A multi-objective ensemble learning approach based on the non-dominated sorting differential evolution for forecasting currency exchange rates

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***Abstract* – Currency exchange rates forecasting is paid a considerable attention of the researchers in the field of forecasting. The neural network is a well-known tool in machine learning. However, two issues are always interested by the scientists: getting toward to global convergence of extreme solutions and determining the optimal weight of the network. This paper proposes the multi-objective method of ensemble learning techniques based on the non-dominated sorting differential evolution (NSDE, a kind of direction-based methods) for training neural networks and application in Foreign Exchange forecasting problems. Two objectives of the selected model are defined based on the Mean Squared Errors and Diversity respectively, in which we used the concept of fitness-sharing based diversity. We experimented the model on four data sets of currency and compared with some of the others that the research community has announced. Through the performance forecasting indicators to show that our new method gives outstanding forecasting results.**

Keywords - ***Currency exchange rates forecasting, ensemble learning, multi-objective evolutionary, non-dominated, differential evolution.***

I. INTRODUTION

Scientists have shown in the field of forecasting the ensemble learning model provides better performance than that of the single model [1] - This is the motivation for the interest of research community. In addition, the combination of the ensemble learning model with evolutionary algorithms to improve the performance of classification and regression methods due to that fact that the ensemble forecasting approach has better productivity than the single model approach, as Gebhard [2] applying time series forecasting with ensemble models based on the single-objective model to build a repeated forecasting in order to find out the number of ensemble members to improve the productivity of the forecasting model; Valentini [3] and the authors proposed time series forecasting using a Hybrid multi-objective evolutionary algorithm in order to optimise the structure of RNNs network, which based on two objectives (number of individuals which are under a threshold Pareto front and training error); Gu [4] the authors demonstrated the balance between the diversity between members of ensembles and the accuracy. Overall these studies mostly focused on considering the amount of community members or diversity (DIV) of the solution or building the objective function in a subclass problem that has a little reference to post regression [5].

Therefore, we designed a new algorithm , namely ELNS_DE, based on NSDE algorithm and adds ensembles learning technique to determine the optimal parameters of the model in order to improve the performance of Foreign Exchange problem (essentially, the problem of regression). In this way, we hope that the advantange of the direction-based approach will be strongly employed to define the efficient ensemble. Two selected goals : mean of square error (MSE) and diversity (DIV) which is the fitness sharing. About the data, we test on 4 data sets (HKD, JPY, EUR and USD) during the time period of 19th October, 2012 to 04th June, 2015 [15]. Test results, being compared with single community approach objectives, NSGA-II algorithm, algorithm NSDE. The proposed method has confirmed the power of ensembles learning technique based on the direction-based evolutionary multi objective algorithms.

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The content of the paper consists of: Section 2 presents the theoretical foundation; the proposed methods for forecasting problem is presented in Section 3; the experimental results and model comparisons are discussed in Section 4; and then Section 5 concludes our paper.

II. LITERATURE REVIEW

A. Time series

1) Definition

A time series is a special conept of a sequential set of data points, which is measured typically over consecutive time steps. It is mathematically defined as a set of vectors $x(t), t = 1, 2, ...$ where t trepresents the time elapsed. The variable $x(t)$ is treated as a random variable [6].

2) Time series analysis

The method of time series analysis is often used to realise the fluctuation of the phenomenon over time. In this approach, observable values are not independent of each other; on the contrary, the dependence of observable values in a number sequence is the foundation of setting up time series forecasting models. The original factors which create oscillate feature include: trend, seasonality, cyclical and irregular [7].

B. Artificial Neural Network

According to Alpaydin [8], neural networks is considered to be a powerful tool to solve the problems that nonlinear forecasting, complex and particularly in cases where the relationship between the processes is not easy to establish explicitly. During the process of training a neural network , it is necessary to determine two components: a network architecture and a set of linked weight values. The identification of network architecture often requires the intellectual of expert (predetermined). The determination of the weight value, while, often use the Back-Propagation (BP) algorithm.

C. Nondominated Sorting Differential Evolution (NSDE) algorithm

This approach was proposed in [9]. It is a modification of the NSGA-II [10]. The difference between this approach and NSGA-II is in the method for generating new individuals. NSGA-II uses a real-coded crossover and mutation operator, but in NSDE, these operators were replaced with the conventional operators of Differential Evolution, a direction-based approach. New candidates are generated using the DE/current-to-rand/1 strategy. The results of the NSDE outperformed those produced by the NSGA-II.

D. Ensemble learning

Ensemble learning is a technique of machine learning that many practitioners used to solve the problems of classification or regression.

In contrast, to the normal machine learning approach that tries to understand a single hypothese from the training data, ensemble learning approach tries to build a set of hypotheses and combines them to use [11] **(Fig. 1)**

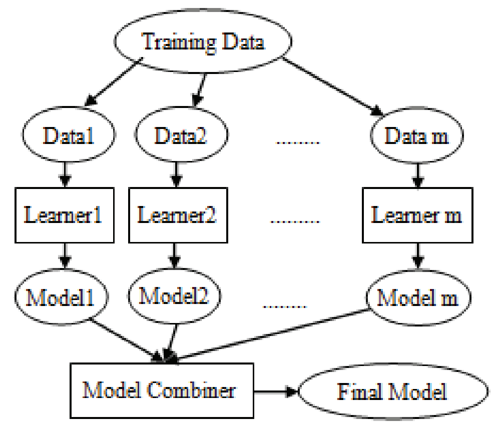

Fig. 1. Ensemble learning model

Krogh & Vedelsby [12] proved that, in a single data point, the squared error of the ensemble's prediction is always less than or equal to the squared error average of the component prediction.

III. ENSEMBLE LEARNING MODEL BASED ON DIFFERENTIAL EVOLUTION AND ITS APPLICATION IN FORECASTING EXCHANGE RATES.

A. The idea

In this research, the authors used a sliding window as shown in **Fig. 2**, in which N input values are ones at consecutive time points in the time series and an output value is next forecasted data value, through the process of training using back-propagation (BP) algorithm will give a weight of the ANNs.

However, BP algorithm has a drawback. That is the network is initialized with randomly chosen weights so it may easily fall into local minima. The reason is that BP uses a gradient-descent procedure, a BP network follows the contour of an error surface with weight updates moving it in the direction of steepest descent. The network will always find an errorless solution (Such errorless solutions are called global minima). However, complex error surfaces can contain many local minima, some minima are deeper than others so it is difficult for gradient descent to find a global minima. Instead, the network may fall into local minima which represent suboptimal solutions (**Fig. 4**).

In this research the authors will design a ensemble learning method based on an evolutionary algorithm NSDE to optimize the network's weight. Specifically, we will try to find out the region containing the global extreme and put BP's starting location in this region to avoid being trapped in a local extremes.

In [7] the authors came up with a solution to this problem by encoding each individual is a weight of ANN and using NSGA-II to find out the pareto front containing optimal individuals. Then we set the individuals as initializations of ANN.

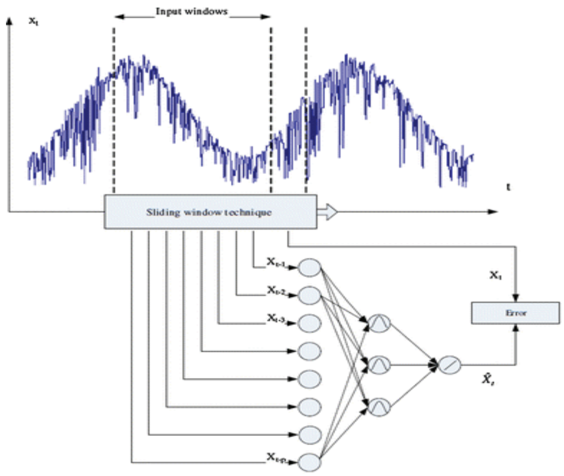

Fig. 2. Window and ANN in time series.

This solution has given good results, however by taking the whole individuals locating on the pareto front so there are some individuals that their error values are not really good (but they ensure good diversities), this leads to the error average value of all the individuals were decreased. And this is the reason we offer a new idea for community learning solution with a desire to find out a group of individuals that not only have the smallest error values but also ensure the diversity among the individuals. The general idea of solution is shown in **Fig. 3**

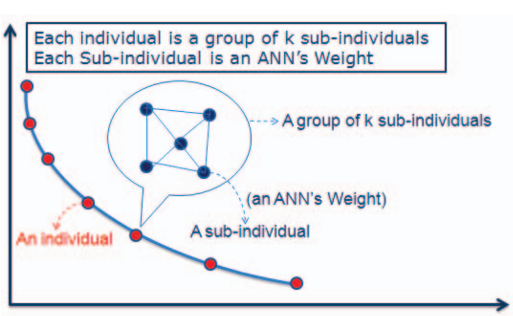

Fig. 3. The general idea of proposed solution

Here, we set up each individual in the population is a group of K sub-individuals, each sub-individual is a ANN's weight (**Fig. 5**). Initially, these individuals will be assigned random values, after the process of evolution (using crossover, mutation and selection operators of Differential evolution (DE) algorithm), individuals that best meet all objective functions (using Non-dominate sorting procedure of NSGA-II algorithm) will be retained.

However, instead of taking all these individuals, we will only select individual that has the smallest error. This individual itself is a set of K sub-individuals (or K ANN's weights).

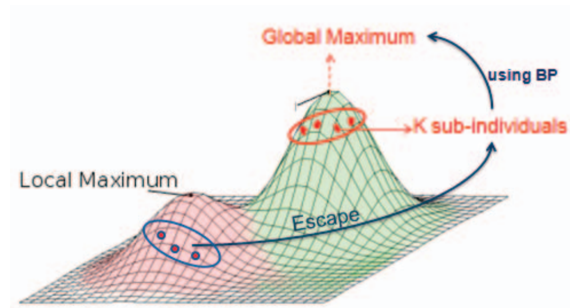

Fig. 4. The local and global maximum

We will choose these K sub-individuals, however it should be noted that they are still in the area that contains the global extreme but not totally focused on that point (**Fig. 4**). Therefore, in order to further optimize, we continue refine these K sub-individual by the BP algorithm. Our final results will be K optimal ANNs. This means we will have a community of K learning models $(ANN_1, ANN_2, \ldots, ANN_K)$ and the final forecast results will be averaged from this ensemble learning.

B. Individuals encodings

The weights (and biases) in the neural network are encoded as a list of D real numbers **(Fig. 5)** or each sub-individual is a D-dimensional parameter vector.

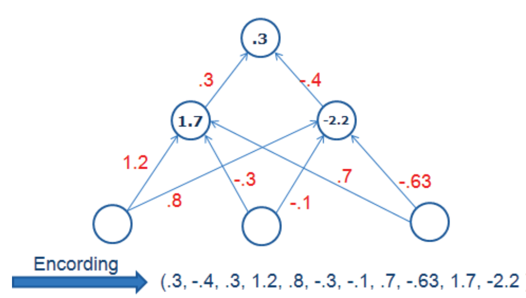

Fig. 5. Encording a Network on an Individual.

In this study, the genes (nodes) are randomly initialized in the range (-1.5, +1.5).

C. Operators

Here we use mutation and crossover operators of the DE algorithm and selection operator of the NSGA-II.

1) Mutation

The mutation is performed between nodes at the same position of parents. New node are generated by adding the weighted difference between two population nodes to a third node. There are some variants of the mutation: DE/rand/1; DE/Current- to-rand/1;... (**Fig. 6**).

Here "F" scales the influence of the set of pairs of solutions selected to calculate the mutation value.

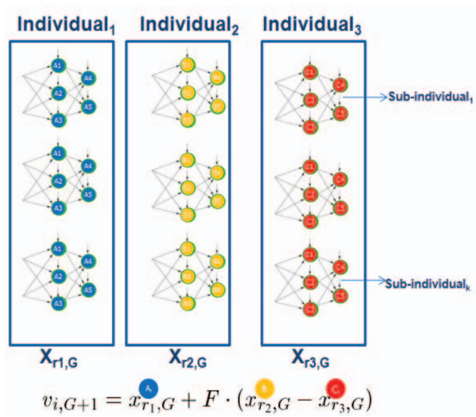

Fig. 6. Illustration of the mutation process

For each individual, a mutant vector is generated according to: $V_{i,G+1}= X_{r1,G}+F.(X_{r2,G}-X_{r3,G})$ (1)

with random indexes r_1, r_2, r_3 ϵ {1,2,..NP}(NP is the population size) integer, mutually different. It means that for each node jϵ{1,2...D*K }(with K is the number of sub-individuals and D is the number of nodes in each sub-individual), the mutant vector $V_{ji,G+1}= X_{jr1,G}+F.(X_{jr2,G}-X_{jr3,G})$.

2) Crossover

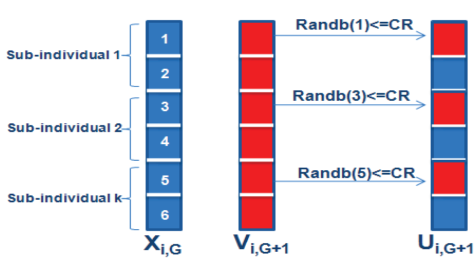

Fig. 7. Illustration of the crossover process for 6-dimensional vectors. (j=1,2.., D*K=6)

In order to increase the diversity of the perturbed parameter vectors, crossover is introduced. Here, we use crossover-nodes method (**Fig. 7**). New individuals are generated by the formula (2):

$$U_{i,G+1}=(U_{1i,G+1}, U_{2i,G+1},..., U_{(D*K)i,G+1}) \quad (2)$$

where $U_{ji,G+1}=\begin{cases} V_{ji,G+1} \ if (rand(j) \leq CR) \ or \ j = rndi \\ X_{ji,G} \ if \quad else \end{cases}$

j=1,2...D*K. (3)

In (3), *rand(j)* is the jth evaluation of a uniform random number generator with outcome ϵ[0;1]. CR is the crossover constant ϵ [0;1] which has to be determined by the user. *rndi* is a randomly chosen index ϵ1,2,..., D*K which ensures that $U_{i;G+1}$ gets at least one parameter from $V_{i;G+1}$

Here "CR" controls the influence of the parent in the generation of the offspring. Higher values mean less influence of the parent in the features of its offspring.

3) Selection

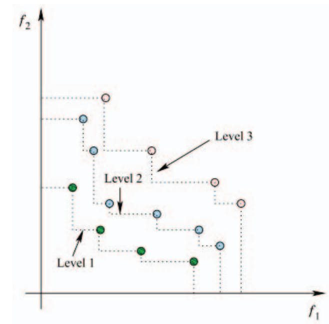

Fig. 8. Ranking process of the nondominated sorting approach.

At each generation, parents and children are compared in order to select the best of them to conform the next population. One of the most popular mechanisms used to select the best individuals from the combined population of parents and children is the so-called nondominated sorting approach (**Fig. 8**). This approach is based on the Pareto ranking mechanism firstly proposed by Goldberg in 1989 [13]. The nondominated sorting mechanism ranks the individuals of the population in different levels in the following way and Individuals with lower rank are always preferred for selection.

D. Objective functions

In the forecast, the accuracy is the most important factor, it is to be measured through error values. There are many available to quantify the error Measures time series prediction performance, but the more accurate measure are commonly adopted Forecasting namely the Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE). In this paper the authors choose MSE which is calculated according to the formula (4) as the first objective function.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(x_t - x_{t+1}\right)^2 \quad (4)$$

Where: n - the number of data value; x_t - real value; x_{t+1} - forecasting value (This value is averaged from K ANNs).

Another factor is also very important is the diversity of individuals. Especially with ensemble learning, since each machine can only respond well to certain inputs. Therefore, the more diverse machines are the more they responds well to many types of different input data.

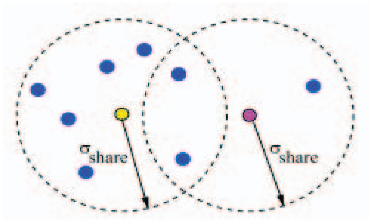

Fig. 9. Fitness sharing method.

In this study, we base on the Fitness sharing method [14] (**Fig. 9**) to calculate the diversity of each individuals. Each individual i, the diversity (DIV_i) is calculated by the following formula:

$$DIV_i = \sum_{j \in Pop} Sh\left[d[i,j]\right] \tag{5}$$

$$\begin{cases} Sh[d] = 1 - d/\sigma share \ (d \le \sigma share) \\ Sh[d] \ = \ 0 \ (d \ge \sigma share) \end{cases}$$

```
NP: Number of individuals population
NS: Number of Sub-individual in an individual

BEGIN
  %-------------Step 1: Using NSDE to get best individuals---------
    Create a random initial population xi,G ∀i, i = 1, . . . , NP
    Calculate 2 objectives: MSE and DIV for each xi,G ∀i, i = 1, . . . , NP
    DO
       FOR EACH Individual_i in population
          FOR EACH Sub-Individual_j in Individua_i
             FOR EACH genes in a sub-individual_j
                Using Mutate and Crossove of DE to create new genes
             END FOR
          END FOR
          Calculate 2 objectives: MSE and DIV for new Individual
          Add new individual to population.
       END FOR
       // Using NSGA2 to Select NP best individuals.
       Ranking base on 2 objectives and create Fronts
       Select NP best individuals from the Fronts into new population.
    WHILE(Condition)
    %---------------Step 2: Refine using BP--------------------
    Get individuals in Front(0)
    Sort in descending order base on MSE value.
    Select individual which has lowest MSE value (or best individual).
    FOR EACH Sub-Individual_i in Best individual
       Using BP to train Sub-individual_i
    END FOR
    %-----------Step 3: Calculate forecasting accuracy (MFE)----------
    FOR EACH Sub-Individual_i in Best individual
       Calculate error_i
    END FOR
    Calculate Mean Forecast Error (MFE) = SUM (error_i) / NS
END
```

Fig. 10. The pseudocode of proposed algorithm

Where: $d[i,j]$ - the Euclidean distance between two individuals i and j; σ_{share} - the radius of the neighborhood.

In short, in this study we use two objective function as follows:

$$\begin{cases} f_1 = MSE \\ f_2 = DIV \end{cases} \tag{6}$$
$$\min\{f_1\}; \max\{f_2\}$$

E. Ensemble learning using NSDE (ELNS_DE algorithm)

The pseudo code of algorithm is shown in **Fig. 10**. The algorithm consists of three main steps:

+ Step 1: Find out the region that contains the global extreme by using algorithms NSDE.

+ Step 2: Using the algorithm BP to drag the best individual to the extreme point.

+Step 3: Using the refined individual in forecasting the exchange rate.

In the first step, once the new individual is obtained using DE operators, the new population is combined with the existing parents population and then the best members of the combined population (parents plus offspring) are chosen based on the fast nondominated sorting approach of NSGA-II.

In the second step, only individual that has lowest MSE value is chosen to continue refining. We consider it as the best individual because it satisfies both criteria: the smallest forecasting error (this is the most important criteria) and sub-individuals that it contains have allowed diverse level.

In the third step, a community of best sub-individuals in the best individual will be used as the learners (Fig. 2). At this time, we put real data sets through each of the sub-individual (or ANNs) to calculate each forecasting data set. The final forecasting error value will be calculated based on the real data set and the average of forecasted data set which is produced by ensembles of the sub-individuals.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Data description

In this experimental, we used 4 data sets (HKD, JPY, EURO and USD) in the period from 2012 to 2015. In order to evaluate the effectiveness of proposed algorithm, the total available data were divided into two parts: training data and test data. Currently, we selected test data rate of 30%.

B. The trial setting parameters

Based on the proposed approach and the 4 data sets presented above, authors conducted the installation program. The program has features such as: training, analysing and forecasting forecasting exchange rates. In order to assess the effectiveness of the proposed algorithm, we compared it with others predictions. Table 1 and Table 2 show the parameter settings. The values of these parameters are selected through experiments.

TABLE 1. EXPERIMENT PARAMETTERS OF ANN MODEL.

ANN	
Learning rate	0.03
Number inputs	5
Number hiddens	10
Number outputs	1
The iterations of BP	1000
Rate test data (%)	30

TABLE 2. EXPERIMENT PARAMETTERS OF ELNS_DE ANGORITHM.

ELNS_DE	
Population size	50
Crossover probability	0.9
Mutation probability	0.5
Generations	1000
Number inputs	5
Number hiddens	10
Number outputs	1
The iterations of BP	1000
Rate test data (%)	30

C. Experimental Results

The authors ran randomly 30 times experiments to compare three types of mutations to the selection of the members of different ensemble learning (K = 5,7,9,11) on the same 4 data sets exchange rate. The results showed that K = 5 and 2 mutation types (DE/Current- to -rand/1, DE_Rand_1) give small error values. In comparison, DE/Current-to-rand/1 type gives smaller error values than DE/Rand/1 type on 4 data sets (see Table 3). In addition, the authors also compare the proposed method with other methods: EMSEMBLE_Selection, RANDOM FOREST (by using Weka [16]), NSGA-II and 2 models of ELNS_BP [7] in both 2 types of mutations. The results in Table 3 clearly indicate that ELNS_DE method gives smallest error values with most of test data (except JPY case) (see Table 3). Finally, the authors compare running time of algorithms. The results in Table 4 show that in order to achieve smaller error values, ELNS_DE algorithm has to barter between smaller error values and running time. Consequently, ELNS_DE algorithm has longer running time. On 4 data sets with 3 methods, the running time of ELNS_DE algorithm is faster than NSGA-II on 2 data sets (HKD and USD).

V. CONCLUSION AND FUTURE RESEARCH

This paper has proposed an Ensemble learning using NSDE algorithm in forecasting Currency Exchange Rates. The experimental results indicate that the proposed algorithm could significantly outperform NSGA-II and NSDE on these test instances. In this ensemble learning model, the role of the learners are the same, the final result is the average value of these learners. This is not the optimal solution of the ensemble learning where each learners will have a different impact on each different data sets. In the future, we plan to develop this algorithm by applying the idea of Adaboost algorithm.

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[15] http://www.rba.gov.au/statistics/frequency/exchange-rates.html.
[16] http://www.cs.waikato.ac.nz/ml/weka/

TABLE 3. COMPARING RESULTS OF ELNS_DE METHOD TO OTHER FORECASTING METHODS
(Smallest error value given in **Bold**, *italic*)

Method		JPY				HKD			
		MSE		MAE		MSE		MAE	
		Train	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*
EMSEMBLE_Selection		***0.00E+00***	***0.00E+00***	3.70E-03	5.10E-03	***0.00E+00***	1.00E-04	6.00E-04	7.70E-03
RANDOM FOREST		0.00E+00	1.00E-04	1.30E-03	7.80E-03	***0.00E+00***	2.00E-04	3.00E-04	9.70E-03
NSGA-II		4.47E-08	3.97E-08	1.86E-04	1.70E-04	5.70E-06	5.86E-06	2.11E-03	2.04E-03
ELNS_BP1 (K1=1) [7]		3.62E-09	1.39E-08	4.39E-05	9.81E-05	3.58E-07	4.70E-06	4.40E-04	1.92E-03
ELNS_BP2 (K=3) [7]		4.17E-09	1.12E-08	4.64E-05	7.70E-05	4.24E-07	2.53E-06	4.59E-04	1.22E-03
ELNS_DE	DE/Rand/1	4.72E-09	2.78E-09	4.95E-05	2.60E-05	5.82E-07	1.85E-07	5.42E-04	1.91E-04
	DE/Current- to -rand/1	4.31E-09	2.65E-09	4.66E-05	***2.45E-05***	5.56E-07	***1.83E-07***	5.23E-04	***1.83E-04***

Method		EURO				USD			
		MSE		MAE		MSE		MAE	
		Train	*Test*	*Train*	*Test*	*Train*	*Test*	*Train*	*Test*
EMSEMBLE_Selection		3.00E-04	3.00E-04	9.00E-03	1.18E-02	1.00E-04	8.00E-04	4.70E-03	1.69E-02
RANDOM FOREST		***0.00E+00***	4.00E-04	2.40E-03	1.40E-02	***0.00E+00***	7.70E-03	2.10E-03	6.16E-02
NSGA-II		5.21E-04	4.66E-04	2.03E-02	1.90E-02	2.76E-04	4.63E-04	1.46E-02	1.86E-02
ELNS_BP1 (K1=1) [7]		4.15E-05	1.04E-04	4.68E-03	7.55E-03	2.14E-05	8.13E-05	3.38E-03	6.90E-03
ELNS_BP2 (K=3) [7]		4.79E-05	2.76E-04	4.94E-03	1.35E-02	2.33E-05	2.52E-04	3.53E-03	1.25E-02
ELNS_DE	DE/Rand/1	5.31E-05	4.79E-05	5.15E-03	***4.12E-03***	3.86E-05	2.51E-05	4.62E-03	2.04E-03
	DE/Current- to -rand/1	5.33E-05	***4.69E-05***	5.15E-03	***4.12E-03***	3.64E-05	***2.44E-05***	4.44E-03	***2.02E-03***

TABLE 4. COMPARING THE RUNNING TIME OF DIFFERENT FORECASTING METHODS TO ELNS_DE METHOD
(Smallest error value given in **Bold**, *italic*)

Method		Time			
		JPY	*HKD*	*EURO*	*USD*
NSGA-II		***1.05E+02***	9.23E+01	***1.03E+02***	6.33E+01
ELNS_BP1 (K1=1) [7]		7.06E+02	8.32E+02	2.11E+02	8.13E+01
ELNS_BP2 (K=3) [7]		4.42E+02	***2.54E+03***	6.40E+02	***2.38E+02***
ELNS_DE	DE/Rand/1	2.29E+01	2.17E+0	2.64E+01	1.54E+01
	DE/Current- to -rand/1	2.27E+01	2.27E+01	2.63E+01	1.63E+01