the prediction is greater than the threshold value, the trading system would decide to buy or (short-) sell. The threshold value can be assigned as the average of the actual return in a specific period. The threshold is assumed as the historical average of the exchange rates' negative and positive rates of returns.

$$order \quad Buy \qquad if \quad f_t > \bar{\pi}_t^+ \tag{35}$$

$$order \quad Sell\ (short) \quad if \quad f_t < \bar{\pi}_t^- \tag{36}$$

Here f_t is the forecast of return for time t, and $\overline{\pi_t}$ is the historical positive or negative average return. All the buy and (short) sell orders are submitted based on ask and bid prices, respectively.

3.4.2 Adaptive Trading Strategy

The adaptive markets hypothesis states that strategies of trading evolve as traders in the markets adapt their behavior to changing conditions. According to the research by Neely and Weller in 2013, the adaptive behavior in trading increases the profit-making opportunities for considerable periods of time. The long-term profitability of strategies based on technical analysis in the foreign exchange (forex market) also suggests the better market functioning of adaptive markets hypothesis (Neely & Weller, 2013).

Adaptive trading is a system that can modify the submitted pending order by using the adaptive forecasts of changing circumstances in the market. The pending orders are in two types of limit and stop orders. For automatic fulfillment of the submitted orders, the take profit and stop loss variables should be assigned for each quote (Austin et al., 2004).

The adaptive trading algorithm starts with submitting an order based on the one-step-ahead forecast of rate of return. If it is positive and the system has already bought before, the pending sell limit order is submitted in a price higher than the forecasted value. If the expected positive return realizes and prediction for the next minute is again positive, the new pending price would be updated by the higher new price target value (called take profit order) while the stop loss is modified in opposite direction to lock the gain amount based on progressive stop strategy. If the price cannot reach to the assigned take profit level and reverse, the stop loss order would be triggered.

In the situation where the one-step-ahead forecast of rate of return is negative and the system has already sold before, a pending buy limit order is submitted in a price lower than the forecasted value and again stop loss is modified in opposite direction to lock the gain amount. All the buy and (short) sell orders are submitted based on ask and bid prices, respectively. The trading system can only handle one open position at the same time and each quoted order is valid only for the next one minute, meaning that it should be filled or modified before the expiration time. The advantages of expanding sequential positive or negative (in short-sell) returns are the accumulation of the amounts of the returns and decrease in transaction costs and commission fees by reducing the number of executed trades. But, still it might be a hypothesis that should be tested in empirical findings section (3.5). The empirical findings are presented in Tables 10 to 15.

3.5 Empirical Results

An automated trading system is coded with MATLAB and MQL syntax on the Metatrader platform. The trading robot is developed based on the synergistic forecasting model with the simple long/short trading order sending mechanism. Table 6 presents the descriptive statistics of the actual and predictive returns in the market. The numbers are showing the amount of average returns per minute. NZD/USD has the greatest amount of obtainable average return size. The third column in Table 6 shows that the predicted average daily returns are very close to the actual average returns for all the pairs of currencies in this study.

3.5.1 Economic Significance and Trading Performance

First, we examine the returns before related trading costs and then assess the results of transaction costs in our returns. Moreover, the robustness of the economic profit has been examined for different pairs of exchanges forecasted in different periods. The amounts of profit size numbers in Tables 7, 8, 9 and 10 are presented as 10,000 times the actual unit to have a fixed trade size of one mini-lot (10,000$) for all of the trades.

Tables 7 and 8 show that the proposed synergistic forecasting model performs well economically by high accumulated daily returns before and after per-trade percentage-based commission fees based on the simple trend following trading system. Table 8 shows that maximum of 17 and minimum of 13 trades executed per hour with simple trend following algorithm.

Tables 9 and 10 show the accumulated returns and profitability after per-trade percentage-based commission fees of high-frequency adaptive trading strategies before and after per-trade percentage-based commission fees. Table 9 shows that maximum of 12 and minimum of 9 trades are executed per hour with the adaptive trading algorithm.

According to Table 7 and 9, the daily accumulated profit size of trading pairs of currencies with synergistic forecasting model are between 1.7% to 4% and 4.7% to 11% for simple trend following and adaptive trading strategies, respectively. In Tables 8 and 10, we can see that, even after deducting the per-trade percentage-based commission fees, the considerable amounts of profit still remain.

Table 6. Descriptive statistics of returns

FX pairs	Actual Average Return*	Average Positive Return	Average Negative Return	Predicted Average Return
EUR/USD	8.6866e-005	4.3944e-005	4.2922e-005	6.9385e-005
EUR/GBP	5.2766e-005	2.6457e-005	2.6309e-005	4.2123e-005
NZD/USD	1.2396e-004	5.9863e-005	6.4101e-005	9.8793e-005
USD/JPY	1.1463e-004	6.1413e-005	5.3214e-005	9.0950e-005
Bearish EUR/USD	8.0059e-005	3.4276e-005	4.5783e-005	6.3962e-005
Bullish EUR/USD	4.7335e-005	2.4896e-005	2.2439e-005	3.7796e-005

Note: *Average amount of exchange rate return for overall, positive, and negative price movement per minute.

Table 7. Descriptive statistics of long-short simple trend following trading strategies before transaction costs

FX pairs	Buy Profit*	Number of Buys	Sell Profit**	Number of Sells	Total Profit***	Number of Trades
EUR/USD	106.1818	170	121.7355	171	227.9173	341
EUR/GBP	64.43.26	200	63.5783	218	128.3079	418
NZD/USD	183.4223	200	153.6446	191	337.0669	391
USD/JPY	195.3091	207	115.1872	209	310.4963	416
Bearish EUR/USD	127.9525	170	274.9749	146	402.9274	316
Bullish EUR/USD	78.6212	211	92.1679	217	170.7890	428

Note: * Cumulative amount of the profit size gained after buy orders multiplied by 10000.
** Cumulative amount of the profit size gained after sell orders multiplied by 10000.
*** Total cumulative amount of the profit size gained after both of buy and sell orders multiplied by 10000.

Table 8. Daily accumulated returns after per-trade percentage-based commission fees for long-short simple trend following trading strategies

	One Basis Point			Half Basis Point		
FX pairs	Buy Profit	Sell Profit	Total Profit	Buy Profit	Sell Profit	Total Profit
EUR/USD	106.1712	121.7234	227.8945	106.1765	121.7294	227.9059
EUR/GBP	64.4262	63.86.89	128.2951	64.4294	63.7821	128.3015
NZD/USD	183.4040	153.6292	337.0332	183.4131	153.6369	337.332
USD/JPY	195.2896	115.1757	310.4653	195.2993	115.1815	310.4808
Bearish EUR/USD	127.9397	274.9474	402.8871	127.9461	274.9611	402.9073
Bullish EUR/USD	78.6133	92.1586	170.7719	78.6172	92.1632	170.7805

Table 9. Descriptive statistics of long-short adaptive trading strategies before transaction costs

FX pairs	Buy Profit	Number of Buys	Sell Profit	Number of Sells	Total Profit	Number of Trades
EUR/USD	391.9810	112	401.6096	129	793.5907	249
EUR/GBP	228.9456	125	258.0966	161	487.0423	286
NZD/USD	559.7252	155	593.0605	147	1152.7857	302
USD/JPY	552.7052	131	490.0085	158	1042.700	289
Bearish EUR/USD	326.1124	125	448.6338	107	774.7460	232
Bullish EUR/USD	249.5564	126	227.7725	141	477.3289	267

Table 10. Daily accumulated returns after per-trade percentage-based commission fees on long-short adaptive trading strategies

	One Basis Point			Half Basis Point		
FX pairs	Buy Profit	Sell Profit	Total Profit	Buy Profit	Sell Profit	Total Profit
EUR/USD	391.9418	401.5695	793.5113	391.9614	401.5896	793.5510
EUR/GBP	228.9227	258.0708	486.9936	228.9342	258.0837	487.0179
NZD/USD	559.6693	593.0012	1152.6705	559.6972	593.0308	1152.728
USD/JPY	552.6499	489.9595	1042.600	552.677	489.9840	1042.700
Bearish EUR/USD	326.0798	448.5889	774.6687	326.0961	448.6113	774.7075
Bullish EUR/USD	249.5315	227.7497	477.2812	249.5440	227.7611	477.3051

Table 11. Per-trade percentage-based commission fees amount for the both trading strategies based on synergistic forecasting model

FX pairs	Simple Trend Following Strategy			Adaptive Trading Strategy		
	One Basis Point	Half Basis Point	Average	One Basis Point	Half Basis Point	Average
EUR/USD	0.0794	0.0397	0.0595	0.0228	0.0114	0.0171
EUR/GBP	0.0487	0.0244	0.0365	0.0128	0.0064	0.0096
NZD/USD	0.03370	0.01685	0.0252	0.1152	0.0577	0.0864
USD/JPY	0.1120	0.0120	0.0620	0.0310	0.0155	0.0232
Bearish EUR/USD	0.0773	0.0385	0.0579	0.0403	0.0201	0.0302
Bullish EUR/USD	0.0477	0.0238	0.0357	0.0171	0.0085	0.0128
Total Average Commission Fees on Trading Strategies			0.04614			0.02988

Table 11 displays the comparison results for the amount of per-trade percentage-based commission fee payments for both trading strategies. The payment amount is the difference between the total profit before and after per-trade percentage-based commission fees for every trading pair of exchanges. The last row in Table 11 suggests that, on average, the simple trend-following trading strategy cost (0.04614) is higher than the adaptive trading strategy cost (0.02988) during the sample period. Subsequently, we checked to see if the results were significantly different from one another.

The normal t-test was conducted on data to check the significance of the results. In order to test the hypothesis, whether mean amounts of the payments are different from one another, the t-test was conducted on the results of Table 11. The Welch's t-test was used due to unequal variances in the sample data.

$$t - statistics = \frac{\check{X}_1 - \check{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}} = \frac{0.04614 - 0.02988}{\sqrt{\frac{0.000241}{6} + \frac{0.000821}{6}}} = 1.221 \tag{36}$$

$$\begin{cases} H0:\ \check{X}_1 = \check{X}_2 \\ H1: \check{X}_1 \neq \check{X}_2 \end{cases} \tag{37}$$

The null hypothesis (H0) states that the mean values of the average of per-trade percentage-based commission fee payments are the same. It was not rejected by t-statistics (1.221). Thus, the values of the average of per-trade percentage-based commission fee payments are not significantly different from one other. Accordingly, these two algorithms have no benefit in comparing the per-trade percentage-based commission fees of half and one basis.

To check the impact of higher commission fees, we extended the costs to four and six basis points (Austin et al., 2004). Tables 12, 13, and 14 show the empirical results of charging higher commission fees.

In Table 14 (according to the calculations based on equations 36 and 37), the null hypothesis states that the mean values of the average of per-trade percentage-based commission fee payments are the same. That hypothesis was clearly rejected by t-statistics (-5.77), and the alternative hypothesis, the mean values of average per-trade percentage-based commission fee payments are significantly different from each other, was accepted. According to the last row in Table 14, for larger per-trade percentage-based commission fees, these two algorithms differ when compared to one another (on average). It appears that the adaptive trading strategy costs more than the simple trend-following strategy.

$$t - statistics = \frac{0.41313 - 0.02708}{\sqrt{\frac{0.000077}{6} + \frac{0.026767}{6}}} = -5.7716 \qquad (38)$$

The next test was done to investigate the economic significance of both trading algorithms in terms of charging fixed commission fee per trade. Return after total transaction cost (RAT) is calculated through the equation (34), and it yields the payable transaction cost in units of percentage in points (PIPs). PIP is the smallest unit of change (0.0001) in the Forex market pairs for currency prices; see columns 5 and 9 in Table 15.

Table 12. Daily accumulated returns after six basis and four basis per-trade percentage-based commission fees for long-short simple trend following trading strategy

	Six Basis Points			Four Basis Points		
FX pairs	Buy Profit	Sell Profit	Total Profit	Buy Profit	Sell Profit	Total Profit
EUR/USD	106.1181	121.6625	227.7805	106.1393	121.6868	227.8261
EUR/GBP	64.39394	63.54015	128.2309	64.40683	63.55287	128.2566
NZD/USD	183.3122	153.5524	336.8647	183.3489	153.5831	336.9321
USD/JPY	195.1919	115.1181	310.31	195.231	115.1411	310.3721
Bearish EUR/USD	127.8757	274.8099	402.6856	127.9013	274.8649	402.7662
Bullish EUR/USD	78.57403	92.1126	170.6865	78.58975	92.13103	170.7207

Table 13. Daily accumulated returns after six basis and four basis per-trade percentage-based commission fees for long-short adaptive trading strategy

	Six Basis Points			Four Basis Points		
FX pairs	Buy Profit	Sell Profit	Total Profit	Buy Profit	Sell Profit	Total Profit
EUR/USD	391.7458	402.8089	794.5547	391.8242	402.8895	794.7137
EUR/GBP	229.6216	260.7303	490.3519	229.6675	260.7825	490.4500
NZD/USD	595.6436	604.0947	1199.7383	595.7628	604.2156	1199.9784
USD/JPY	566.2493	503.7902	1070.0395	566.3626	503.8910	1070.2536
Bearish EUR/USD	335.1159	458.3515	793.4674	335.1830	458.4432	793.6262
Bullish EUR/USD	249.4067	228.2154	477.6221	249.4566	228.2610	477.7176

Table 14. Per-trade percentage-based commission fees amount for both trading strategies based on synergistic forecasting model

FX pairs	Simple Trend Following Strategy			Adaptive Trading Strategy		
	Six Basis Points	Four Basis Points	Average	Six Basis Points	Four Basis Points	Average
EUR/USD	0.034	0.017	0.025	0.477	0.318	0.397
EUR/GBP	0.020	0.010	0.015	0.294	0.196	0.245
NZD/USD	0.048	0.024	0.036	0.800	0.500	0.650
USD/JPY	0.040	0.020	0.030	0.700	0.400	0.550
Bearish EUR/USD	0.047	0.024	0.035	0.476	0.317	0.397
Bullish EUR/USD	0.025	0.013	0.019	0.286	0.191	0.238
Total Average Commission Fees on Trading Strategies			0.02708			0.41313

Table 15. Daily fixed commission fee for both trading strategies based on synergistic forecasting model

FX pairs	Simple Trend Following Strategy				Adaptive Trading Strategy			
	Total Profit**	Number of Trades	Basis Points	DTC***	Total Profit**	Number of Trades	Basis Points	DTC
EUR/USD	227.917	341	0.5*	170.5	793.590	249	0.5*	124.5
			1	341			1*	249
			2	682			2*	498
			4	1364			4	996
			6	2046			6	1494
EUR/GBP	128.307	418	0.5	209	487.042	286	0.5*	143
			1	418			1*	286
			2	836			2	572
			4	1672			4	1144
			6	2508			6	1716
NZD/USD	337.066	391	0.5*	195.5	1152.786	302	0.5*	151
			1	391			1*	302
			2	782			2*	604
			4	1564			4	1208
			6	2346			6	1812
USD/JPY	310.496	416	0.5*	208	1042.700	289	0.5*	144.5
			1	416			1*	289
			2	832			2*	578
			4	1664			4	1156
			6	2496			6	1734

Bearish EUR/USD	402.927	316	0.5*	158	774.746	232	0.5*	116
			1*	316			1*	232
			2	632			2*	464
			4	1264			4	928
			6	1896			6	1392
Bullish EUR/USD	170.789	428	0.5	214	477.328	267	0.5*	133.5
			1	428			1*	267
			2	856			2	534
			4	1712			4	1068
			6	2568			6	1602

Note: * The profitable trades including transaction costs.

** The amount of profit before transaction costs.

*** Daily total fixed commission fee (PIPs)

Table 15 shows that the simple trend-following trading system can only profit when a very low transaction cost (half basis point) is charged per trade. However, the adaptive trading strategy might be more profitable if higher transaction costs exist (i.e., 0.5, 1, and 2 basis points) because of the lower number of executed trades. Still, there is no chance of making a profit due to the high transaction cost rates (i.e., 4 and 6 basis points).

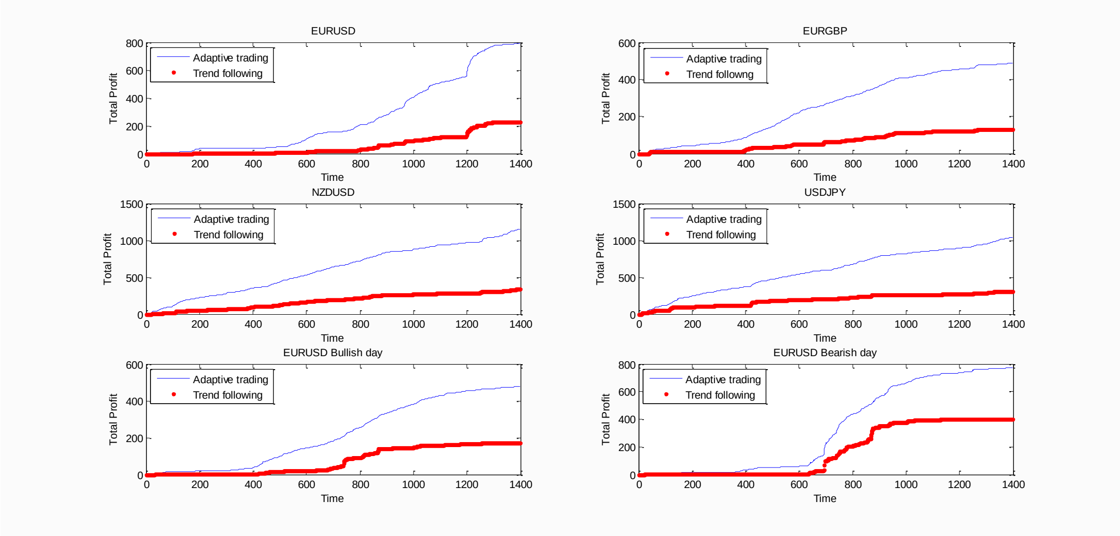


Figure 6. Total profit gain from adaptive and simple trend-following trading strategies

Figure 6 shows the trading strategies total profits (cumulative), which were captured by running an automated trading system during the sample period with both trading strategies for all pairs of exchanges in the FX market. Clearly, the adaptive trading strategy profit gains are higher than the simple trend-following strategy profit gains.

Overall, according to these empirical findings, while lower transaction costs are charged for the trades from Forex brokers, the weak-form market efficiency is not supported due to the generation of abnormal returns, which are systematically generated by means of the synergistic prediction model. Even after considering trading costs, the proposed model outperforms all of the other models, based on the daily return.

Chapter 4

CONCLUSIONS

Developing a method of prediction with the lowest possible forecasting error is one of the most challenging issues in finance. Due to the high frequency volatility of prices in the financial markets, it is essential to be as fast and adaptive as possible to achieve forecasting accuracy. There are a variety of forecasting models differ in goals, and mathematical methods employed and the nature of available information.

According to the researches, fundamental variables relevant to exchange rate are changing very rarely and are not useful in explaining the dynamics of exchange rate movements in less than one year. So those are not appropriate at high frequencies applications. Time series models are performing better in short to medium term predictions.

In the short-term, most of the fluctuations come from the psychological moods of investors in the market, and technical analysis indicators can shed light on the market psychology. Studies have shown that for short-term forecasting, the performance of technical analysis is relatively better and excess returns are obtainable from technical analysis trading rules in one-minute high frequency predictions.

We develop a synergistic forecasting model of high-frequency data for FX pairs of currencies rates of returns. It is an information fusion approach which is combining data from several resources with different methods to reach to a more accurate prediction. The term,” synergy” is for investigating the hybridization effect between classical time series forecasting and soft-computing techniques in this study.

The synergistic approach combines the structural model of the lags of technical analysis indicators, RSI, ATR, OBV, and MFI which are demonstrating the future price and volume dynamics of exchange rates, with the intra-market model that captures the relationship between the lags of current and future ER returns (AR model). The modified extended Kalman filter, which is able to work with non-normal distributed data, uses the estimates of the preceding two-standalone models as its inputs to predict a more accurate output. The structural model of the technical analysis indicators is substituted with measurement model h and intra-market model is substituted with state model f for the Kalman filter. The goal of this research is to forecast the one-minute FX price returns with a modified EKF model that dynamically sets the Q parameter according to the market dynamics.

Q is one of the important functional parameters of the Kalman filter which is known as process noise covariance error. In the most of Kalman filter applications this parameter is set as a fixed number calculated from statistical approach on historical data. But in our application taking into account the fluctuations in the market and changing vitalities, it is essential to set this number and update it based on the predicted volatility of the next step according to market conditions. This is done by using a generalized regression neural network (GRNN) with Gaussian radial base kernel function to find a relationship among RSI, ATR, SD, spread, volume, and Q.

The empirical results of the simulations for different FX pairs in random periods of time and different market conditions show that, according to Table 5, the synergistic forecasting model outperforms the both standalone forecasting models and the random walk model in terms of correct direction change prediction (%CDCP) and root mean square error (RMSE). So, it is concluded that the model is statistically significant. Also, to the best of our knowledge, the proposed model is better than the other similar models in high frequency forecasting.

In addition to its superior performance, the advantages of the proposed model include a simple computational procedure and no need to store huge amounts of historical data making the process of forecasting fast for high-frequency trading systems. The last superiority of the proposed dynamic system is to generate forecasts from the publicly observable information.

The theory of efficient market hypothesis states that there is no opportunity to make benefit from trading with publicly available data. Even if forecasting models might be statistically significant they may not end up with the economic profit because of the associated trading costs. The second goal of the research is to investigate the economic significance of the synergistic prediction model to explore the possibility of making profit from the forecasting.

To this end, we develop two algorithmic trading programs based on a simple trend-following trading and an adaptive trading system, trading virtually in the FX market based on the synergistic forecasting model. The simple-trend following trading system will send executive orders based on the next predicted return while the adaptive trend following system will send pending orders (limit/stop orders) based on the next return forecast and will wait for filling of the order until the ultimate predictable turning point. Naturally, the market microstructure realities—such as the presence of transaction costs like: bid and ask spread, fixed commission fee, and per-trade percentage-based commission fee—are incorporated into the model. In the FOREX trading commission fees are divided to three types of relative commission fee, fixed commission fee, and per-trade percentage-based commission fee which are charged per trades by the brokers.

The empirical results according to Tables 7, 8, 9, 10, 12 and 13 prove the economic significance of the forecasting model by the utilization of both automated trading systems before and after per-trade percentage-based commission fees. The empirical results in Table 11 and 14 confirm the outperformance of the adaptive trading strategy in comparison with the simple trend following strategy while the existence of per-trade percentage-based commission fees.

According to the Table 15, by applying fixed commission fee to each trade, it is observed that, the simple trend-following algorithm is only profitable if the trades are charged by half basis point transaction cost. For the rest of the transaction costs (1, 2, 4, and 6 basis points) the cumulative amounts of the fixed commission fees are greater than the cumulative profit size because of the large number of trading orders. The adaptive trading system is more beneficial than the simple-trend following strategy, although it is not profitable in the scenario of high transaction costs for four and six basis points. This higher profitability of adaptive trading system might come from the utilization of the limit orders. It was suggested that the trader better off using limit orders while the presence of bid and ask spread in fast moving markets.

Finally, the potential results may provide evidence for the new theory of adaptive market hypothesis, which states that the returns of exchange rates are predictable depending on changing market conditions (Charles et al., 2012).

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