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# A SYNERGISTIC FORECASTING MODEL FOR HIGH-FREQUENCY FOREIGN EXCHANGE DATA

*Abstract. In this study, 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 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 is statistically outperform and superior to each of the both standalone models as well as to the benchmark random walk model in the literature.*

*Keywords: Foreign exchange, Kalmanfilter, forecasting, high-frequency data, technical analysis indicators.*

**JEL Classification: F31, G17, F37**

### 1. Introduction

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. Twotypes 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. Researchers and practitioners argue that for short-

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term forecasting, the relative importance of technical analysis data becomes larger (Castro et al., 2016).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., Evans et al., 2012).

Even though time series models have demonstrated better performance than theoretical traditional models in forecasting exchange rates in the short to medium term (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.

High-frequency trading in particular, which has been reshaping the dynamics of financial markets, creates new challenges and opportunities for researchers using time series data. Utilization of publicly available intra-day high frequency FX data and applying more sophisticated 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).Cai & Zhang (2016) 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).Taking into account the discussion in the literature, we develop a code that captures high frequency *one-minute* interval FX price data as well as technical analysis indicators from the popular Metatrader FX trading platform. We do not incorporate macroeconomic fundamental data due to its low frequency.

In this paper, 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, 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 (Autoregressive time series model)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. 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 might not be constant over time, and these parameters should be treated as time varying due to the nature of the data used.
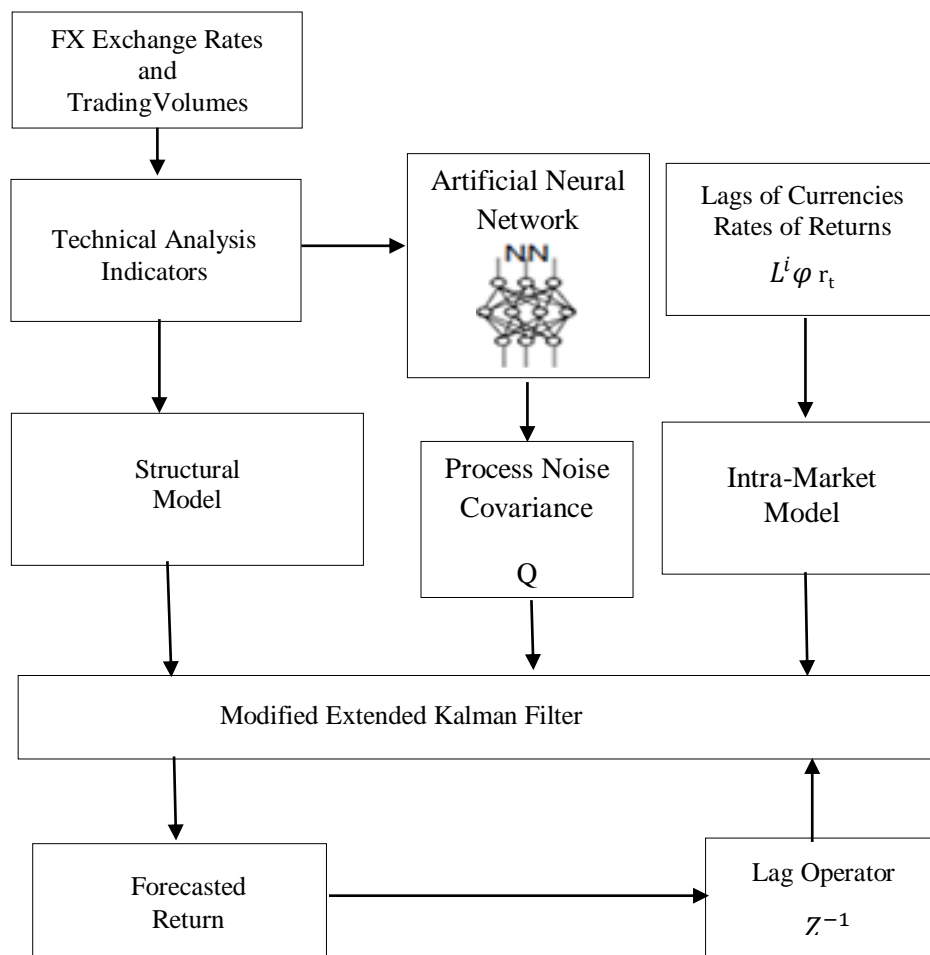
The empirical results of forecasting accuracy show that our synergistic model provides better forecasting accuracy in comparison to the two standalone models, the technical analysis structural model and the intra-market model. The information fusion approach is effective and the resulting model have statistically significant better forecasting accuracy results 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.

## 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" uses in studies for investigating the hybridization effect between classical and soft-computing techniques for time series forecasting (Lai et al., 2006). 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 pass 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 (NN), 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 ( $L^i \varphi$ r$_t$). Those are the endogenous variables of the intra-market 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

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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.

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┌─────────────────┐
│ FX Exchange     │
│ Rates and       │
│ TradingVolumes  │
└─────────────────┘
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FX Exchange Rates and TradingVolumes

Technical Analysis Indicators

Artificial Neural Network

NN

Lags of Currencies Rates of Returns

$L^i \varphi\, r_t$

Structural Model

Process Noise Covariance

Q

Intra-Market Model

Modified Extended Kalman Filter

Forecasted Return

Lag Operator

$Z^{-1}$

**Figure 1. Synergistic model flow chart**

### 2.1 The structural model

Technical analysis indicators play an important role in forecasting the fluctuations and turning points of price trends(Bekiros, 2015; Evans et al., 2012). There are hundreds of technical analysis indicators. However, we use the indicators that are

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supported by principal component analysis in the FX market and show the market dynamics and trend reversion (Neely & Weller, 2012).

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).

As the first indicator, we usethe RSI. RSI (see equation (1)) issued as a criterion for measuring the velocity and the magnitude of directional price changes (Kirkpatrick&Dahlquist, 2010).In equation (1) $\Delta\overline{P}_i^{+}$ and $\Delta\overline{P}_i^{-}$ are average positive (+) and negative (-) price change respectively during the last$n$ minutes ago and the best assigned $n$ is 14.

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

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(Kirkpatrick&Dahlquist, 2010)..

$$ATR_t = \frac{1}{n}\sum_{i=1}^{n} TR_i \tag{2}$$

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

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 supplyvolumes by assessing the trading volumes ($V_t$) and the change in OBV.

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

The fourth indicator, the money flow indicator (MFI; see equations (5) and (6)), is an indicator refers to the forecasting reliability of the buyer enthusiasm trend (Kirkpatrick&Dahlquist, 2010).

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

(Positive or Negative)$Money\ flow_t = \frac{price_t^{high} + price_t^{low} + price_t^{close}}{3} \times volume_t$ (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($r$) 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).

$$\hat{r}_{m,t} = \Phi_0 + \sum_{m=1}^{4}\sum_{i=1}^{14} L^i \Phi_1 D(RSI_{m,t}) + \sum_{m=1}^{4}\sum_{j=1}^{14} L^j \Phi_2 D(ATR_{m,t}) +$$

$$\sum_{m=1}^{4}\sum_{k=1}^{14} L^k \Phi_3 D(OBV_{m,t}) + \sum_{m=1}^{4}\sum_{l=1}^{14} L^l \Phi_4 D(MFI_{m,t}) \tag{7}$$

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 $L\varphi$'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 14minutes.

### 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.

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

In equation (8), the $L\varphi$'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.

### 2.3 The Kalman filter

The Kalman filter presents a recursive solution to filter the linear discrete data (Kalman, 1961). It is a set of mathematical equations with optimal estimator, predictor, and corrector phases, which sensibly minimize the estimation error covariance. This filter is effective for normally distributed data (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; $\theta$ represents regression coefficients to be estimated, $\epsilon$ is the disturbance term, and k is the time.

$$z_k = \theta . X_k + \epsilon_k \quad (9)$$

The maximum likelihood error solution of the nonlinear equation is

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

where

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

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

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

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

$r_k = z_k - z_{robust}$ and $z_{robust}$ are the location parameters of exchange rate

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returnsobtained for a sample of data usingan iteratively reweighted least square(IRLS). This scale parameter $s_k^2$ is consecutively updated by equation (14) (Mirza, 2011):

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

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).

The next challenge is discovering what happens if the relationship with the measurement process is nonlinear. The extended Kalman filter (EKF) is the nonlinear extension of the Kalman filter (Welch & Bishop, 2001). In the equation 15,$f$is the time update (prediction) phase function that relates the state parameters in the previous time steps to the current time $k$.

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, w_{k-1}) \qquad (15)$$

$$P_k^- = A_k P_{k-1} A_k^T + Q_{k-1} \qquad (16)$$

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. $Q_k$ isthe covariance of process noise. $A_k$ is the Jacobian matrix of partial derivatives of $f$ with respect to x.

$$A_{[i,j]} = \frac{\partial f_{[i]}}{\partial x_{[j]}}(\hat{x}_{k-1}, u_k, 0) \qquad (17)$$

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 $z_k$:

$$\hat{z}_k = h(x_k, v_k) \qquad (18)$$

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 (19) and (20).

$$K_k = P_k^- H_k^T (H_k P_K^- H_k^T + R)^{-1} \qquad (19)$$

$$P_k = (I - K_k H_k) P_k^- \qquad (20)$$

The Kalmanfilter modified by robust sequential estimator (RSE) is incorporated at this stage by assigning the appropriate $\hat{x}_k^-$ to obtain the conditional *aposteriori* 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 (21).The weighted innovation term $K_k(z_k - \hat{z}_k)$ is added to *apriori* 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:

$$\begin{cases} \hat{x}_k^- & if \quad y_k is \quad an \quad outlier \\ \hat{x}_k = \hat{x}_k^- + K_k(z_k - \hat{z}_k) & otherwise \end{cases} \qquad (21)$$

In equation (21), the term $\hat{x}_k$, 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 Kalmanfilter coefficient.$H$ is the Jacobian matrix of partial derivatives of $h$ with respect to *x*.

$$H_{[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[j]}} (\tilde{x}_k, 0) \qquad (22)$$

### 2.4 Artificial neural network for filter parameters and tuning

As mentioned previously, the Kalmanfilter 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 (23) and (24), and it remains as a

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fixed number during the forecasting period.

$$e_k = r_k - \tilde{r}_k \tag{23}$$

$$Q = Var(e_k) \tag{24}$$

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 Kalmanfilter. There are various approaches to estimating these matrices(Welch & Bishop, 2001). 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. The GRNN is designed with the MATLAB neural network toolbox, 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 2. 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. For each pair of currencies, we train the GRNN through the supervised method of learning using the results of equations (23) and (24).
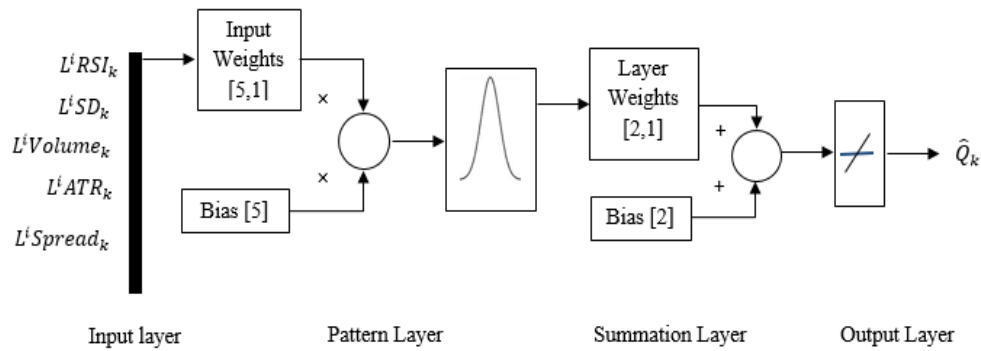
**Figure2. GRNN Artificial neural network for estimating adaptive dynamic Q (MATLAB output)**

In Figure 2, lags of the $RSI$, $SD$, $Spread$,and $Volume$ are the inputs, and $\hat{Q}_k$ 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 tothe supervised learning period, $\hat{Q}_k$ is generated for each market situation in line with the technical indicators and market microstructure parameters at the prediction time. 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 (25).

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

(25)

### 3. Data and forecasting performance measures

### 3.1 Data

Our sample data consists of the one-minute high-frequency FX spot price rates of return and the technical analysis indicators of four dominant pairs of currencies that are widely traded in the FX market: EUR/USD, EUR/GBP, NZD/USD, and USD/JPY(BIS, 2014). We randomly picked the sample period. The MQL code collects dataset for five working days of the week between00:00 and 23:59.

**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 |

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|---|---|---|---|
| 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 |

In Table 1, Panel A shows the descriptive statistics for one day (1,440 observations) on 12/8/2013, and 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.Additionally, the randomly selected bearish and bullish days are on 20/6/2013 and 4/4/2013, respectively and 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 to check the robustness of our model.

### 3.2 Measuring forecasting performance

There are several forecasting performance measurement techniques. The RMSE is much more popular in high-frequency data. Also, predicting the probability of the direction of the changes is very important for trend-following trading techniques (Cai& Zhang, 2016).As shown in equation (26), 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).

$$\% \ correct \ direction \ change \ prediction = \frac{1}{T-(T_1-1)}\sum_{t=T_1}^{T} Z_{t+s} \qquad (26)$$

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.

$$Z_{t+s} = 1 \ if \ (y_{t+s} - y_t)(f_{t,s} - y_t) > 0 \qquad (27)$$
$$Z_{t+s} = 0 \qquad otherwise$$

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. 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 at1% statistical significance level can be approximated for the random walk model by the following equation (28) (Cai& Zhang, 2016):

$$\sigma_{0.01\%} = \frac{\sim 3.719016}{2\sqrt{n}} \tag{28}$$

where$n$ is the number of predictions, and½comes 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 statisticcan be calculated by%CDCP - 50%. If its value is greater than the$\sigma_{0.01\%}$critical value, we can conclude that the synergistic model out performs the benchmark random walk model in forecasting directional changes.

## 4. Empirical results
### 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.The results of the estimated structural regression model (equation (7)) capturing the effects of the selected lagged technical indicators on FX returns$r_t$ are shown in Table 2. All technical indicators have some statistically significant values in their lags. This model is used as the measurement model in the Kalman filter algorithm.

**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.

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 Kalmanfilter algorithm as a state model$f_t$.Table 3 shows the statistically significant lags of FX rates of return for predicting the next one-minute for every pair of exchanges.

When the artificial neural network (ANN) is used for tuning the Kalmanfilter, 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.

**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[**] | s2.291329 |

*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.

Tables 4 shows the corresponding RMSE values for the synergistic model with dynamic ANN Q are much less than those achieved with the synergistic model with static *Q*. But 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 4for the synergistic model with dynamic ANN *Q* are greater than the %CDCP values for the synergistic model with static *Q*.

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. 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 structural and the intra-market models. These results show the outperformance of the proposed synergistic model (i.e., minimum %CDCP value is 73.58)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% (Cai& Zhang, 2016; Bekiros, 2015).

In comparison to the random walk model, the statistical values of the synergistic model (the last columns of Table 5) are greater than the critical values$\sigma_{0.01\%}$. Thus, we conclude that the proposed synergistic model also outperforms the random walk model.

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**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. 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%.

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## 5. Conclusions

Developing a method of prediction with the lowest possible forecasting error is one of the most challenging issues in finance.

We develop a synergistic forecasting model of high-frequency data for FX pairs of currencies rates of returns. The synergistic approach combines the structural model of technical analysis indicators 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 uses the estimates of the preceding two-standalone models as its inputs. 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. Taking into account the fluctuations in the market, this is done by using an artificial neural network to find a relationship among RSI, ATR, SD, spread, and volume.

The empirical results of the simulations for different FX pairs in random periods of time and different market conditions show that the synergistic model outperforms the both standalone models and the random walk model and to the best of our knowledge, better than the other similar models in high frequency forecasting. In addition, superiority of the proposed dynamic system is to generate fast forecasts by simple computational procedure from the publicly observable information and no need to store huge amounts of historical data.

In future research, we plan to investigate the economic significance of our proposed model and to explore the possibility of profiting from the predictions by the market microstructure realities (like the presence of transaction costs).

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