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# Optimal Multi-Foreign-Currency Holding Positions by Genetic Algorithm

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**Abstract:** A foreign exchange bank may hold multi-foreign-currency to provide the customers with various foreign exchange services. When the short position occurs and deviates to the optimal holding position, the local trading bank will take a Non-Instantaneous Receipt (NIR) to revert the optimal holding position. The focus of this study is to use the ARMA-GARCH model and Fuzzy Non-Linear Programming (FNLP) to build a multi-foreign-currency fuzzy NIR-EOQ model. Finally, this study uses genetic algorithm to solve the optimal holding position problem. The result of this study can provide the decision maker of local trading bank as a reference for multi-foreign-currency positions controlling.

**Key words:** Foreign currency optimal holding position, ARMA-GARCH, fuzzy non-linear programming, genetic algorithm

## INTRODUCTION

In the bank-customer market, generally speaking, the bank accepted the customer to buy or to sell the foreign currency, if the amount of buying is more than the amount of selling, it comes into overbought, in adverse, it comes into oversold. The foreign exchange banks may keep the situation of overbought or oversold, then it forms long position or short position. The long position and the short position are the inventory position of foreign exchange currency, which the foreign exchange banks hold.

Furthermore, the commercial bank promises to provide foreign currency to its customers, holding foreign currency imposes opportunity costs and the exchange risk. Opportunity costs arise because the foreign exchange rate drops or the returns can be earned on the other investment, hence, the local trading bank hold the optimal foreign currency inventory level to reduce the cost of inventory.

Harris (1915) addressed the assumptions of inventory model for single period single-item and developed what is now known as the Economic Order Quantity (EOQ) model. The model has modified inventory model characteristic under different types of receipt what is the advantageous position in using EOQ model.

A commercial bank may hold foreign currency under the maximum inventory level in hand to provide service to its customers, but the demand and the foreign exchange rates are constantly changing. It may hold more or little foreign currency inventory if the demand situation changes. Hence, this research attempts to use Fuzzy Non-Linear Programming (FNLP) theory for the formulation of the inventory model.

In fuzzy decision making development, first Bellman and Zadeh (1970) defined a fuzzy decision making problem as the confluence of fuzzy objectives and constraints operated by max-min operators. Zimmerman (1976) developed a tolerance approach to transform a fuzzy decision making problem to a regular crisp optimization problem and showed that this approach can be solved to obtain a unique exact optimal solution with highest membership degree using classical optimization algorithms.

Nakatsuma and Tsurumi (1999) are used three Bayesian methods to estimate the parameters of the Autoregressive Moving Average-Generalized Autoregressive Conditional Heterosedastic Autoregressive (ARMA-GARCH model) to forecast the weekly foreign exchange of five major currencies. Meade attempted a linear ARMA-GARCH model and four non-linear methods, including three nearest neighbor methods and locally weighted regression to forecast the short term foreign exchange rates.

Genetic Algorithm (GA) is used as optimization techniques for decision-making problems. GA approach

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for EOQ optimization was first tested by Stockton and Quinn (1993). Their theoretical study concerned an EOQ model based on signal product with a complex cost function. The authors concluded that the GA heuristic may be an attractive optimization tool for the management, who can design their own cost function for the selection of the order quantity.

Braglia and Gabbrielli (2001) presented a particular genetic algorithm approach for identifying EOQs and the relative reorder points in a multi-item signal-supplier inventory system. Mondal and Maiti (2002) used genetic algorithms to solve multi-item fuzzy EOQ models under fuzzy objective goal of cost minimization and imprecise constraints on warehouse space and number of production runs with crisp/imprecise inventory cost.

The objective of this study is to build a multi-foreign-currency fuzzy NIR-EOQ model under minimum inventory cost and using ARMA-GARCH model to forecast the foreign exchange rate. Finally, this study uses genetic algorithm to solve the local trading bank optimal holding position problem.

## FUZZY NON-LINEAR PROGRAMMING AND MEMBERSHIP FUNCTIONS

A FNLP problem with fuzzy objective and imprecise resources is formulated as follows: Find $q_i$ to minimize $\tilde{f}_0(q_i)$ such that

$$\text{Min } \tilde{f}_0(q_i) \tag{1}$$

$$\text{s,t } \tilde{f}_k(q_i) \le \tilde{b}_k \quad i = 1,\ 2,\ \ldots,\ n\ ;\ k = 1,\ 2, \ldots,\ m,$$

Where, $q_i$ can be the ith foreign currency, $g_k$ is the kth constraints, $\tilde{b}_k$ is the kth constraint's right hand side value and it is a fuzzy number, m, n are, respectively, the number of constraints and decision variables and the symbol '~' represents the fuzziness of the parameter.

Bellman and Zadeh (1970) made use of the properties of the membership function and the max-min composite operator for combining membership function offer the means for trials and experiment with various aspiration levels and for trying out various combinations of objectives and constraints. This research uses max-min operator, the solution of the problem (1) can be obtained from:

$$\text{Max } \tau \tag{2}$$

$$\text{s. t. } \tilde{f}_0(q_i) \le \mu_0^{-1}(\tau), \qquad \tilde{f}_k(q_i) \le \mu_k^{-1}(\tau)$$
$$q_i \ge 0,\ \tau \in [0,1], \qquad q_i = (x_1, x_2, \ldots, x_n)^T$$

In this case,

$$\mu_0^{-1}(\alpha) = b_0 + (1-\tau)P_0 \text{ and } \mu_k^{-1}(\tau) = b_k + (1-\tau)P_k$$

## MULTI-FOREIGN-CURRENCY FUZZY NIR-EOQ MODEL

When building a multi-foreign-currency NIR-EOQ model, three assumptions are needed and shown as follows.

- The total cost of multi-foreign-currency NIR-EOQ model is the amount of holding cost and replenishment cost. The replenishment cost is independent of the size of order; in other words, replenishment cost is a constant.
- In the NIR-EOQ model, the cycle of demand changing during the time as a fixed distribution, for example, the normal distribution.
- When the short position occurs and deviates from the optimal holding position, the bank will take a non-instantaneous receipt to revert the foreign currency inventory to the optimal holding position during a specific period that the buy and sell orders commonly happened.

Based on these three assumptions, the multi-foreign-currency NIR-EOQ of foreign currency model can be written as:

$$q_i = [2k_i d_i / c_i (1 - \frac{s_i(t)}{p_i(t)})]^{\frac{1}{2}},\ i = 1,\ 2,\ \ldots,\ n \tag{3}$$

Where, $q_i$ is the economic order quantity of the ith foreign currency (the optimal holding position), $k_i$ is the replenishment cost of the ith foreign currency for each time, $d_i$ is the daily average demand quantity of the ith foreign currency, $c_i$ the daily holding cost of the ith foreign currency of one unit, $s_i(t)$ is the sell quantity for the ith foreign currency in the tth trading day, $p_i(t)$ is the buy quantity for the ith foreign currency in the tth trading day. The values of $s_i$ and $p_i$ here is to be decided by observed data.

The mathematical model for the problem, based on minimizing the total cost per unit time (for example, daily), is as follows:

$$\text{Min } f(q) = \sum_{i=1}^{n} [\frac{c_i(1 - \frac{s_i(t)}{p_i(t)})q_i}{2} + \frac{k_i d_i}{q_i}] \tag{4}$$

$$\text{s. t. } \sum_{i=1}^{n} q_i r_i \le Q$$

$$\sum_{i=1}^{n} \frac{q_i - d_i}{\sigma_{d_i}} \ge z$$

$$q_1, q_2, \ldots, q_n \ge 0, \; r_1, r_2, \ldots, r_n \ge 0, \; 0 \le z \le 1$$

When the maximum foreign currency holding position (in new Taiwan dollar) exists, number of orders become fuzzy, the Eq. 4 is transformed to:

$$\text{Min } f(q) = \sum_{i=1}^{n} [\frac{c_i(1 - \frac{s_i(t)}{p_i(t)})q_i}{2} + \frac{k_i d_i}{q_i}] \quad (5)$$

$$\text{s. t. } \sum_{i=1}^{n} q_i r_i \le \tilde{Q}$$

$$\sum_{i=1}^{n} \frac{q_i - d_i}{\sigma_{d_i}} \ge z$$

$$q_1, q_2, \ldots, q_n \ge 0, \; r_1, r_2, \ldots, r_n \ge 0, \; 0 \le z \le 1$$

Following Zimmerman (1976) the above fuzzy model reduces to

$$\text{Max } \tau, \quad (6)$$

$$\text{s. t. } \sum_{i=1}^{n} [\frac{w_i q_i}{2} + \frac{k_i d_i}{q_i}] \le c_0 + (1-\tau)P_0 \quad (7)$$

$$\sum_{i=1}^{n} q_i r_i \le Q + (1-\tau)P_n \quad (8)$$

$$q_1, q_2, \ldots, q_n \ge 0, r_1, r_2, \ldots, r_n \ge 0$$

Where, $p_0$ and $p_n$ are the tolerance of $c_0$ and Q individually, $c_0$ and Q are the objective values of the non-linear programming.

## ARMA-GARCH MODEL

An ARMA model is built for the observed time series to remove any serial correlations in the data. For most asset return series, this step amounts to remove the sample mean from the data if the sample mean is different from zero. For some daily return series, a simple AR model might be needed. The squared series $h_t$ is used to check for conditional heterosedasticity, where $\varepsilon_t = r_t - \mu_t$ is the residual of the ARMA model.

To capture the temporal dependence in the second moment of time series data, Engle (1982) developed an Autoregressive Conditional Heteroskedastic (ARCH) model. The basic idea of ARCH models is that the mean-corrected asset $\varepsilon_t$ is serially uncorrelated, but dependent and the dependence of $\varepsilon_t$ can be described by a simple quadratic function of its lagged values. Specifically, an ARCH(p) is modeled in the following form:

$$r_t = \mu_t + \varepsilon_t \quad (9)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \quad (10)$$

Where:

$$\alpha_0 > 0, \; \alpha_i \ge 0, \; \sum_{i=1}^{p} \alpha_i < 1 \; (i = 1, \cdots, p)$$

$\Omega_{t-1}$ is the usability information set at the t-1 period.

In this ARCH (p) model, the conditional variance at time t is a positive function of squared errors in the last p periods. This specification for the conditional variances implies positive serial correlation in the unconditional variance of the time series process. However, the ARCH model does not allow the conditional variance at time t to have a stochastic component. Bollerslev (1986) extended the ARCH model and developed the Generalized ARCH (GARCH) model, in which the current conditional variance is a function of not only the squared errors in the last p periods, but also the conditional variance in the corresponding periods. The GARCH (p, q) model can be represented in the following from:

$$r_t = \mu_t + \varepsilon_t \quad (11)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

$$\mu_t = E(r_t | \Omega_{t-1}), \; h_t = Var(r_t | \Omega_{t-1}) = E[(r_t - \mu_t)^2 | \Omega_{t-1}] \quad (12)$$

Generally, it can be rewritten as follow,

$$r_t = \varphi_0 + \sum_{i=1}^{m} \varphi_i r_{t-i} + \varepsilon_t. \quad (13)$$

And it is what the ARMA(m) model,

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-j}. \quad (14)$$

Where the $r_t$ is the log-returns of data series for each t, $h_t$ stands for the conditional variance of the residuals for the mean equation, $\alpha_0$ is the average, $\alpha_0$, $\beta_j$>0, p is the ARCH term order and q is the GARCH term order.

## GENETIC ALGORITHM

GA was invented by John Holland in the 1960s and developed by Holland and his students and colleagues at the University of Michigan in the 1960s and 1970s (Mitchell, 1996). GA is a stochastic method for optimization problems based on the mechanics of natural selection and natural genetics and has demonstrated a considerable success in providing good solutions to many complex optimization problems.

In this study, based on Mondal and Maiti (2002), GA has been developed for non-linear programming problems with fuzzy objective goal for multi-foreign-currency fuzzy NIR-EOQ model. The procedure of GA as follows.

**Step 1: Initialization of population:** In this study, at the beginning of computation in GA, a set of $q_i$, i = 1, ..., n, is randomly initialized.

**Step 2: Primary evolution loop:** Three main operators in the primary evaluation loop in each generation, including reproduction, crossover and mutation.

**Step 2.1: Reproduction:** Reproduction contains the calculation of fitness and selection procedure. A roulette wheel selection is used to reproduction process in this study.

**Step 2.2: Crossover:** Based on Adewuya it is defined as a linear combination of two vectors. For each pair of parent chromosomes (e.g., vectors $q_1$ and $q_2$), selected randomly, the crossover operator on $q_1$ and $q_2$ will produce two children chromosomes $q'_1$ and $q'_2$ as follows.

$$q_1' = aq_1 + (1-\alpha)q_2 \qquad q_2' = (1-\alpha)q_1 + aq_2 \quad (15)$$

Where, $\alpha$ ($\geq 0$) is a uniform random generated number between 0 and 1.

**Step 2.3: Mutation:** The mutation operator is implemented on the premise non-uniform mutation. The non-uniform mutation operator is defined as follows (Michalewicz, 1996). If $q'_i = (x_1^{t+1}, x_2^{t+1}, ..., x_m^{t+1})$ is a chromosome and the element $q'_k$ is selected for this mutation (here, domain of $q'_k$ is $[x_k^{low}, x_k^{up}]$), the result is a vector $x_x^{t+1} = (x_1^{t+1}, ..., x_k^{t+1}, ..., x_m^{t+1})$, with $k \in \{1, ..., n\}$ and

$$x_k^{t+1} = \begin{cases} x_k^t + \Delta(t,\ x_k^{up} - x_k^t) & \text{if a random digit is 0,} \\ x_k^t - \Delta(t,\ x_k^t - x_k^{low}) & \text{if a random digit is 1,} \end{cases} \quad (16)$$

Where the function $\Delta(t, \gamma)$ returns a value in the range $[0, \gamma]$ such that the probability of $\Delta(t, \gamma)$ being close to 0 increases as t increases.

## ARMA(1)-GARCH(1,1) MODEL FOR DAILY FOREIGN EXCHANGE RATES

This study estimates ARMA(1)-GARCH(1,1) model of foreign exchange rates are the New Taiwan Dollar (NTD) against the United States Dollar (USD), the Japanese Yen (JPY) and the Hong Kong Dollar (HKD) from the Central Bank of China. The sample period of daily foreign exchange data is from the January 2002 to December 2003. The sample size is 502.

The stationary test of the return series for the samples of NTD-USD, NTD-JPY and NTD-HKD by two unit root tests, ADF and PP Tests and the results are summarized in Table 1. The result indicates that NTD-USD and NTD-JPY are significant at 10% level, but the NTD-HKD is significant at 5% level. Hence, all of the foreign exchange rate series are in a stationary condition.

Table 1: The stationary test for foreign exchange rate

| Exchange rate | Test | Statistical test |
|---|---|---|
| NTD-USD | ADF Test | -7.3836* |
| | (Lag) | (p = 1) |
| | PP Test | -6.5663* |
| | (Lag) | (p = 1) |
| NTD-JPY | ADF Test | -7.2809* |
| | (Lag) | (p = 1) |
| | PP Test | -6.7407* |
| | (Lag) | (p = 1) |
| NTD-HKD | ADF Test | -13.6153** |
| | (Lag) | (p = 1) |
| | PP Test | -15.7958** |
| | (Lag) | (p = 1) |

Notes: "**" and "*" denoted statistical significance at 5 and 10% level, respectively. The number in the table is t-value and in parenthesis is the lag period. ADF is the augmented Dickey-Fuller Test and PP is the augmented Phillips and Perron, both are used to test for the stationary of the return series

Table 2: Estimated parameters of ARMA(1)-GARCH(1,1) model for the daily exchange rate

| | | | ARMA(1)-GARCH(1,1) | | |
|---|---|---|---|---|---|
| | | Parameter | NTD-USD | NTD-JPY | NTD-HKD |
| ARMA (1) | | $\varphi_0$ | 1.0929759 | 0.0168903 | 0.1065000 |
| model | | (t-value) | (4.30360) | (1.72430) | (324.28635) |
| | | $\varphi_1$ | 0.9686778 | 0.9462578 | 0.9759000 |
| | | (t-value) | (131.13297) | (30.02907) | (39216.983) |
| GARCH | | | | | |
| (1,1) model | | $\alpha_0$ | 0.0035228 | 0.0000001 | 0.00000709 |
| | | (t-value) | (4.53208) | (0.48711) | (4.18451) |
| | | $\alpha_1$ | -0.5918352 | 0.1623705 | 0.5096000 |
| | | (t-value) | (-2.55374) | (1.33434) | (4.95630) |
| | | $\beta_1$ | 0.6413895 | 0.3842882 | 0.5725000 |
| | | (t-value) | (6.82672) | (0.33958) | (15.24854) |
| Model | | | | | |
| test | Resid | Q(6) | 5.0735000 | 9.2893000 | 10.7048000 |
| | | (t-value) | (0.27984) | (0.57949) | (0.03009) |
| | Residsq | $Q^2(6)$ | 49.5152000 | 19.5723000 | 32.1729000 |
| | | (t-value) | (0.00000) | (0.00330) | (0.00000) |

Table 3: The values of $r_i$, i = 1, 2, 3 by ARMA-GARCH model

| Date | $r_1$ (NTD-USD) | | $r_2$ (NTD-JPY) | | $r_3$ (NTD-HKD) | |
|---|---|---|---|---|---|---|
| y/m/d | Observation | Forecast | Observation | Forecast | Observation | Forecast |
| 2004/1/12 | 33.717 | 33.823 | 0.316 | 0.316 | 4.343 | 4.354 |
| 2004/1/13 | 33.718 | 33.754 | 0.316 | 0.316 | 4.343 | 4.345 |
| 2004/1/14 | 33.690 | 33.755 | 0.317 | 0.316 | 4.339 | 4.345 |
| 2004/1/15 | 33.700 | 33.728 | 0.317 | 0.317 | 4.341 | 4.341 |
| 2004/1/16 | 33.685 | 33.737 | 0.318 | 0.317 | 4.339 | 4.343 |

This study is carried out by BHHH to estimate the parameter of ARMA(1)-GARCH(1,1) model for forecasting the daily foreign exchange rate. The result of the parameters of ARMA(1)-GARCH(1,1) model for foreign exchange rate is reported in Table 2. Based on Table 2, the ARMA(1)-GARCH(1,1) model of NTD-USD, NTD-JPY and NTD-HKD can be written as follows:

The forecasting model of NTD-USD:

$$r_t = 1.09297586 + 0.9686778 r_{t-1}, \quad \varepsilon_t \left| \Omega_{t-1} \sim N(0, h_t), \right.$$
$$h_t = 0.0035228 - 0.5918352\, \varepsilon_{t-1}^2 + 0.6413895\, h_{t-1}. \qquad (17)$$

The forecasting model of NTD-JPY:

$$r_t = 0.016890 + 0.9462578 r_{t-1}, \quad \varepsilon_t \left| \Omega_{t-1} \sim N(0, h_t), \right.$$
$$h_t = 0.0000001 + 0.1623705 \varepsilon_{t-1}^2 + 0.384288 h_{t-1}. \qquad (18)$$

The forecasting model of NTD-HKD:

$$r_t = 0.1065 + 0.9759 r_{t-1}, \quad \varepsilon_t \left| \Omega_{t-1} \sim N(0, h_t), \right.$$
$$h_t = 0.00000709 + 0.5096\, \varepsilon_{t-1}^2 + 0.5725\, h_{t-1}. \qquad (19)$$

Based on the adequate test by Ljung-Box Q statistics the p-values of foreign exchange rate are summarized in this study where Q(6) and $Q^2(6)$ are the standardized and squared standardized residuals at the lag period of six of NTD-USD, NTD-JPY and NTD-HKD. The results show all the value of Q(6) and $Q^2(6)$ are significant at 5% level respectively, thus, the ARMA-GARCH model appears to be adequate.

The results of forecasting the daily foreign exchange rate of NTD-USD, NTD-JPY and NTD-HKD are presented in Table 3. The results show the movement of the observation and forecast in foreign exchange rate are very close.

## RESULTS FOR SINGLE-FOREIGN-CURRENCY AND MULTI-FOREIGN-CURRENCY FUZZY NIR-EOQ MODEL BY GENETIC ALGORITHM

The daily trading data for USD, JPY and HKD is from one of the commercial bank branch office in Hualien, R.O.C. For numerical illustration, this research considers three-foreign-currency for fuzzy multi-foerign-currency NIR-EOQ model with input data as shown in Table 4. $C_0$ is defined as the minimum demand quantity of the ith foreign currency from observational trading data multiplied by the average foreign exchange rate. $P_0$ is defined as the maximum demand quantity of the ith foreign currency from observational trading data multiplied by the average foreign exchange rate. Q(t) is the minimum demand quantity from the observational trading data multiplied by the daily forecasting foreign exchange rate. $P_n(t)$ is the maximum demand quantity from the observational trading data multiplied by the daily forecasting foreign exchange rate.

Table 4: Input data for fuzzy NIR-EOQ model

| Input data | USD | JPY | HKD |
|---|---|---|---|
| $C_i$ (year) | 0.15 | 0.01 | 0.7 |
| $K_i$ | NT$ 1.0186 | NT$ 0.0095 | NT$ 0.1310 |
| $D_i$ | US$ 21,160 | ¥ 71,695 | HK$ 5,748 |
| $\sigma_{di}$ | US$ 26,527 | ¥ 126,650 | HK$ 10,109 |
| z | 0.95 | 0.95 | 0.95 |
| $C_0$ | NT$ 105,388.15 | NT$ 287.12 | NT$ 221.25 |
| $P_0$ | NT$ 3,188,025 | NT$ 197,251 | NT$ 165,936 |
| $S_i(1/12)/P_i(1/12)$ | 0.3290 | 0.0650 | 0.5100 |
| $W_i(1/12)$ | NT$ 3.4067 | NT$ 0.0017 | NT$ 1.9721 |
| Q(1/12) | NT$ 103,362.05 | NT$ 315.62 | NT$ 217.70 |
| $P_n(1/12)$ | NT$ 3,126,735 | NT$ 216,830 | NT$ 3,557,017 |
| $S_i(1/13)/P_i(1/13)$ | 0.7280 | 0.1590 | 0.0630 |
| $W_i(1/13)$ | NT$ 1.3769 | NT$ 0.0030 | NT$ 1.4904 |
| Q(1/13) | NT$ 103,151.87 | NT$ 315.85 | NT$ 217.26 |
| $P_n(1/13)$ | NT$ 3,120,377 | NT$ 216,994 | NT$ 3,549,725 |
| $S_i(1/14)/P_i(1/14)$ | 0.7410 | 0.0380 | 0.1140 |
| $W_i(1/14)$ | NT$ 2.7639 | NT$ 0.0027 | NT$ 2.8516 |
| Q(1/14) | NT$ 103,154.83 | NT$ 316.33 | NT$ 217.26 |
| $P_n(1/14)$ | NT$ 3,120,467 | NT$ 217,318 | NT$ 3,549,828 |
| $S_i(1/15)/P_i(1/15)$ | 0.5680 | 0.1470 | 0.4570 |
| $W_i(1/15)$ | NT$ 1.3119 | NT$ 0.0031 | NT$ 2.6936 |
| Q(1/15) | NT$ 103,071.94 | NT$ 317.12 | NT$ 217.05 |
| $P_n(1/15)$ | NT$ 3,117,960 | NT$ 217,863 | NT$ 3,546,417 |
| $S_i(1/16)/P_i(1/16)$ | 0.6090 | 0.2190 | 0.0240 |
| $W_i(1/16)$ | NT$ 2.1863 | NT$ 0.0027 | NT$ 1.6505 |
| Q(1/16) | NT$ 103,101.55 | NT$ 317.18 | NT$ 217.05 |
| $P_n(1/16)$ | NT$ 3,118,855 | NT$ 217,905 | NT$ 3,547,756 |

This study is used GA to solve the daily optimal holding position of USD, JPY and HKD. Let the daily economic order quantity of each foreign currency $q_i$ be the chromosome in the population. The GA trials are 100,000 times, the crossover rate is designed as 0.5 and the mutation rate is designed as 0.1 in this case.

Table 5 and 6 show the values of $\tau$ and $q_i$, i = 1, 2, 3 in the single-foreign-currency and multi-foreign-currency

Table 5: The values of $q_i$, i = 1, 2, 3 for single-foreign-currency Fuzzy NIR-EOQ model

| Date | τ | $q_1$ (US$) | τ | $q_2$ (¥) | τ | $q_3$ (HK$) |
|---|---|---|---|---|---|---|
| 2004/1/12 | 0.6000 | 12,998.54 | 0.3908 | 162,268.40 | 0.5839 | 24,074.00 |
| 2004/1/13 | 0.5323 | 30,536.94 | 0.4039 | 341,892.30 | 0.6394 | 30,463.40 |
| 2004/1/14 | 0.6480 | 24,708.16 | 0.3753 | 410,104.70 | 0.4242 | 31,761.26 |
| 2004/1/15 | 0.3334 | 24,934.78 | 0.7413 | 178,153.30 | 0.4437 | 29,484.18 |
| 2004/1/16 | 0.5505 | 31,104.58 | 0.7735 | 126,515.10 | 0.7106 | 35,460.36 |

Table 6: The values of $q_i$, i = 1, 2, 3 for multi-foreign-currency fuzzy NIR-EOQ model

| Date | τ | $q_1$ (US$) | $q_2$ (¥) | $q_3$ (HK$) |
|---|---|---|---|---|
| 2004/1/12 | 0.9808 | 5,044.17 | 193,489.04 | 1,056.87 |
| 2004/1/13 | 0.9615 | 8,168.16 | 232,550.75 | 4,523.60 |
| 2004/1/14 | 0.9875 | 3,904.38 | 152,619.59 | 2,238.69 |
| 2004/1/15 | 0.9751 | 5,903.86 | 173,514.37 | 4,799.03 |
| 2004/1/16 | 0.9772 | 17,942.58 | 172,437.43 | 14,812.69 |

Table 7: Test for forecast accuracy of $q_i$, i = 1, 2, 3 for foreign currency

| | Single-foreign-currency and multi-foreign-currency fuzzy NIR-EOQ model | MAD | RMSE |
|---|---|---|---|
| USD | Single-foreign-currency | 9,134.83 | 13,083.82 |
| (US$) | Multi-foreign-currency | 4,696.00 | 6,263.63 |
| JPY | Single-foreign-currency | 222,383.39 | 250,992.10 |
| (¥) | Multi-foreign-currency | 129,138.98 | 138,232.95 |
| HKD | Single-foreign-currency | 22,703.82 | 24,434.48 |
| (HK$) | Multi-foreign-currency | 2,719.99 | 4,896.29 |

Table 8: The values of $T(q_i)$, i = 1, 2, 3 by single-foreign-currency and multi-foreign-currency fuzzy NIR-EOQ model

| Date | Observation (NT$) | $T(q_i)$ by Single-foreign-currency (NT$) | $T(q_i)$ by Multi-foreign-currency (NT$) |
|---|---|---|---|
| 2004/1/12 | 960,922.72 | 498,343.55 | 138,942.03 |
| 2004/1/13 | 788,377.31 | 1,099,971.96 | 197,808.08 |
| 2004/1/14 | 1,036,211.40 | 1,349,326.64 | 437,365.18 |
| 2004/1/15 | 955,657.49 | 944,965.12 | 194,464.24 |
| 2004/1/16 | 780,312.60 | 1,067,914.01 | 548,761.11 |

Notes: The formula of total inventory cost of foreign currency. Where $q_i(t)$ is the economic order quantity of the ith foreign currency in the tth trading day and $r_i(t)$ is the forecasting daily foreign exchange rate of the ith foreign currency in the tth trading day as follows:

$$\sum_{i=1}^{n}[q_i(t)+(p_i(t)-s_i(t))]r_i(t)$$

fuzzy NIR-EOQ models solved by genetic algorithm. Table 7 shows the compare with the ability of forecasting of single-foreign-currency and multi-foreign-currency fuzzy NIR-EOQ model. Table 8 shows the daily total cost, $T(q_i)$, i = 1, 2, 3 by single-foreign-currency and multi-foreign-currency fuzzy NIR-EOQ model. All results show the multi-foreign-currency fuzzy NIR-EOQ model can generate the more accurate optimal holding position of foreign currency and decrease the daily total cost effectively.

## CONCLUSION

In this study, the multi-foreign-currency fuzzy NIR-EOQ model solves the multi-foreign-currency optimal inventory problem by genetic algorithm in effect. This means that the multi-foreign-currency fuzzy NIR-EOQ model can provide more effective decision for the decision makers of commercial bank. In the future research, the fuzzy theory and genetic algorithm can attempt to solve the multi-item inventory problem to make the inventory manage more efficiently.

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