Contents

1. Introduction

1.1 Problem Statement

Never will currency exchange fail to become an essential part of people's life. As a basic service provided by retail banks, foreign exchange (FX) settlement and sale gains importance in an age of globalization with mass international trading.

Since many of currency transactions are expected to happen beforehand, or the actual payment can be deferred, there is a time window that allows people to observe the change of the FX and wait for a better price. For example, international students may know the amount of tuition fee months ahead, and the foreign currency pending repayment in the credit card can be paid days or months later. However, for many individuals and companies, monitoring the exchange rate is energy-consuming and time-squandering. Besides, their insufficiency in FX knowledge makes it harder for them to make wise exchange decision. It is under this situation do we propose an AI agency service on foreign exchange settlement and sale to assist customers transact with better price.

1.2 Motivation and Value Proposition

The proposed solution addresses customers' pain point and is expected to increase bank's revenue from a service charge. Moreover, by offering our algorithmic FX trading solution to customers, we expect the bank to have a competitive advantage over customer experience and increase customer stickiness or even attract new customers. To further expound：

- Bank, as a professional financial institution, help customers monitor the fluctuation of foreign exchange rate relentlessly and assist them set the trading order at a preferable price.
- Bank can project the exchange rate more accurately hence foresee a preferable price with more confidence, making the transaction more lucrative for customers.
- Customers who gained benefits from the AI trading will be more likely to use it to trade for next and the following time. They are also likely to introduce this program to friends and families. This will create a cross-sell and up-sell opportunity for the bank.

Based on the ideas above, this project establishes a rudimentary AI agency service in foreign exchange for bank usage. The following contents will include four major parts: contract design, foreign exchange prediction model, mechanism behind the execution model and a specific use demo to show how the whole process goes from head to toe.

2. Literature Review

Scholars have already done a raft of research in forex exchange area. We looked up articles focused on forex prediction or forex trading strategy, more of the which are about the former than the latter.

From a general perspective of the published articles, although they could reach prediction accuracy and gain revenue at some level, few of them performed outstandingly. L Munkhdalai, T Munkhdalai, KH Park, et al. (2019) suggested that although statistical and econometric methods such as exponential smoothing and ARIMA have advantages of not requiring data normalization and can deal with non-stationary time series by differencing transformations, their prediction performances could be poor depending on financial time series characteristics. The deep-learning model they proposed achieved better performances compared with other baseline models on six foreign exchange rates.

Myszkowski and Bicz (2010) used an evolutionary algorithm application based on decision tree containing only technical indicators to generate strategies to trade future contracts on foreign exchange market, the result of which was unstable and unreliable to be applied to real world.

Yun-Cheng Tsai, Jun-Hao Chen and Jun-Jie Wang (2020) interestingly transferred input data from quantitative numbers to images, used CNN to train and predicted the forex trend. The experimental results show that if the strategy is clear enough to make the images obviously distinguishable, the CNN model can predict the prices of a financial asset accurately at some level.

It is concluded from the literatures that the room for improving the prediction accuracy is still big. However, increasing the prediction accuracy is also challenging as market shocks are generally hard to capture. Therefore, we are looking for a methodology that strives to achieve accurate prediction and tries to offset the negative impact brought by prediction inaccuracy at the same time by leveraging the power of decision. Since the goal of our product is slightly different from general forex trading – the bank only profits from the commission fee from clients who buy the agency service contract, naturally our prediction and decision strategy should be different from those proposed in the past.

3. Contract Design

We will essentially provide a contract to customers who want to perform currency exchange. The goal of the contract is to provide customers with foreign currency at or above the target exchange rate. For example, if the contract target exchange rate is set to be EUR/USD = 1.1762 and the customer wants to convert his/her Euro to 10,000 USD, then the goal of the contract is to buy the 10,000 USD for the customer at a conversion rate of equal to or higher than 1.1762 so that the customer could benefit from it. Banks then charge a fixed percentage of service fee.

An exchange contract can be a contract to buy or a contract to sell. For a contract to buy, the bank guarantees to return the specified amount of target currency to buy; for a contract to sell, the bank guarantees to exchange all the specified amount of original currency for target currency. The logic behind both types of contracts is symmetric, and we only illustrate the mechanism of the buy-type contract in this report.

A typical buy-type contract consists of five elements: contract timespan, target exchange rate, contract fee, exchange amount of target currency & authorized amount of original currency. The contract time span and the exchange amount of target currency is specified by the customer. The value of other elements is calculated by our model.

3.1 Contract Timespan

Contract timespan decides how much time the AI agency has discretion to trade. The bank will generally provide contracts of different timespan to suit customer needs, ranging from several weeks to several months. Typically, the bank may provide a few of fixed long-term or short-term timespans for customer to choose from because the timespan directly affects the time frequency to be used in the prediction and the decision model.

3.2 Target Exchange Rate

This is the converted exchange rate we guarantee to our customers, which is calculated based on the long-term prediction outcome.

We offered two plans for setting the target exchange rate, Plan A and Plan B. The initiative of Plan A comes from statistical concept of “confidence interval”, thus we used standard deviation as a buffer parameter to calculate the target exchange rate. Plan A is more rigid and can be used both when predicted price is better than the current price and when predicted price is worse than current price. Plan B is more flexible and should be used only when predicted price is better than current price. If the bank is not confident enough in the prediction and want to control the risk further, it may adjust the parameter α to a small value, otherwise α could be set large for our model to act more progressively and further benefit the customer. The specific pricing strategies are as followed:

Plan A: $target\ xr$[1] $= predicted\ xr - last\ period\ std$[2] $\times current\ xr$

Plan B: $target\ xr = \alpha \times predicted\ xr + (1-\alpha) \times current\ xr,\ 0 < \alpha < 1$

The predicted exchange rate used in the formula is the second maximum predicted exchange rates within the timespan, which will be explained later in the section of Long-term Prediction Model.

For plan B, α should be tested and set according to the model’s performance evaluated on the portfolio level. In this report we simply use α=0.75. It is worth mentioning that α could also be set case by case. For example, the bank can use machine learning strategy to learn the best α for each case. In this report we do not explore further in that direction.

Please be noted that if the target exchange price is worse than the spot price, we still provide

[1] For all xr in the formulas, $xr := \frac{original\ currency}{target\ currency}$.

[2] It is the standard deviation of the actual exchange rates in the last period, which is the period right before the contract starts. The length of this period should be the same as the timespan of the contract, and the actual exchange rates used here should be of the same frequency as the long-term prediction model used to predict the exchange rates for the contract execution period.

the contract (with contract goal set by plan A) and leave the choice to customers as to whether they want to do business with us.

3.3 Exchange Amount of Target Currency & Authorized Amount of Original Currency

It is better to use an example to explain these two concepts. If a customer wants to exchange EURO for 10,000 USD, then USD is the target currency and 10000 is the exchange amount. The amount of original currency, EURO, transformed by 10,000 USD using the target exchange rate, e.g., EUR/USD=1.1720, is the authorized amount, which is 8532.4232 EUR.

3.4 Contract Fee

A fixed percentage of commission fee is allocated to each contract. In general, if customers want to exchange X EUR to 10,000 USD, the bank will charge $\max\{X * last\ period\ STD * 0.1,\ X * 0.0015\}$ as its commission fee. For example, if the standard deviation in the last period is 5%, contract exchange rate is 1.1720, then X should be 8532.4232 and this contract will be charged for a commission fee of 8532.4232*0.05*0.1 = 42.66 EUR.

4. Execution Mechanism

4.1 Overall Strategy

To support the proposed service, an automated prescriptive analytic process is devised to combine dynamic forecasting with a data-driven prospect-based decision frame.

4.1.1 Dynamic Forecasting

Our forecasting model uses relevant historical data to predict future exchange rate. The forecasting process is dynamic in two senses:

- In the first sense, for contracts with different timespans and for the shortening timespan as time progresses to the end of the contract, we need to adjust the timespan of training data accordingly. Long-term and short-term forecasting are combined for better decisions.
- In the second sense, as time progresses, historical data updates continually, and we are supposed to use the up-to-date data for short-term prediction. Since our goal is to achieve an outcome at least slightly better than user themselves rather than maximizing profit, pursuing an impressive prediction accuracy is less of a concern in this project. Instead, we place more emphasis on a robust decision strategy that can avoid failing the contract.

4.1.2 Decision Framework

The decision framework is based on the Divide and Conquer Strategy and consists of two sub-frameworks: task allocation and task execution.

The task allocation decision serves to schedule the execution amount of task for each sub-period within the contract timespan. In this way, we distribute the execution risk across time. Within each sub-period, the task execution framework guarantees that the model fully completes the amount of task scheduled for this sub-period and that the execution decisions are sensible enough to achieve the overall goal.

4.2 Task Allocation Model

For different contract timespans, the overall execution period is divided into sub-periods of different lengths. The average exchange rate for each sub-period will be predicted in one shot before the contract starts using historical data. For example, for a contract timespan of several weeks, exchange rate will be forecasted on a daily average basis; for a contract timespan of several months, exchange rate will be forecasted on a weekly average basis.

The task allocation model decides how much target currency should be bought or sold within each sub-period based on the forecasting results. The total amount of task is the exchange amount of target currency required by the customer. For a buy-type contract, the model allocates the total amount to each sub-period following a series of decision rules:

- The last sub-period serves as a time buffer and is allocated with all the remaining task.
- For sub-periods before the last one, task is scheduled according to the difference between the target exchange rate and the predicted average exchange rate for this sub-period. The difference is characterized using two variables:
    - $std \coloneqq the\ standard\ deviation\ of\ all\ predicted\ sub\text{-}period\ exchange\ rates$
    - $rpd \coloneqq relative\ percentage\ difference\ between\ the\ predicted\ exchange\ rate$
      $and\ the\ target\ exchange\ rate$

$$rpd_t = \frac{|predicted\ xr_t - target\ xr|}{predicted\ xr_{max} - predicted\ xr_{min}}$$

Task allocating rules:

$For\ sub\text{-}period\ t,$

$$base\ task = \frac{total\ amount\ of\ task}{number\ of\ sub\text{-}periods}$$

- If $predicted\ xr_t \le target\ xr - std,$
  $$task_t = \min\left(base\ task \times (1 - rpd), remaining\ task\right)$$
- If $target\ xr - std < predicted\ xr_t \le target\ xr + std,$
  $$task_t = \min\left(base\ task, remaining\ task\right)$$
- If $predicted\ xr_t > target\ xr + std,$
  $$task_t = \min\left(base\ task \times (1 + rpd), remaining\ task\right)$$

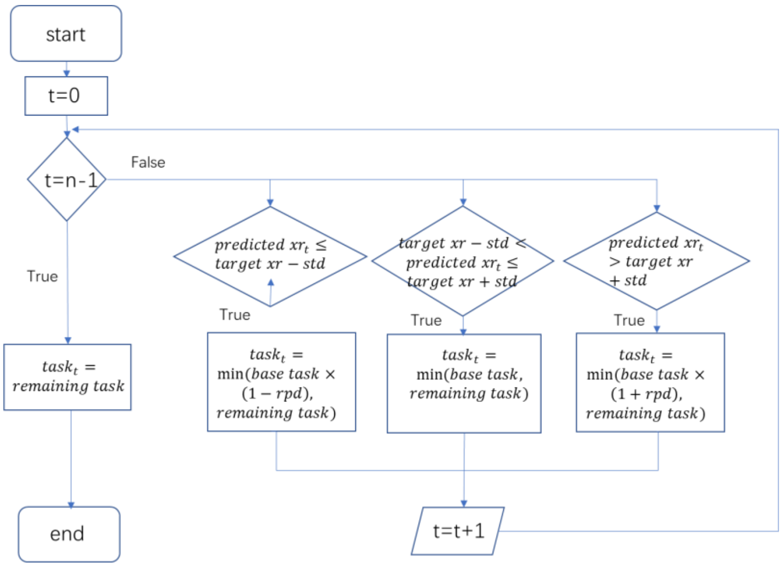


Figure 1 Decision Flow of Task Allocation

4.3 Task Execution Model

After scheduling sub-period tasks, tasks allocated to each sub-period will be completed by the task execution model. Exchange execution is the collaborative work of a spot-rate monitor, a future-rate predictor, and an exchange executor:

- Spot-rate Monitor:

  The spot-rate monitor constantly collects the real-time exchange rate on a N-min frequency basis. We call the N-min interval as a time unit. N is decided according to the timespan and the allocated amount of task of the sub-period. For instance, if the length of the sub-period is one week, N could be 15; if the length of the sub-period is one day, N could be 5. The spot-rate collected is the real-time exchange rate at the beginning of each time unit.

- Future-rate Predictor:

  The future-rate predictor produces the prediction for exchange rate after the next N-min with the recent historical data collected by the monitor. The short-term prediction model used by the predictor will be illustrated in the following sections.

- Exchange Executor:

  The exchange executor decides whether to execute an exchange and execute the exchange amount instantly at the beginning of every time unit.

  The execution decision is made according to the actual spot rate and the prediction of the exchange rate of the next time unit. In each time unit the executor decides whether to execute an exchange, with decision result as WAIT or ACT, and the corresponding execution amount if ACT. Typically for a buy-type contract, if the current exchange rate is not desirable and the predicted future exchange rate is better, the executor will choose to WAIT, otherwise ACT. Since the goal of contract execution is to exchange for the guaranteed amount of target currency within the authorized amount of original currency, attention is paid more on risk control rather than striving for a better price and the execution strategy is essentially conservative.

The decision model considers the accuracy of the predictor, the remaining time and task, the difference between the current rate and the predicted future rate, and the difference between the current rate and benchmark rates (the predicted average rate of current sub-period and the target exchange rate). Listed below are the decision factors and rules adopted by the executor for a buy-type contract:

Constructed Factors:

- The accuracy of the predictor is characterized by $lag\text{-}1\ MAPE$:

  $lag\text{-}1\ MAPE_t \coloneqq mean\ absolute\ percentage\ error\ of\ all\ predictions\ made\ before\ time\ unit\ t.$

  And we use $conf_t = 1 - lag\text{-}1\ MAPE_t$ to dynamically characterize the model confidence.

  Such characterization is intuitive as a small $lag\text{-}1\ MAPE$ suggests that the model generally produces less error and therefore we have more confidence in the model. However, model confidence should range between 0 and 1 but $lag\text{-}1\ MAPE$ can exceed 1. Therefore, we have:

$$conf_t = \begin{cases} 1 - lag\text{-}1\ MAPE_t, & 0 \le lag\text{-}1\ MAPE_t < 1 \\ 0, & lag\text{-}1\ MAPE_t \ge 1 \end{cases}$$

- At time unit t,

  $predicted\ xr_{t+1} \coloneqq predicted\ future\ exchange\ rate\ of\ the\ next\ time\ unit,$

  $xr_t \coloneqq current\ exchange\ rate\ fetched\ the\ monitor,$

  $risk\ xr_{t+1} \coloneqq estimated\ worst\ exchange\ rate\ of\ the\ next\ time\ unit$

  In a sense, $risk\ xr_{t+1}$ partially characterizes the risk to be taken if the executor decides to WAIT at time t simply because the predicted exchange rate of the next time unit is better than current rate. We use the difference between $predicted\ xr_{t-1}$ and xr_{t-1} to calculate $risk\ xr_{t+1}$:

  $risk\ xr_{t+1} = predicted\ xr_{t+1} - |predicted\ xr_{t-1} - xr_{t-1}|$

  We then adjust $predicted\ xr_{t+1}$ with $risk\ xr_{t+1}$ and $conf_t$

- The predicted exchange rate of the next time unit is then adjusted with model confidence and the estimated worst exchange rate of the next time unit:

  $pred_{adj} xr_{t+1} = conf_t \times predicted\ xr_{t+1} + (1 - conf_t) \times risk\ xr_{t+1}$

  The executor will use $pred_{adj}\ xr_{t+1}$ to decide WAIT or ACT.

- We want to compare the current exchange rate with the overall target exchange rate to decide the execution amount of task at each time unit. However, notice that the contract goal can only be achieved when all exchange task is executed at or above the target exchange rate, which means we cannot simply execute all remaining amount of task when current exchange rate exceeds the target exchange rate. The worst situation is that all past executions (including tasks completed in all past sub-periods) were carried out at a price worse than the target price. To take such possibility into account to some extent, we adjust the target exchange rate accordingly before using it as a benchmark rate for comparison.

$$target_{adj}xr_t = \ target\ xr\ \times (1 + \frac{all\ executed\ task_t}{total\ task})$$

Decision Rules:

Within each sub-period,

- The last time unit serves as a time buffer and is allocated with all the remaining task scheduled for this sub-period.
- For time unit t before the last one:

$$\begin{aligned} decision_t &:= execution\ decision\ made\ at\ time\ unit\ t, \\ &\quad take\ the\ value\ of\ WAIT\ or\ ACT \end{aligned}$$

$$\begin{aligned} execution_t &:= amount\ of\ task\ to\ execute\ at\ time\ unit\ t;\ for\ a\ buy\text{-}type \\ &\quad contract, it\ is\ the\ amount\ of\ target\ currency\ to\ buy. \end{aligned}$$

$$\begin{aligned} scheduled\ xr &:= the\ average\ exchange\ rate\ predicted\ for\ this\ sub\text{-}period \\ &\quad before\ task\ allocation \end{aligned}$$

$$\begin{aligned} remaining\ task_t &:= remaining\ amount\ of\ scheduled\ task \\ &\quad (task\ amount\ allocated\ for\ this\ sub\text{-}period)\ at\ time\ unit\ t \end{aligned}$$

- If $xr_t < target\ xr\ and\ xr_t < pred_{adj}xr_{t+1}$,
  $decision_t\ = \text{WAIT, otherwise, decision}_t = \text{ACT}$

  If $decision_t\ = \text{WAIT},\ execution_t = 0;$

  If $\text{decision}_t = \text{ACT}$:

$$base\ execution = \max\ (\frac{scheduled\ xr}{total\ number\ of\ time\ units\ within\ this\ sub\text{-}period}, 1)$$

- If $xr_t \geq target_{adj}xr_t$,
  $execution_t = remaining\ task_t$
- If $scheduled\ xr \leq\ xr_t < target_{adj}xr_t$,

$$execution_t = \min\ (base\ execution\ \times \left(1 + \frac{xr_t - scheduled\ xr}{target_{adj}xr_t - scheduled\ xr}\right), remaining\ task_t)$$

- If $xr_t <\ scheduled\ xr$,
  $execution_t = \min\ (base\ execution\ , remaining\ task_t)$

Following the above execution rules, the executor makes sure that the exchange task allocated to each sub-period can be completed within the same sub-period, and at each time unit, it generally increases the execution amount when exchange rate is more desirable.

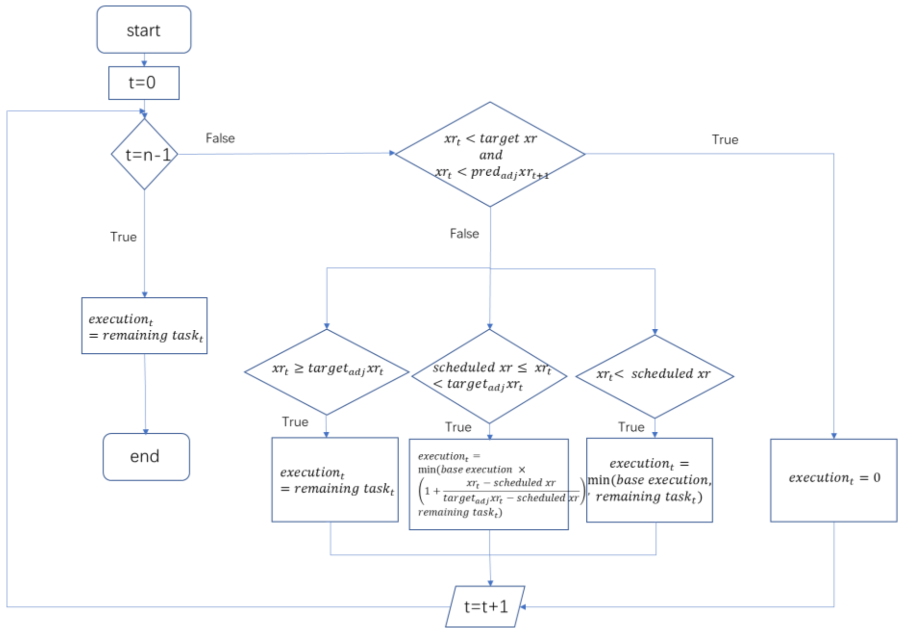


Figure 2 Decision Flow of Task Execution

5. Modeling of Long-term & Short-term Exchange Rate Prediction

5.1 Long-term Prediction

ARIMA model is used for long-term prediction. ARIMA is employed here because it can easily produce prediction for multiple future periods in one shot, and the model only requires the past data of the time series itself to predict future. The accuracy of ARIMA model on FX forecasting may not be satisfying, but combined with our decision framework, the prediction outcome may still be acceptable enough to provide reference for exchange decision making. The timeseries model also uses a rigorous statistical approach that may provide extra information for reference. Therefore, we still adopt ARIMA model for long-term prediction because of its simplicity and richness of information.

In the model, we use the past 5 years' data of the close price to predict the future close price for sub-periods within the contract timespan. Weekly or daily average close price will be used for forecasting according to the length of sub-periods. The process of ARIMA can be divided into three steps: difference log transformed data to make data stationary on both mean and variance if needed; plot ACF and PACF to identify potential AR and MA model; identify the best fit ARIMA model. Hence, different dataset will give different p, d and q values. However, it is also possible that ARIMA might give constant prediction value for most sub-periods when the data doesn't fit ARIMA assumptions. In those cases, we must use other timeseries models, e.g., Holt Winter's Exponential Smoothing. This is also one of the major limitations of ARIMA model, and for future improvement, more capable and universal model should be explored.

We will use the use case demo in section 6 to illustrate the use of ARIMA in practice.

5.2 Short-term Prediction

LSTM model is adopted for short-term prediction. The model predicts the close price of EUR/USD a time unit forward by looking at last 20-time units of data. The original features provided in the dataset includes “timestamp”, “open price”, “close price”, “high price”, “low price”, and “trading volume”. Our model constructs extra 9 features from the original ones and put the total 15 features in the LSTM model for training.

We will use a use case demo in the next section to illustrate our model further and show the model performance.

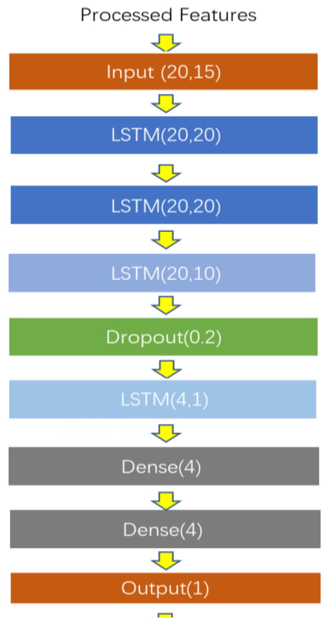


Figure 3 LSTM Model Structure

6. Implementation – Use Case Demo

Suppose today is 31st Dec 2016 and a customer wants to exchange his EURO for 10000 USD before 1st April 2017. He logs into his mobile bank app and goes to the foreign exchange AI agency service. The app will then generate a contract for him, tells him how much Euro is needed for foreign exchange and how much commission fee he should pay. If he accepts and signs the contract, he authorizes the bank to exchange those EURO for USD on his behalf and pays the commission fee. On 1st April 2017, the bank will return him 10000 USD together with the remaining Euro he authorized if any.

In this use case demo, we simulated the automatic contract generation and execution process for this foreign currency buy-type contract and evaluated the execution outcome.

6.1 Contract Generation and Task Allocation

We first used the long-term prediction model trained on the currency exchange data of EUR/USD from 1st Jan 2010 to 31st Dec 2016 to predict the weekly average exchange rate 3-month forward (i.e.,1st Jan 2017- 31st Mar 2017).

The ARIMA model provides a straight-line prediction for the 3-month period with RMSE = 0.0087 and MAPE = 68.38%. The overall accuracy is not satisfying, and the model does not catch any fluctuation within this period. However, it gives a very close prediction for the ending week of this period and precisely captured the overall increasing trend. It also generates confidence interval for each predicted value as the upper bounds and lower bounds, but as shown in the picture, the confidence interval is way too large compared with the scale of the exchange rate itself and becomes useless.

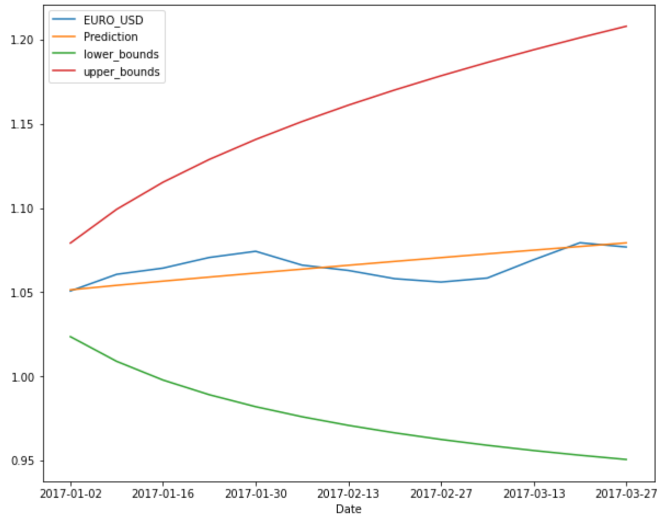


Figure 4 ARIMA Model Prediction for Weekly Average Exchange Rate 3 Months Forward

There are 13 sub-periods (i.e., 13 weeks) in this 3-month period. We used the second maximum of the 13 predicted weekly average rates to calculate the target exchange rate and other components of the contract as illustrated in Section 3.1.2. The calculation formula of plan A requires the standard deviation of the exchange rate in the last period. In this case, the standard deviation of the weekly average exchange rate of last three months (i.e., 1st Oct 2016 – 31st Dec 2016) is calculated and applied.

For this buy-type contract, both plan A and plan B for the setting of contract goal is applicable. We generated both contract A and contract B for this demo accordingly. We then simulated the execution of both contracts and compared the model performance for each contract.

Contract	Contract A	Contract B
Currency to Buy	10000.0 USD	10000.0 USD
Contract Timespan	2017-01-01~2017-03-31	2017-01-01~2017-03-31
Target Exchange Rate	EUR/USD = 1.052134	EUR/USD = 1.069948
Currency Should be Authorized	9505.0 EUR	9347.0 EUR
Currency Needed If Buy Now[1]	9541.0 EUR	9541.0 EUR
Commission Fee	22.75 EUR	22.38 EUR
*Note: If the amount of EURO authorized by the client is not sufficient, the bank will have to pay extra EURO by itself to fulfill the contract.		

Table 1 Contract Details Generated Following Plan A and Plan B

We defined a scheduler according to our task allocation model illustrated in section 4.2. Given a generated contract and the long-term prediction results, the scheduler can automatically allocate the execution task (10000 USD) to each of the 13 weeks and produce a schedule table for execution. See appendix for the schedule tables generated for contract A and contract B.

The estimated resource consumed within a certain week is the amount of EURO that will be used to buy the scheduled amount of USD for this week at the corresponding predicted weekly average exchange rate. After allocating the task, the scheduler calculates the total resource that will be consumed in this 3-month period and compares it with the authorized amount of EURO required by the contract. If the authorized amount is sufficient, the scheduler will say that the contract goal is ATTAINABLE, otherwise UNATTAINABLE. An unattainable contract goal suggests that the bank will have to pay extra EURO by itself to buy enough USD for the customer as promised in the contract, i.e., there will be loss taken by bank. For an attainable goal, the scheduler calculates the estimated extra saving (remaining resources) for the customer. For an unattainable goal, the scheduler calculates the estimated loss for the bank.

Contract A	Contract B
• ATTAINABLE Goal • Estimated Extra Saving for Customer: 122.14 EUR	• UNATTAINABLE Goal • Estimated Loss for Bank: 1.02 EUR

Table 2 Task Allocation Result for Contract A and Contract B

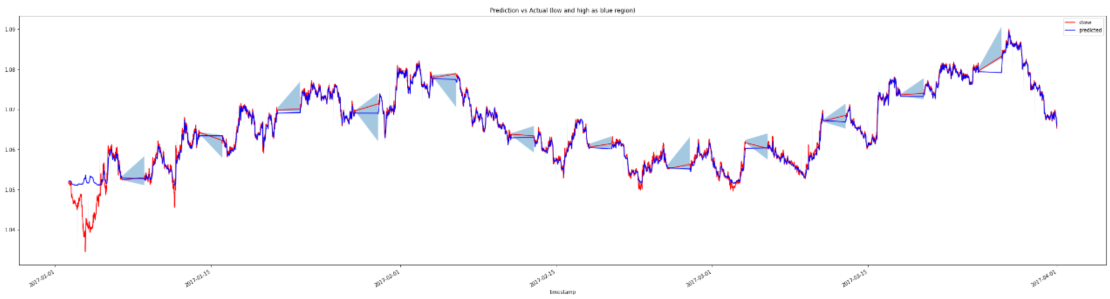
It should be noted that, generally, the bank is not suggested to provide an unattainable contract to the customer, especially when the estimated loss is huge. For this case, we suggest the bank

[1] Here we use the weekly average exchange rate of the last week of 2016 as current exchange rate to calculate the amount of EURO needed to buy 10000 USD if the customer executes the foreign exchange settlement at that moment, but in real practice, the current exchange rate should be the exchange rate at the time when the contract is generated for the customer.

provide contract A to the customer.

6.2 Task Execution

We first simulated the dynamic prediction illustrated in section 5.2. We pretrained our short-term prediction model on the 15-min interval EUR/USD exchange rate data from 1st Jan 2010 to 31st Dec 2016 and predicted the 15-min interval EUR/USD exchange rate for the contract execution period of 1st Jan 2017- 31st Mar 2017. For each 15-min-interval time unit t, we use historical data from time unit t－20 to time unit t to predict the exchange rate of time unit t+1. Since we already have all the data from 1st Jan 2017- 31st Mar 2017, we predicted the future exchange rate in one-shot for convenience. However, in actual practice, this is impossible, and we should predict the exchange rate of time unit t+1 at time unit t.



The blue line is the predicted close price, the red line is the real close price, and the blue region is the range between the high price and the low price. The accuracy of the short-term prediction model is generally acceptable with a MSE of 3.51e-06 and a MAE of 8.5e-04.

Figure 5 LSTM Model Prediction for the Exchange Rate of the Next Time Unit

We defined an executor according to our task execution model illustrated in section 4.3. Given a schedule table produced by the scheduler, the current and past exchange rate, and the short-term prediction result for the next time unit, the executor can automatically make exchange decision and buy a certain amount of USD accordingly at each time unit t. After the task of buying 10000 USD is completed, the executor will return the amount of extra saving for the customer or the amount of loss taken by the bank.

Contract A	Contract B
•Contract Execution Completed •Extra Saving for Customer: 122.22 EUR	•Contract Execution Completed •Loss Taken by Bank: 8.79 EUR

Table 3 The Execution Result for Contract A and Contract B

6.3 Results Analysis and Product Evaluation

In this demo, the execution of contract A behaves better than that of contract B. It achieves the contract goal and provides more profit for the bank. Its execution gap is also smaller. Nevertheless, contract B generates more savings for the customer, which makes the service more attractive.

Contract	**Contract A**	**Contract B**
Contract Fulfilled[1]	TRUE	TRUE
Attainable Goal	TRUE	FALSE
Goals Achieved[2]	TRUE	FALSE
Execution Gap[3]	0.08 EUR	-7.77 EUR
Extra Savings[4]	122.14 EUR	None
Total Savings[5]	158.22 EUR	194.00 EUR
Loss Taken by Bank	None	8.79 EUR
Actual Profit for Bank[6]	22.75 EUR	13.59 EUR

Table 4 Model Performance on Contract A and Contract B

[1] According to the design of our model, any reasonable contract should be fulfilled as long as the model is implemented correctly.

[2] i.e., execution completed within the total amount of EURO authorized by the customer, no loss taken by the bank.

[3] The gap between scheduled execution result and actual execution result, defined as:

$$execution\ gap = scheduled\ amount\ of\ EURO\ to\ be\ used - actual\ amount\ of\ EURO\ used$$

[4] Compared with the total amount of EURO authorized by the customer as required in the contract.

[5] Compared with the total amount of EURO to be used if the customer chooses to buy 10000 USD by themselves at the moment the contract is generated.

[6] Defined as $commission\ fee - loss\ taken\ by\ bank$, the cost of execution is not considered here.

When working on contract goal set by plan B, the scheduler and executor both generate loss for the bank. As a result, all EURO authorized by the customer for this contract is used up and the bank has to spend extra 8.79 EUR by itself to return the guaranteed 10000 USD to the customer. There are four possible explanations for this loss:

- For this specific case, the goal set by plan B is too progressive and we need to adjust the parameter: e.g., from $\alpha = 0.75$ to $\alpha = 0.7$.
- The long-term prediction outcome of EUR/USD exchange rate is not acceptable, and we need to use more accurate prediction to schedule the execution.
- Either the scheduler or the executor should be designed to be more progressive in chasing the better price.
- The outcome is acceptable:
    - The loss is negligible compared to the total execution amount.
    - After taking the commission fee into consideration, there is actually no loss for the bank in this case. The bank still earns a profit of 13.59 EUR.
    - On the portfolio level, we do not know whether it is acceptable to use plan B to set target exchange rates. We do not know the overall loss and profit on the portfolio level.

We cannot identify which explanation is right unless we conduct portfolio-level experiment to test our model.

So far, the use case demo has demonstrated that our solution is feasible and can be beneficial for both the bank and the customer, yet the model performance on a single use case is far from convincing. Stress test and portfolio-level experiment is essential for model evaluation, and the parameters and formulas used in our model should be adjusted interactively in this process. We will address the model limitations and future improvements in detail in section 7.

6.4 Risk Measures

Risk control is essential in the financial industry. When trading currency, or trading in any other markets, price goes up and down. When the price moves in the opposite direction of what we expect, we are exposed to market risk. A risk measure quantifies the capital required to make its risk acceptable. We will use the demo case to calculate two risk metrics: VaR and ES. Please note that under the real scenario, risk metrics are computed based on portfolio rather than a currency pair.

6.4.1 VAR for EUR/USD

The Value at Risk, or VaR, is a statistical measure that calculates the risk of loss for investments. It answers the question of “how bad can things get”. When the losses are normally distributed with mean μ and standard deviation σ, VaR is given as:

$$VaR_{\alpha} = \mu + \sigma\Phi^{-1}(\alpha)$$

$$T\_day\ VaR = 1\_day\ VaR \times \sqrt{T},$$
$$assume\ no\ autocorrelation\ \rho$$

In this demo, according to Plan A, we long 9505.0 EUR at the exchange rate of 1.05 for 10000 USD. Suppose that the change in the value of the asset over a one-day period follows a normal distribution with a mean of zero. We want to find out VaR with a confidence interval of 99%, which corresponds to a z-score of 2.33. For relatively short time horizons, μ is often assumed to be zero.

Detailed calculations are as follows:

$$1\text{-}day\ volatility/SD = 0.00532 = 0.53\%$$

This is calculated based on the daily rate from 1st Jan 2016 to 31st Dec 2016. On any day, we expect the position to change by $10000 * 0.53\% = 53\ USD$. Thus,

$$1 - \text{day VaR} = 53 \times 2.33 = 123.5\ USD$$
$$90 - \text{day VaR} = \sqrt{90} \times 123.5 = 1171\ USD$$

This means that we are 99% confident that we will not lose more than 123.5 USD over a one-day period. Another way to interpret this is that there is 0.01 chance that the portfolio will fall in value by more than 1171 USD in 3 months. The real data from 1st Jan 2017 to 31st Mar 2016 proves that above calculation is correct.

6.4.2 ES for EUR/USD

The expected shortfall, or conditional VaR is the expected loss given that the loss is greater than the VaR level. It answers the question of "if things do get bad, what is our expected loss". When the losses are normally distributed with mean μ and standard deviation σ, ES is given as:

$$ES_{\alpha} = \mu + \sigma \times \frac{\phi\Phi^{-1}(\alpha)}{1-\alpha},$$
$$\phi(\text{x})\ is\ the\ p.d.f\ of\ the\ standard\ normal\ distribution$$

$$T\_day\ ES = 1\_day\ ES \times \sqrt{T}$$

We have already calculated the 1-day and 90-day VaR for this demo. Under the same confidence level of 99%, the calculation for 1-day ES and 90-day ES is:

$$\text{1-day ES} = 53 \times \frac{e^{-\frac{2.33^2}{2}}}{\sqrt{2\pi} \times 0.01} = 141.2\ USD$$
$$\text{90-day ES} = \sqrt{90} \times 146.6 = 1340\ USD$$

This suggests the average amount lost over a 1-day period will be 141.2 USD, assuming the loss is greater than the 99th percentile of the loss distribution.

7. Model Limitation, Challenge, and Future Improvement

The devised model can be considered as a prototype and a few limitations and potential areas for future improvement are identified.

7.1 Prediction Accuracy Needs Further Improvement

Prediction accuracy is so crucial that it determines the success of the project. Long-term prediction impacts on both the pricing strategy of the contract and the overall savings for customers. Short-term prediction, on the other hand, provides decision basis for the execution model.

As shown in the use case demo, the short-term prediction accuracy is generally acceptable, but the long-term prediction accuracy is far from satisfying. However, the long-term prediction is required for task allocation and should be produced in one shot before the execution period starts, which means we lack the up-to-date data for prediction and cannot use the same forecasting strategy as our short-term model. This largely determines the difficulty of long-term prediction and limits the model capacity. For further improvement, we need not only a more advanced model, but also more useful features for long-term prediction, e.g., features for sentiment analysis.

7.2 Further Parameters Tuning and Time Frame Selection

The parameters used in our model, although constructed in a way trying to characterize some decision logic that seems reasonable, are still preliminary and not optimal due to the lack of testing. The formulas we established are straightforward and embryonic too. This thus poses challenge to our model and any discrepancy of the model might impact our revenue of this product. For areas to improve, we may need to further tune parameters associated with mathematical models. Moreover, the time interval of short-term prediction is set to 15 minutes in the demo. However, in real situation, transaction opportunities are fleeting in a blink of eye. There could potentially be a large fluctuation within 15 minutes. Henceforth, a model with a shorter time interval is more dynamic and reflects the real market change. One challenge associated with this might be how to strike a balance between model prediction accuracy and prediction costs. Besides, for the long-term prediction, we still want to make the system more perfect to protect from a bigger drawdown in a sharply volatile foreign exchange market after we add more important features, decide the more accuracy parameters and evaluate the updated model. To be exact, our model needs further stress test using different turbulent periods and do survival analysis in the future.

7.3 Transaction Strategy

First, we only consider one-way action in the model. In other words, if a client wants to buy EUR for USD, our model will only long the target currency and not short it. The reason we do this is to prevent the case that once our model prediction is consecutively wrong, the double-direction transaction will amplify the loss. However, once the prediction model is more accurate, it is possible to both long and short and make it more lucrative to customers.

Second, the stop-loss condition could be further advanced. Our original model sets a strict and rigor trigger to stop the loss. Yet in the real case, a looser trigger may let the AI to wait for a better price when the currency price is temporarily unfavorable and reduce the loss.

This deficiency is a derivative from the inaccuracy of prediction. The intricate part of it is that it could be solved only after the problem 7.1 is solved.

8. Conclusion

Foreign exchange (FX) is indispensable to a country. On a macro-level, it serves as an important indicator of a nation's economic health. It is crucial to individuals and companies who perform cross-border transaction as well. For banks, if they can provide a service which monitors the fluctuation of exchange rate and help clients to buy or sell at the designated price they want, banks are able to gain a competitive advantage over customer experience and increase customer stickiness.

We thus created this algorithmic FX trading solution to enhance banks' position. The report lays out the guideline and detailed use case. We invented a model that consists of two parts: task allocation and task execution. In the task allocation part, we did a long-term forecasting of exchange rate for the contract timespan using ARIMA. Based on that, we divided tasks to be carried out on a certain basis and execute those tasks using our proposed mathematical model. We also analyzed the result and evaluated the product in the use case demo and provided further risk measures.

Overall, our model yields relative good results in our demo. However, as mentioned in section 7, our model still faces challenges and there are indeed rooms for future improvement. For instance, our use case is based off a single currency pair, but we need to consider more complicated circumstances and edge cases. Formulas and algorithms can be further calibrated to meet real-life scenario.

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10. Appendix

10.1 Appendix I: Schedule Tables for both contracts

Schedule Table for Plan A Contract

Period	Start Date	Bench_Pred	Execution_Amount	Remaining_Resource	Executed_Task	Remaining_Task
0	2017-01-02	1.051443	731.59	8773.41	769.23	9230.77
1	2017-01-09	1.054140	729.72	8043.69	769.23	8461.54
2	2017-01-16	1.056633	728.00	7315.69	769.23	7692.31
3	2017-01-23	1.059047	726.34	6589.35	769.23	6923.08
4	2017-01-30	1.061417	724.72	5864.63	769.23	6153.85
5	2017-02-06	1.063756	723.13	5141.50	769.23	5384.62
6	2017-02-13	1.066067	721.56	4419.94	769.23	4615.39
7	2017-02-20	1.068351	720.02	3699.92	769.23	3846.16
8	2017-02-27	1.070609	718.50	2981.42	769.23	3076.93
9	2017-03-06	1.072840	717.00	2264.42	769.23	2307.70
10	2017-03-13	1.075046	715.53	1548.89	769.23	1538.47
11	2017-03-20	1.077226	714.08	834.81	769.23	769.24
12	2017-03-27	1.079381	712.67	122.14	769.24	0.00

Schedule Table for Plan B Contract

Period	Date	Bench_Pred	Execution_Amount	Remaining_Resource	Executed_Task	Remaining_Task
0	2017-01-02	1.051443	247.02	9099.98	259.73	9740.27
1	2017-01-09	1.054140	316.85	8783.13	334.00	9406.27
2	2017-01-16	1.056633	381.05	8402.08	402.63	9003.64
3	2017-01-23	1.059047	442.93	7959.15	469.08	8534.56
4	2017-01-30	1.061417	724.72	7234.43	769.23	7765.33
5	2017-02-06	1.063756	723.13	6511.30	769.23	6996.10
6	2017-02-13	1.066067	721.56	5789.74	769.23	6226.87
7	2017-02-20	1.068351	720.02	5069.72	769.23	5457.64
8	2017-02-27	1.070609	718.50	4351.22	769.23	4688.41
9	2017-03-06	1.072840	717.00	3634.22	769.23	3919.18
10	2017-03-13	1.075046	715.53	2918.69	769.23	3149.95
11	2017-03-20	1.077226	714.08	2204.61	769.23	2380.72
12	2017-03-27	1.079381	2205.63	-1.02	2380.72	0.00

10.2 Appendix II: Data Source

LT_Prediction contains two files:

(1) 2011-2021 Source Data: from https://excelrates.com/

This contains daily EURO-USD rate from 2011 to 2021.

(2) Weekly Value: weekly average EURO-USD rate derived from (1).

For example, 1/2/2017 represents the average weekly rate from 1/2/2017-1/8/2017.

For Short-term prediction:

(1) EURUSD_M15.csv

Data Source: https://www.kaggle.com/lehomme/forex-currencies-m1m5m15m30h1h4d1