



Foreign exchange forecasting and portfolio optimization strategy based on hybrid-molecular differential evolution algorithms

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Abstract

At present, the COVID-19 epidemic is still spreading at home and abroad, and the foreign exchange market is highly volatile. From financial institutions to individual investors, foreign exchange asset allocation has become important contents worthy of attention. However, most intelligent optimization algorithms (hereinafter IOAS) adopt the existing data and ignore the forecasted one in the foreign exchange portfolio allocation, which will result in a huge difference between portfolio allocation and actual demand; at the same time, many IOAS are less adaptable and have lower optimization ability in portfolio problems. To solve the aforementioned problems, this paper first proposed a DETS based on hybrid tabu search and differential evolution algorithms (DEAs), which has excellent optimization ability. Subsequently, the DETS algorithm was applied to support vector machine (SVM) model. Experiments show that, compared with other algorithms, the MAE and RMSE obtained by using DETS optimization parameters are reduced by at least 3.79 and 1.47%, while the CTR is improved by at least 2.19%. Then combined with the DETS algorithm and Pareto sorting theory, an algorithm suitable for multi-objective optimization was further proposed, named NSDE-TS. Finally, by applying NSDE-TS algorithm, the optimal foreign exchange portfolio is acquired. The empirical analysis shows that the Pareto front obtained by this algorithm is better than that of NSGA-II. Since the lower the uniformity index and convergence index, the stronger the optimization performance of the corresponding algorithm, compared with NSGA-II, its uniformity and convergence index decreased by 15.7 and 39.6%.

Keywords Differential evolution algorithm · Tabu search algorithm · Exchange rate forecast · Foreign exchange portfolio · Pareto principle

1 Introduction

Since 2021, the COVID-19 epidemic has still been spreading abroad. Due to the rebound of the US dollar exchange rate index, the international capital flow has been affected to a certain extent, and foreign exchange shows different fluctuations. From financial institutions such as financial institutions to individual investors, foreign

exchange portfolio planning has become important contents worthy of attention (Nicole and Alsafi 2020; Kinat-eder and Campbell 2021; Feng et al. 2021).

In foreign exchange portfolio optimization, the most important thing is exchange rate forecast and portfolio allocation. If we can scientifically predict exchange rate fluctuations and allocate foreign exchange assets reasonably, we can avoid risks and realize the appreciation and preservation of assets (Plíhal 2021). In the field of foreign exchange forecasting, the basic analysis method of exchange rate was first developed, including the interest rate parity theory and the purchasing power parity theory (Du et al. 2021; Černý et al. 2021). These theories establish a linear model between economic factors and exchange rates, such as autoregressive integrated moving average model, the generalized autoregressive conditional heteroskedasticity model and other models, and can be

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certainly explained to some extent the long-term behavior of exchange rate fluctuations (Bollerslev 1986; Al-Gounmeem and Ismail 2020; Lu et al. 2022). Subsequently, scholars turned to technical analysis methods, using historical data affecting exchange rates to make their own forecasts. In recent years, the machine learning model has been continuously developed, and some scholars have introduced it into the exchange rate forecast and achieved good results. Compared with the statistical model, the prediction accuracy of the model has been greatly improved. So, how to establish a model with higher forecasting accuracy and apply it to foreign exchange market forecasting is very important for investors and researchers alike.

In the research in the field of foreign exchange portfolio optimization, the “mean–variance” model proposed by Markowitz was first discussed quantitatively, and then many scholars improved the model (Ortiz and Contreras 2021; Chavez-Bedoya and Rosales 2021; Kang et al. 2021). At the same time, people also began to use this model to quantify benefits and risks and allocate foreign exchange assets according to the quantitative results, so that the theoretical risk is reduced as much as possible and the predicted return rate is improved as much as possible, that is, to solve a multi-objective optimization problem. With the proposal and development of multi-objective optimization algorithms, this problem has been well solved, and scholars are also thinking about how to propose a multi-objective optimization algorithm with stronger optimization ability and more practical significance.

In recent years, with the successful application of classic machine learning models and multi-target investment portfolios in the field of foreign exchange, some scholars have begun to combine the two to realize the whole process from forecasting to portfolio optimization (Li et al. 2015). At present, in the field of foreign exchange, the research in this area is still very rare, and many studies are insufficient and unadvanced, so the research on how to realize the integration model from the accurate forecast of foreign exchange to the optimal allocation of foreign exchange investment portfolio is it has practical significance and theoretical value.

In order to address the above shortcomings, this paper proposed a new optimization algorithm based on hybrid tabu search and DEAs, named DETS, which was adopted to SVM models so that the SVMs could quickly predict data according to historical ones. According to the predicted data, the portfolio was configured with DETS eventually. The main contributions of this paper are as follows: A new optimization algorithm based on hybrid tabu search and DEAs is proposed and named DETS. For the DEAs, this paper proposed a cross factor, improves the out-of-bounds movement rule, and adaptively improves the

tabu rules of TSAs, which makes the results more optimal, diverse, and robust.

1. This paper combines DETS with support vector regression model and optimizes the penalty factor and kernel function variance to obtain the forecast data of the exchange rate. Then merge the forecast data with the existing data. Finally, DETS is applied to the multi-objective optimization algorithm for portfolio allocation with good results.
2. This paper makes an adaptive improvement on the data aggregation method in the field of foreign exchange forecasting. This method avoids data fragmentation, absorbs the characteristics of historical data and also retains the current data characteristics well, which can effectively deal with the situation of large exchange rate fluctuations. The experimental results show that when the exchange rate fluctuates sharply, the method proposed in this paper can reduce the MAE and RMSE by 329.61% and 349.28%, respectively, and the prediction trend increases from 0.5333 to 0.9333, and the prediction effect is significantly improved; when the exchange rate fluctuation is not significant, no matter whether the method is adopted or not, the values of the three indicators are basically unchanged.
3. The empirical study of foreign exchange forecasting shows that the mean absolute error (MAE) and root-mean-square error (RMSE) of DETS algorithm have decreased by 3.79 and 1.47%. In addition, the correct trend rate (CTR) increased by 2.19%. At the same time, for foreign exchange portfolio allocation, the empirical analysis shows that the Pareto front obtained by this algorithm is better than NSGA-II. Since the lower the uniformity index and the convergence index, the stronger the optimization performance of the corresponding algorithm, compared with NSGA-II, its uniformity and convergence index decreased by 15.7 and 39.6%. In addition to portfolio optimization, the stability and optimization ability of the algorithm described in this paper are better than that of the contrast one.

At present, the combination of foreign exchange forecasting and portfolio optimization is relatively late, and there are still many theoretical gaps in related fields. This paper studies the above fields. This article consists of five sections, as follows:

The first section introduces the background and significance of the research problem, sorts out the literature on foreign exchange portfolio allocation research, analyzes the shortcomings of the existing research, clarifies the research objectives, research methods and research innovations, and sorts out the structure of the full text.

The second section sorts out and summarizes the relevant references from the perspective of the application of classic machine learning models in foreign exchange forecasting and the application of intelligent optimization algorithms in investment portfolios and introduces some theories, methods, and models involved in this paper.

The third section first introduces the steps and model principles of DETS and applies it to the parameter optimization of SVR and then proposes a data aggregation method, which can effectively absorb the characteristics of historical data; finally, this paper proposes a non-dominated sorting hybrid differential taboo algorithm that combines DETS algorithm and Pareto sorting theory, named NSDE-TS.

The fourth section introduces the experimental environment, parameter settings, and datasets, etc., and proves that DETS has a good effect on parameter optimization and optimization through experiments. NSDE-TS has good multi-objective optimization capability and practicability. The fifth section summarizes the entire article.

2 Literature review

2.1 Related work

- (1) Exchange rate forecasting model: Cao first introduced machine learning algorithms into foreign exchange forecasting in 2005 and achieved good results (Cao et al. 2005); in 2008, Huang combined the particle swarm optimization algorithm and the support vector machine algorithm, using the particle swarm optimization algorithm based on binary coding. Selecting the kernel parameters of features and support vector machines, the results show that the algorithm can accurately input features and greatly improve the classification accuracy (Huang and Dun 2008); in 2011, Hsieh et al. used the Haar wavelet method to denoise the data. Simulation experiments were carried out on seven international stock indices, and the results showed that the model predictions were highly accurate and could be used in real-time trading systems (Hsieh et al. 2011); in 2014, Amin et al. optimized the parameters of the forward neural network using the GA algorithm. It shows that the prediction accuracy after the introduction of GA algorithm is improved by 7% compared with the previous model (Amin et al. 2014); in 2015, Chai et al. used genetic algorithm, particle swarm optimization algorithm, simplicity method, and grid search method to optimize the least squares support vector machine model, the prediction results show that the genetic algorithm has the best performance (Chai et al. 2015); in 2019, Kozodoi et al. introduced the non-dominated sorting genetic algorithm in the feature selection problem. Compared with the algorithm, the number of features selected by this method is smaller and the corresponding expected return is higher (Kozodoi et al. 2019); in 2021, Punitha et al. mixed the artificial immune system algorithm with the artificial bee colony algorithm and applied it to the neural network. In parameter optimization, the results show that the model performs better (Punitha et al. 2021). Many other optimization methods can be found in Abed-Alguni et al. (2022); Alkhateeb et al. 2022; Abed-Alguni and Alawad 2021).
- (2) In summary, we found that the research on optimizing machine learning models in financial markets mainly focuses on data preprocessing, model parameter optimization, and model fusion and improvement. However, we can find that although some literatures have used hybrid algorithms for parameter optimization problems, there is still no paper that can propose a targeted hybrid intelligent optimization algorithm for foreign exchange forecasting models. Therefore, this paper proposes a strong optimization ability and adaptability good hybrid optimization algorithm. At the same time, in the field of foreign exchange market forecasting, there are very few studies on the selection of data features, and most of them copy the data preprocessing of stock forecasting. Therefore, this paper proposes a data preprocessing method for foreign exchange forecasting.
- (3) Portfolio model: In 2000, Chang et al. were no longer limited to unconstrained combinatorial optimization, but applied various algorithms to solve portfolio optimization problems under cardinality constraints (Chang et al. 2000); Streichert continued to solve the problem using other evolutionary algorithms in 2003. After solving this problem, the experimental results are good (Streichert et al. 2004); then in 2009, Cura used the PSO algorithm to effectively solve the problem and achieved good results (Cura 2009). The above are all studies on single-objective optimization problems, while Lin et al. used multi-objective genetic algorithm to solve the investment portfolio optimization problem as early as 2001. Experiments show that the optimization ability is greatly improved after using the GA algorithm (Lin and Wang 2001); similarly, in 2005, Armananza and Ong, respectively, compared and used a variety of intelligent optimization algorithms to solve multi-objective optimization problems (Crama and Schyns 2003; Ong et al. 2005; Armananzas and Lozano 2005); in 2006, Gomez mixed simulated annealing algorithm and genetic algorithm to solve the

portfolio problem, and the experimental results showed that mixed algorithms are more capable of optimization (Gomez et al. 2006); in 2009, Dallagnol compared particle swarm optimization and genetic algorithms in portfolio applications and showed that PSO is faster than GA in terms of number of iterations and total running time (Dallagnol et al. 2009); in 2012, Villeneuve and FJ et al., by comparing the ant colony optimization algorithm with simulated annealing algorithm and genetic algorithm, found that the portfolio obtained by ACO is better and can optimize the technically incompatible portfolio without using a penalty function (Villeneuve and Mavris 2012); in 2015, Bin Shalan, SA used the hybrid clonal selection and particle swarm optimization algorithm to solve the multi-objective portfolio optimization problem in the Saudi Arabian stock market (Bin Shalan 2015); in 2020, Liu proposed a hybrid imperialist competitive evolutionary algorithm, and it turns out that this algorithm can obtain more efficient frontier solutions (Liu et al. 2020).

Based on the above literature, we can find that the application of intelligent algorithms in investment portfolios mainly focuses on the introduction of new algorithms, the improvement of algorithms, and the fusion of algorithms (Abualigah et al. 2021a, b, 2022; Agushaka et al. 2022; Oyelade et al. 2022; Ezugwu et al. 2022; Mahajan et al. 2022a, b; Ekinici et al. 2022). Early scholars mainly introduced intelligent algorithms in the field of investment portfolios (Al-qaness et al. 2022a, b; AlRassas et al. 2022). In the subsequent research, we gradually began to pay attention to the optimization ability of the algorithm, the adaptability of different problems, the scope of application, and the prediction accuracy after optimizing the machine learning model. However, although there are some literatures that combine the improvement and integration of intelligent optimization algorithms with practical problems, there is still no article that can combine these to realize the real use of intelligent optimization algorithms in different target dimensions, from forecasting to investment. Therefore, this paper proposes a fusion algorithm with strong optimization ability and can realize the whole process optimization.

2.2 Related terminologies

2.2.1 Principle of support vector machine algorithm

Support vector machine (SVM) is a classic machine learning model, which has been widely used to solve classification and regression problems due to its advantages

of simple structure and global optimality in solving small sample data problems (Akhtar et al. 2022). The principle is shown in Fig. 1.

Vapnik et al. further generalized SVM by introducing an insensitive loss function and obtained the support vector regression (SVR) algorithm (Mozaffari et al. 2022). The algorithm can approximate any nonlinear continuous function at arbitrary precision and is suitable for solving the problem of complex nonlinear system identification (Zhang et al. 2022). Because of this, the SVR model has excellent predictive ability under the condition of small samples, which is suitable for the needs of short-term exchange rate forecast (Fernandez-Rodriguez et al. 2000). The main idea of SVR is to use the Mercer kernel expansion theorem to project the input original sample into a high-dimensional feature space with the help of nonlinear mapping method. The linear function is used in the high-dimensional space to correspond to the nonlinear function of the original space.

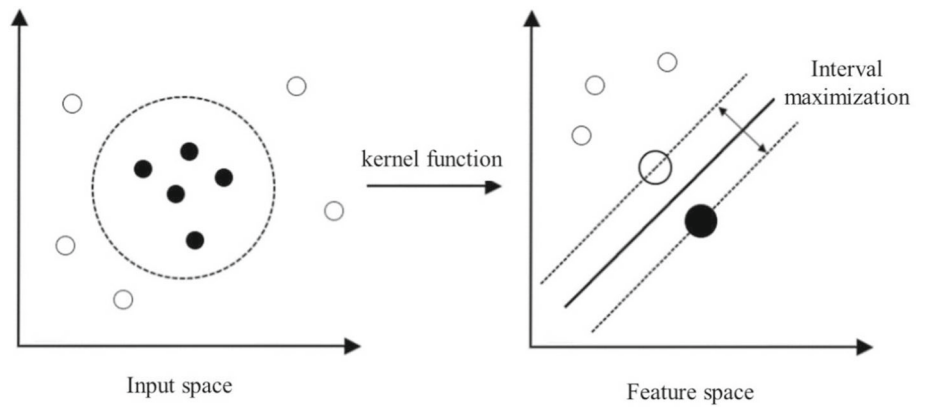
After the data subspace is determined, the generalization ability of the learning machine is optimized by adjusting the ratio between the confidence range of the learning machine and the empirical risk. “Under-learning” means that the smaller the c is set, the smaller the penalty for the training error greater than γ is, and finally, the complexity of the learning machine is smaller and the corresponding empirical risk value is larger; otherwise, it is called “over-learning.” The variance γ of the kernel function clarifies the error requirements of the regression function. When γ is smaller, the error of the regression function is smaller. Therefore, selecting a high-quality $[c, \gamma]$ parameter combination can obtain good prediction results and classification accuracy, so it is very important to determine this parameter combination.

2.2.2 Principle of differential evolution

Differential evolution (DE) was proposed by Storn and Price in 1995, which is a population-based stochastic optimization algorithm and provides a new strategy for solving complex parameter optimization problems (Mashwani et al. 2021). The core idea of the algorithm is to simulate the process of natural selection and mutation. Through the natural selection strategy, the inferior solutions are eliminated; through the reproduction mechanism, the superior solutions are retained.

The differential evolution algorithm is based on a population composed of several individuals with corresponding solutions, iteratively saves the good and the bad by means of difference, mutation, and selection, then realizes the evolution of the population, and finally completes the global optimization task. The biggest feature of the algorithm is that it adopts a self-referential mutation strategy

Fig. 1 Schematic of SVM



during mutation, which significantly improves the search speed of the algorithm. Differential evolution algorithm is an intelligent optimization algorithm based on random parallel global search. Due to its simple structure, good adaptability, and strong global optimization ability, it has achieved success in many fields such as solving complex global optimization problems (He et al. 2021). The pseudocode of DE is as follows.

and Ozsen 2020). The main idea of the TS algorithm is to iterate continuously based on the neighborhood search and to record the searched neighborhood or the optimal movement by setting the storage algorithm of the tabu table, and in the future search, this kind of the reverse movement of the movement is prohibited, so that the entire search process can avoid falling into local optimum, and

Input: variation scaling factor F ; crossover rate CR ; population size NP ;

Output: optimal solution x^*

- (1) Initialize the population, $G=0$;
 - (2) while termination condition not met do
 - (3) for $i=1$ to NP do
 - (4) Three individuals are randomly selected $x_{r1,G}, x_{r2,G}, x_{r3,G}$;
 - (5) $y_{i,G} = x_{r1,G} + F \times (x_{r2,G} - x_{r3,G})$;
 - (6) for $j=1$ to N do
 - (7) if $\text{rand}[0,1] \leq CR$ or $j=j_{\text{rand}}$ then
 - (8) $y_{i,G}^j = t_{i,G}^j$;
 - (9) else
 - (10) $y_{i,G}^j = x_{i,G}^j$;
 - (11) end if
 - (12) end for
 - (13) end for
 - (14) end while
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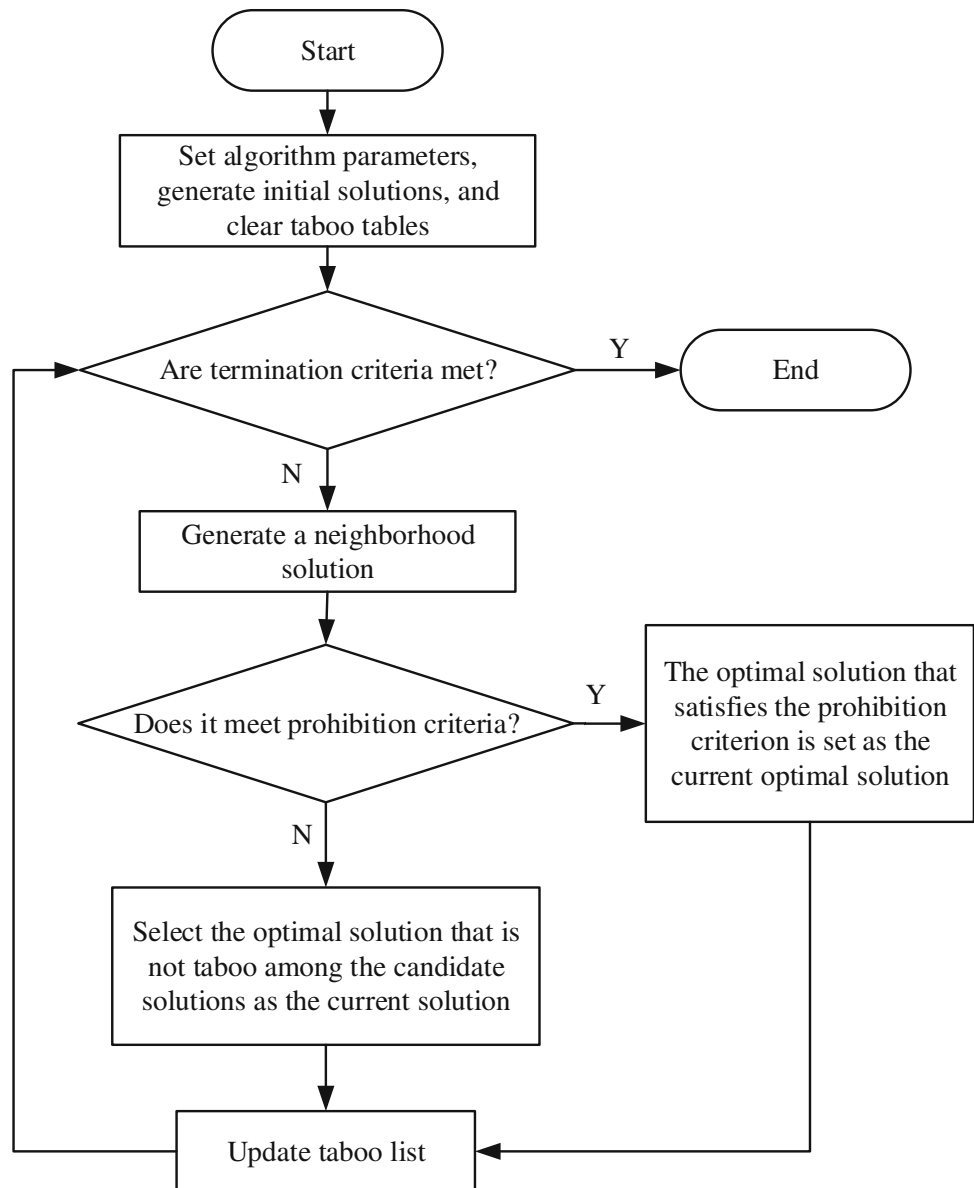
2.2.3 Principle of tabu search

The main idea of tabu search (TS) was first proposed by Glover et al. in 1986. This algorithm simulates the memory function of the human brain and is a sub-heuristic random search algorithm with global and gradual optimization (Lee

the contempt criterion is used to ensure that the movement of the whole search process can obtain a better quality solution is not prohibited, and finally the optimal solution will not be missed in the entire algorithm search process (Rahdar et al. 2022).

The tabu search flowchart is shown in Fig. 2.

Fig. 2 Tabu search steps



3 Proposed methodology

DE can perform random parallel global search and has little dependence on initial values, so it is suitable for front-end initial solution generation algorithm. TS has good hill climbing ability, which is suitable for back-end optimization algorithm. In this paper, DE and TS are fused. The out-of-bounds checking of DE is improved to better keep the original population genes and speed up convergence. Meanwhile, the TS neighborhood moving rules and tabu list are redefined, which can improve the optimization performance and robustness of the algorithm. Based on this, a fusion algorithm based on improved DE and TS is formed, named DETS (Singh and Khamparia 2020;

Mohammed and Duffuaa 2020; Maroufpoor and Maroufpoor 2019).

(1) Support vector machine regression algorithm based on DETS: In this paper, DETS is used to optimize the parameters of the existing support vector machine regression algorithm and make predictions and finally get the prediction result. The detailed process of the overall algorithm is as follows (Sadeghi et al. 2021; Gul and Alpaslan 2021; Zheng et al. 2022):

Step 1 Generate training and test sets and normalize the data to get $Data'_i$.

$$Data'_i = \frac{Data_i - Data_{min}}{Data_{max} - Data_{min}} \tag{1}$$

Step 2 Preprocess the input set X_{test} in the test set and aggregate it.

Step 3 Set the population size (Pop), cross-rate P_c , mutation rate P_m , etc.

Step 4 Population initialization. Each individual is randomly generated, and represents a set of parameter values c and y . The reciprocal of the prediction error is defined as degree of adaption (fitness) of the population.

Step 5 Perform both mutation and crossover at the same time.

(1) Mutation: same as the classic DE algorithm.

In order to avoid premature convergence, the adaptive factor is introduced (Fama 1965):

$$\lambda = e^{\frac{G_m - G}{G_m + 1 - G}} \tag{2}$$

$$F = F_0 \cdot K^\lambda \tag{3}$$

F_0 is a mutation operator; G_m represents the maximum evolution algebra; G represents the current evolution algebra; and K is a selected fixed value.

At the beginning of the algorithm, the adaptive mutation operator is approximately at KF_0 . The size of K needs to be measured according to scale, and the value of $2 \sim 5$ can be taken according to the actual situation. Since the initial F value is large, the individual diversity can be effectively maintained, and the global search can be realized. The mutation rate is close F_0 to each other in the later period, so that the excellent individuals are retained, and the local depth search is realized.

(2) Crossover: cross-exchange the individual $X_m(c_m, y_m)$ with the individual

$X_n(c_n, y_n)$ selected according to roulette to obtain the $X'_m(c_m, y_m)$ and $X'_n(c_n, y_n)$.

(3) Checking: check the updated population individuals one by one.

If the component $X_i > Max_i$, let $X_i = Max_i - rand \times (X_i - Max_i)$; if $X_i < 0$, let

$X_i = rand \times (-X_i)$; ($rand$ is a random number from 0 to 1, Max_i is the maximum boundary value of the component X_i , $X_i \in [-Max_i, 2Max_i]$).

Step 6 Calculate fitness, perform roulette selection, and update the optimal parameter combination and the state of the population. Judge whether the loop end condition is met. Continue, if the conditions are met. If not, jump back to Step 5.

Step 7 Finish the loop and output the optimal combination $[c_{good}, y_{good}]$ in Step 7. At this time, define the spatial movement $[0.5, 0.3, 0.1, 0.05, 0.03, 0.01] \times w$ and the overall movement number G_t , and W represents the maximum boundary value-current value ($k > 0$) or current

value-minimum boundary value of the argument ($k < 0$). This definition also ensures that the corresponding variable does not go out of range when the boundary is moved. The above matrix is a whole movement and an alternate generation taboo table is set, so that the first generation is not the original value $[c + kW, y - kW]$. $[c - kW, y + kW]$ appears in the second generation, which can still speed up the iteration and jump out of the local optimal.

kW is continuously input during each overall movement to generate $[kW, -kW, \dots, 0], \dots, [\dots, kW, \dots, -kW, \dots], \dots, [0, \dots, kW, -kW], \dots, [0, \dots, -kW, kW]$. Record the optimal value and the corresponding coefficient combination for each move, and check whether it meets the taboo condition. The optimal value satisfied is substituted into the next iteration. Finally, output the optimal value $[c_{best}, y_{best}]$.

Step 8 Substitute $[c_{best}, y_{best}]$ to establish and train a SVM model.

Step 9 Predict the test set. Inverse normalization and output the final result. The schematic diagram of the algorithm is shown in Fig. 3.

(2) Data preprocessing based on absorbing historical data: Although the exchange rate does not generally rise and fall, once the exchange rate fluctuates sharply, many models fail. So how to maintain the basic accuracy and trend correctness of the forecast in this situation has become an urgent problem to be solved. For example, since the Russian-Ukrainian conflict, the ruble has experienced sharp rises and falls. Since April, the average daily fluctuation has even reached more than 5%. At this time, the handling of fluctuation data is very tested, and there is no way to rely on prediction models alone. Therefore, this section proposes a data processing method that can absorb fluctuation trends and achieve more accurate predictions.

The dataset input in the test set of this paper is formed by a five-day cycle. However, changes in foreign exchange are historically continuous to some extent, not separated by a 5-day cycle. Therefore, data aggregation is needed to make the data better reflect the historical data of foreign exchange. The aggregation algorithm is as follows.

Step 1 when the number of days $t_k > 5$, this article divides the dataset into $S_1 = [t_k - 4, t_k]$ and $S_2 = [1, t_k - 5]$, and $S = [1, t_k]$, S is the exchange rate value of 100 units of foreign currency to RMB for 228 days.

Step 2 With regard to S_2 , this paper aggregates data with the same trend: $(t_2 - t_1) \times (t_3 - t_2) > 0$, so $[t_1, t_2, t_3]$ aggregates into a data group. As for $(t_3 - t_2) \times (t_4 - t_3) > 0$, and $[t_1, t_2, t_3, t_4]$ aggregate on the basis of the previous data Group until $(t_k - t_{k-1}) \times (t_{k+1} - t_k) < 0$ appears. At this time, perform weighted aggregation on the previous data group $[t_p, t_{p+1}, \dots, t_k]$, i.e., $t'_m = (t_p + \dots + t_k) / (k - p + 1)$. The original datasets $[t_1, \dots, t_{228}]$ are aggregated into $[t'_1, \dots, t'_n]$.

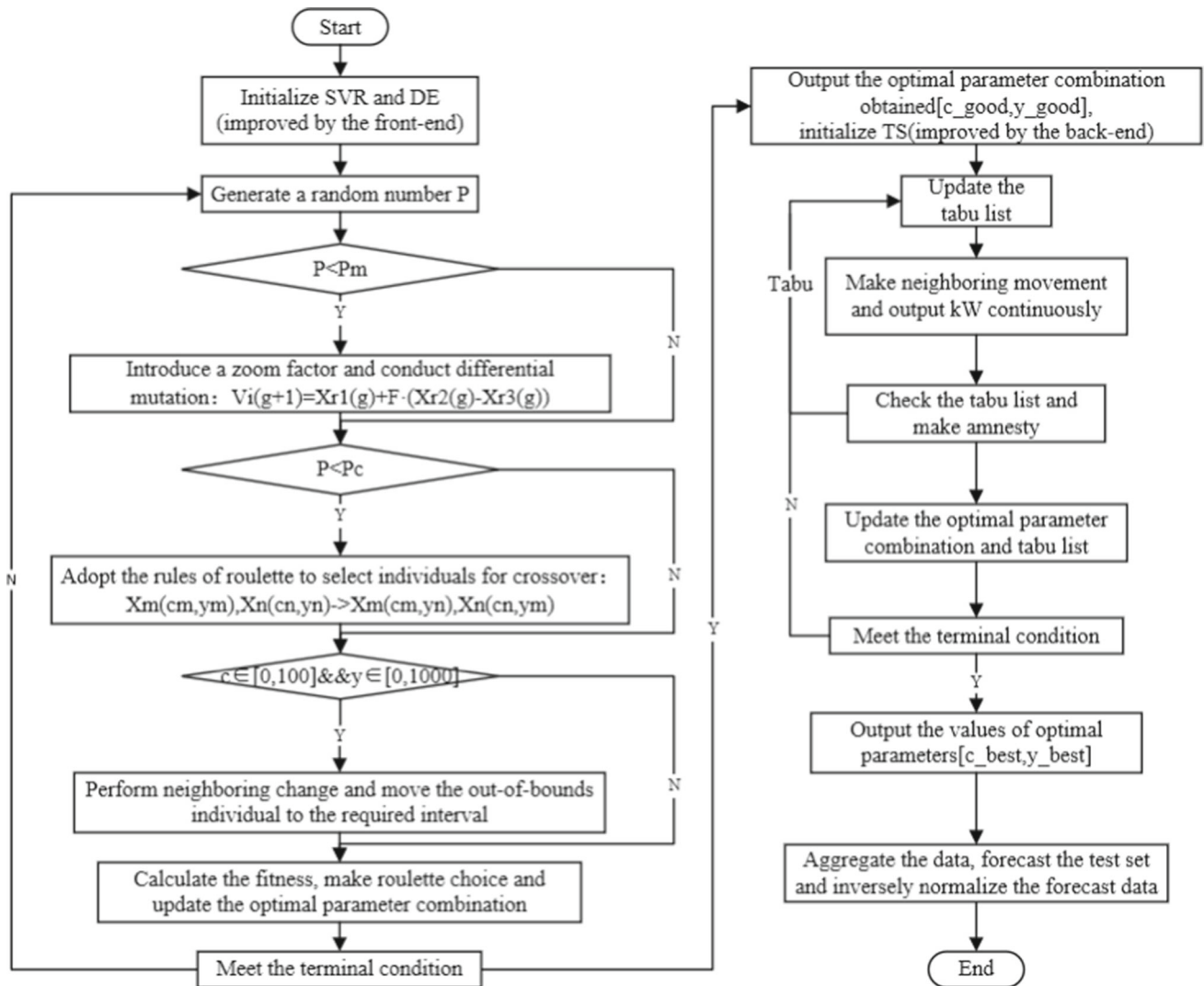


Fig. 3 Schematic diagram of SVR based on DETS

Step 3 For the r th aggregation, judge the quantity m after aggregation.

If $m > 2$, judge whether arbitrary bits are achieved. $(t'_m - t'_{m-1}) \times (t'_{m+1} - t'_m) < 0$

If not, continue aggregation; Else, select the last number t'_n , let $t_{least2} = t'_n$, $t_{least1} = (t'_1 + \dots + t'_{n-1}) / (n - 1)$, $t_{least3} = 0.25 \times (t_{k-4} + t_{k-2}) + 0.5 \times t_{k-3}$, $t_{least4} = 0.25 \times (t_{k-3} + t_{k-1}) + 0.5 \times t_{k-2}$, $t_{least5} = 0.25 \times t_{k-2} + 0.5 \times t_{k-1} + 0.25 \times t_k$. The preprocessing now produces a new test set $[t_{least1}, t_{least2}, \dots, t_{least5}]$.

If $m = 2$, $t_{least1} = t'_1$, $t_{least2} = t'_2$, t_{least3} to t_{least5} defined the same as above.

If $m = 1$, take $t_{least1} = t'_1$, $t_{least2} = 0.5 \times t_{k-4} + 0.5 \times t_k - 3$, $t_{least3} = 0.5 \times t_{k-3} + 0.5 \times t_{k-2}$, $t_{least4} = 0.5 \times (t_{k-2} + t_{k-1})$, $t_{least5} = 0.5 \times t_{k-1} + 0.5 \times t_k$.

Step 4 End the aggregation to generate a new test set.

Through the above preprocessing, the data can better learn about the influence of historical data and can be more effectively applied to the prediction to improve the accuracy of the prediction. In this paper, taking $m > 2$ in Step 3 as an example, the data aggregation diagram as shown in Fig. 4 is drawn.

(3) Portfolio multi-objective optimization algorithm based on DETS: Since the DETS algorithm can search the solution space extensively, it has great advantages in solving multi-objective problems. This paper uses NSGA-II algorithm for reference and applies its non-dominant sorting idea to DETS (Kashyap and Kumari 2020; Jamali and Mallipeddi 2020; Eydi 2021).

Object-function value processing: This paper will take the average value of each objective function of the initial generation population and then compare the mean value of each subsequent objective function, so that all the objective functions are at the same level. Meanwhile, the fitness

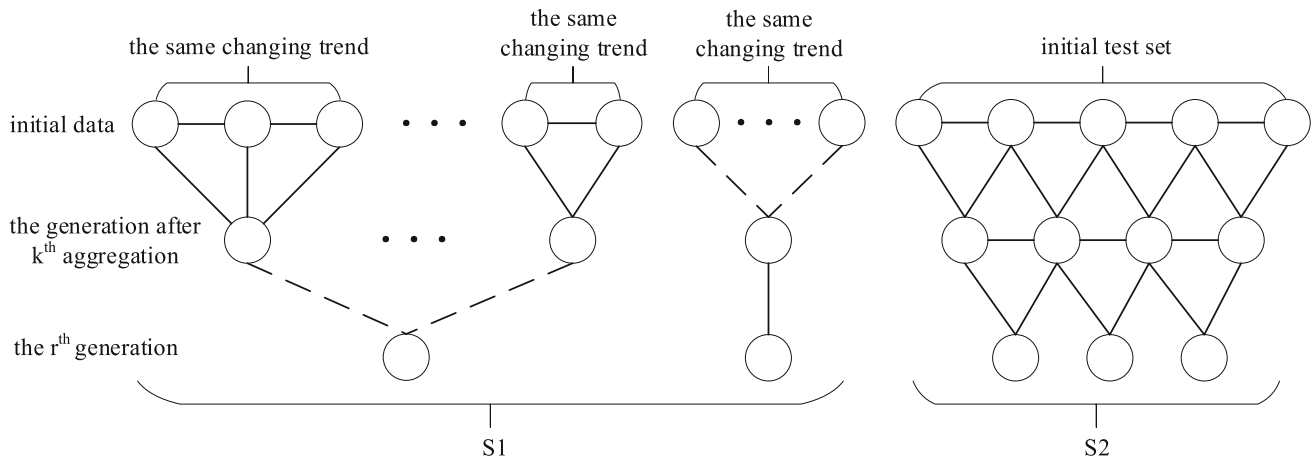


Fig.4 Dataset diagram of preprocessing

function in this paper adopts the return rate $ER(x)$ —risk rate $DR(x)$, the greater the difference, the better the combination.

In this regard, a multi-objective non-dominated sorting algorithm, NSDE-TS, is proposed based on the DE and fusion tabu search. The algorithm steps are as follows.

Step 1 Initialize molecular population and related parameters.

Step 2 Calculate the adaptation value. According to the Pareto evaluation, grades were divided and crowding degree was calculated to generate elite population.

Step 3 Sort and screen populations based on the idea of tournament.

Step 4 Perform DE operation according to probability to optimize population:

- 1) Mutation: The operation is the same as that in DETS algorithm.
- 2) Checking: When the population goes out of bounds, the traditional DE directly replaces the random generation of individuals, but this may lose the original excellent genes of individuals. Therefore, this paper adopts the de-extreme method.

The individuals after variation are scanned, and the coefficients beyond the boundary are deleted. The remaining coefficients are summed, and if the result is greater than 1, the largest value of the remaining coefficients is continuously deleted until the sum result is less than 1. Random number generation is performed on the deleted coefficient bits to ensure that the sum of the final individuals is 1. It is possible to save some coefficient values of the previous solution. An example is shown in Fig. 5.

Crossover: This article sets the cross-adaptation function $y = \left\lfloor \frac{3}{G^2} x^2 \right\rfloor + 1$, the $|y(x)|$ is rounded and y is the number of crossings, which adjusts the crossing bit according to

different algebras. After the cross interchange is realized, the exchanged parts are added to M_1 , and the non-exchanged parts are arranged in value M_1 . If $M_2 = M_1 + m_1 < 1$, the operation will continue until $M_k + m_k > 1$, then the coefficient in M_k will be fixed, and remaining coefficient bits will be generated randomly from large to small, so that the coefficient sum generated will be 1. Figure 6 shows this example.

Step 5 Re-calculate the objective function value and ranking value, etc.

Step 6 Judge the end condition, if not met, return to Step 2; else, move to Step 7.

Step 7 Output the corresponding Pareto optimal solution set and Pareto front.

Step 8 Define the spatial movement $V = [0.5, 0.3, 0.1, 0.05, 0.03, 0.01]$, the overall movement times G_t . The algorithm sets an alternate taboo list. At the same time, when generating $[x_1 + k, x_2 - k, \dots, x_9]$, and if any of the coefficients is greater than 1 or less than 0, the spatial movement is removed, and the rest of the process is the same as that in Sect. 2.2. If the risk income of a portfolio is greater than that of other ones, the portfolio is the optimal; otherwise, the risk value-income value is calculated, and the optimal portfolio is the one with the largest calculation result.

Step 9 Finish the loop when the maximum number of iterations is met. The grade number was re-classified, and the congestion degree was calculated. Output the final Pareto optimal solution set, Pareto front, population, and other information.

(4) Overall program: In this paper, a hybrid algorithm, DETS, is proposed based on DE and TS, and it is applied to optimize the parameters of SVR. After that, the algorithm after parameter optimization is applied to foreign exchange forecast, and more precise foreign exchange forecast data are obtained. Based on the DETS algorithm and Pareto

Fig. 5 Examples of improved checking behavior

-0.55	-0.4	0.21	0.13	0.02	0.19	0	0.22	0.17	1.01
0	0	0.21	0.13	0.02	0.19	0	0.22	0.17	0
0.01	0.02	0.21	0.13	0.02	0.19	0	0.22	0.17	0.03

Fig. 6 Examples of improved crossover behavior

0.35	0.03	0.02	0.07	0.12	0.15	0.33	0	0.09	0.49
0.35	0.03	0.02	0.07	0.12	0.15	0.33	0	0.09	0.49
0.35	0.03	0.02	0.07	0.12	0.15	0.05	0	0.09	0.12

sorting theory, and according to the actual situation of the problem, this paper further proposed a multi-objective optimization algorithm named NSDE-TS and combined it with the forecast data to generate a foreign exchange investment portfolio that meets the actual requirements. Finally, by comparing with the comparison algorithm, this article will evaluate the proposed multi-objective optimization algorithm. The flowchart is shown in Fig. 7.

4 Results and discussion

4.1 Experimental environment and parameter settings

MATLAB R2017a is adopted as the experiment environment. The data in this paper are from the State Administration of Foreign Exchange (<http://www.safe.gov.cn/>). Nine daily RMB exchange rate median prices from April 1, 2021, to April 1, 2022, were selected for comparative experiments, which were the exchange rate values of 100 units of foreign currency to RMB for 244 days. By using the algorithm proposed above, the exchange rate of the sixth day is predicted in a cycle of five days, and the market exchange rate of the next day is updated, and the rolling prediction of the short-term daily exchange rate is realized by sliding backwards continuously every day. The simulation results are the exchange rate prediction values of 239 days for each of the nine exchange rates, which is used as the follow-up data (Colombo and Pelagatti 2020). In terms of parameter setting, this paper chooses RBF as the

kernel function and sets the population size Pop to 100, the evolutionary algebra G_a to 100, the crossover rate P_c to 0.5, and the mutation rate P_m to 0.1.

4.2 Experimental evaluation index

(1) Error indicators: In this paper, the average absolute error, root-mean-square error, and correct trend rate are introduced to evaluate the forecast precision, and the running time of the algorithm is evaluated by the convergence rate (Li et al. 2015).

$$MAE = \frac{\sum_{i=1}^n |y'_i - y_i|}{n} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y'_i - y_i)^2} \tag{5}$$

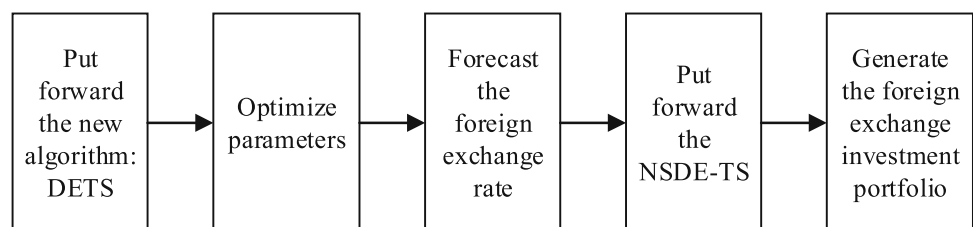
$$CTR = \frac{\sum_{i=1}^n CTR_i}{n} \tag{6}$$

$$CTR_i = \begin{cases} 1, & (y'_i - y_{i-1})(y_i - y_{i-1}) > 0 \\ 0, & (y'_i - y_{i-1})(y_i - y_{i-1}) < 0 \end{cases} \tag{7}$$

In the formula, y_i, y_{i-1} represent the market exchange rate of the foreign currency asset relative to RMB on the day and the previous day, respectively. R_i stands for the return rate of the foreign currency asset on the i th day, i.e., $R_i = (y_i - y_{i-1})/y_{i-1}, i = 1, 2, \dots, n, n = 223$. The expected rate of return is defined as $(y_i - y_{i-1})/y_{i-1}$, and among them, y'_i is the forecast exchange rate for the i th day.

Comprehensive index: In order to better synthesize the relationship between the metrics, we propose

Fig. 7 Schematic diagram of overall plan based on DETS



comprehensive index (abbreviated as CI). CTR is the correct rate of trend prediction, and the larger the index, the better; while MAE and RMSE are error indicators, the smaller the better. Therefore, Comprehensive index 1 and Comprehensive index 2 are defined as:

$$CI_1 = \frac{CTR}{MAE + RMSE}$$

$$CI_2 = \left(\frac{1}{MAE + ARMSE} \right)^{1/CTR}$$

According to the research, MAE+RMSE is always greater than 1 in this problem.

(2) Evaluation indicators of multi-objective algorithm: This paper introduces the convergence indicator, homogeneity indicator, and comprehensive evaluation method to evaluate the solution result of multi-objective algorithm.

1) The convergence indicator: GD represents the average minimum distance from each point in the solution set P to the reference set P^* (Jain et al. 2021).

$$GD(P, P^*) = \frac{\sqrt{\sum_{y \in P} \min_{x \in P^*} \text{dis}(x, y)^2}}{|P|} \tag{8}$$

P is the solution set obtained by the algorithm, the reference set P^* is a set of reference points, and $\text{dis}(x, y)$ represents the Euclidean distance between the points y in the solution set P and the points x in the reference set P^* . The investment portfolio goal is to maximize the return and minimize the risk. Therefore, this paper selects the point with risk of 0 and return of 10% as the only point in the reference set and zooms to divide the current solution by the sum of the absolute values of all solutions. The population size (Pop) is set to 100 and 20 solutions with higher accuracy that is selected.

2) Spacing: The standard deviation that measures the minimum distance of each solution from the other solutions. The smaller the value, the better the uniformity (Nondy and Gogoi 2021).

$$\text{Spacing}(P) = \sqrt{\frac{1}{|P| - 1} \sum_{i=1}^{|P|} (\bar{d} - d_i)^2} \tag{9}$$

represents the minimum distance from the d_i th solution to the other solutions in and \bar{d} represents the mean values of all d_i .

3) Comprehensive evaluation: This section makes a direct data observation. A more intuitive algorithm comparison is made with the same conditional data.

4.3 An empirical study on exchange rate forecast

Taking the forecast results of the US dollar as an example, the obtained three indicators, two aggregate indicators, and

the running time are shown in Table 1. It can be seen that the MAE and RMSE of the algorithm proposed in this paper are both the smallest, and the MAE obtained by the algorithm in this paper is reduced by 3.79% compared with the MAE of the suboptimal algorithm, and the RMSE is also reduced by 1.47%. At the same time, the trend prediction accuracy rate CTR increased by 2.19% compared with the highest, and the aggregate index was the largest and increased by 4.36 and 3.44%, respectively, and the running time was between other algorithms.

Since the change trend of MAE and RMSE is relatively the same, this paper shows the prediction results of nine foreign currency assets in Fig. 3 to show the algorithm comparison chart of RMSE, CTR, CI_1 , and CI_2 , respectively. Note that the direct comparison data cannot be presented more clearly, so this paper uses the algorithm measurement index under the corresponding currency to compare with the algorithm with the worst result of the same currency index, which can better reflect the difference between the algorithms. In order to make a better comprehensive comparison, we will equalize and add the relative comparison values of the nine currencies corresponding to each algorithm and the four evaluation indicators and subtract 1 from this value, so that the algorithm can be optimized more comprehensively. Performance is shown in Fig. 8.

It can be clearly seen from Figs. 8 and 9 that although other algorithms perform well in various situations, the algorithm in this section is optimal in various situations, even ahead of grid search about 9%, so it can be proved that the algorithm proposed in this section has certain advantages in exchange rate prediction.

Figure 10 shows the comparison between the predicted exchange rate and market exchange rate of USD to RMB,

Table 1 Comparison table of optimization effects of different algorithm parameters

	MAE	RMSE	CTR	CI_1	CI_2	time(s)
DETS	0.6370	0.9534	0.9284	0.5837	0.6066	400.23
GS	0.7372	1.0430	0.8676	0.4873	0.5144	1590.82
GA	0.7060	1.0246	0.8733	0.5043	0.5332	392.84
DE	0.6844	0.9813	0.8901	0.5348	0.5639	300.83
TS	0.7049	1.0052	0.8775	0.5132	0.5426	250.12
PSO	0.6541	0.9695	0.9085	0.5593	0.5864	798.25
SA	0.7013	1.0035	0.885	0.5193	0.5474	369.19
AFSA	0.6920	0.9859	0.9081	0.5414	0.5657	431.51
ACA	0.6780	0.9773	0.9036	0.5457	0.5723	692.34
GATS	0.6621	0.9676	0.8822	0.5414	0.5748	569.77
TSA	0.6625	0.9709	0.8978	0.5496	0.5789	372.89

*Comprehensive index is abbreviated as CI

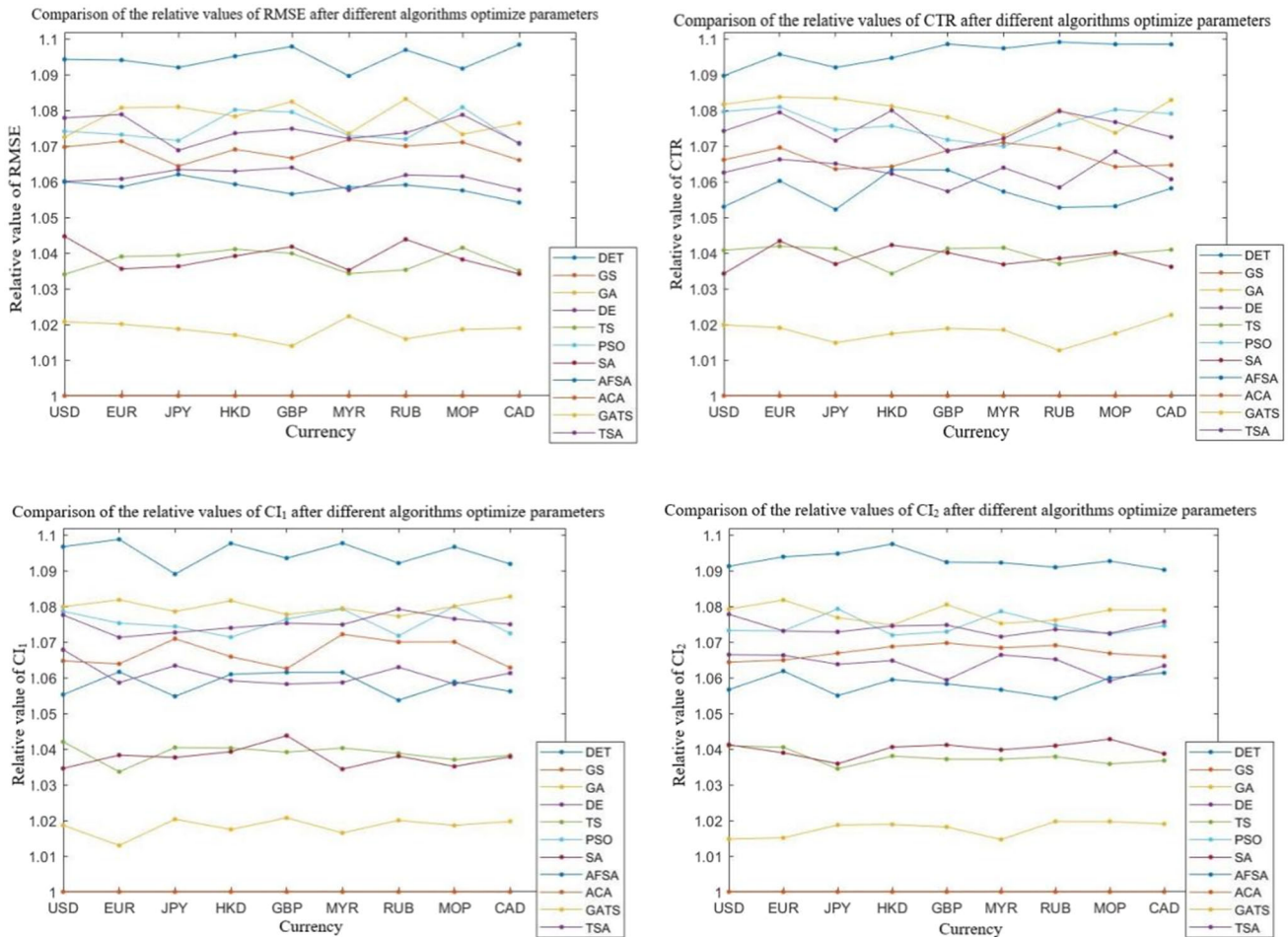
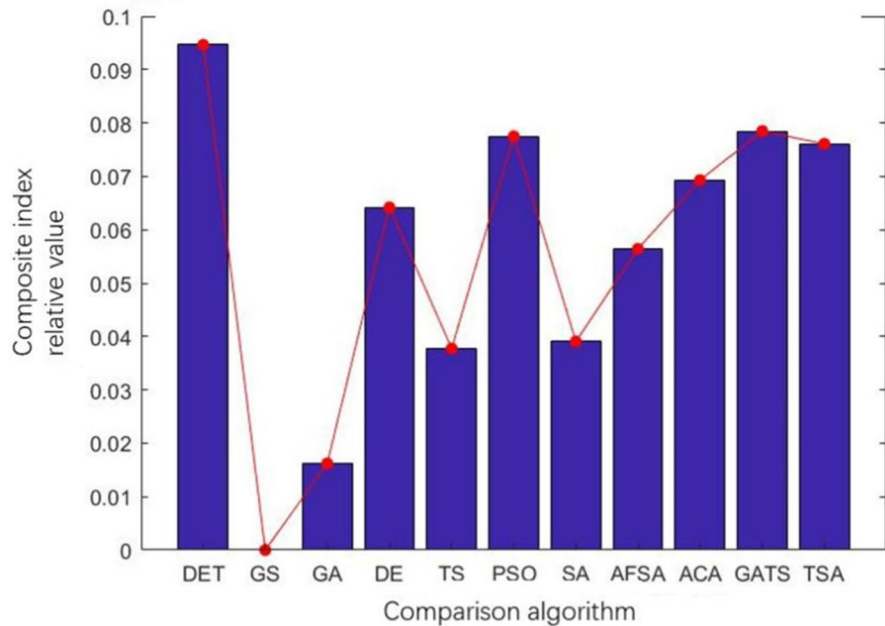


Fig. 8 Comparison chart of relative indicators of each algorithm in different currencies

Fig. 9 Comparison chart of comprehensive relative indicators of each algorithm

The comparison chart of the relative value of the comprehensive index under the optimization of the parameters of different algorithms



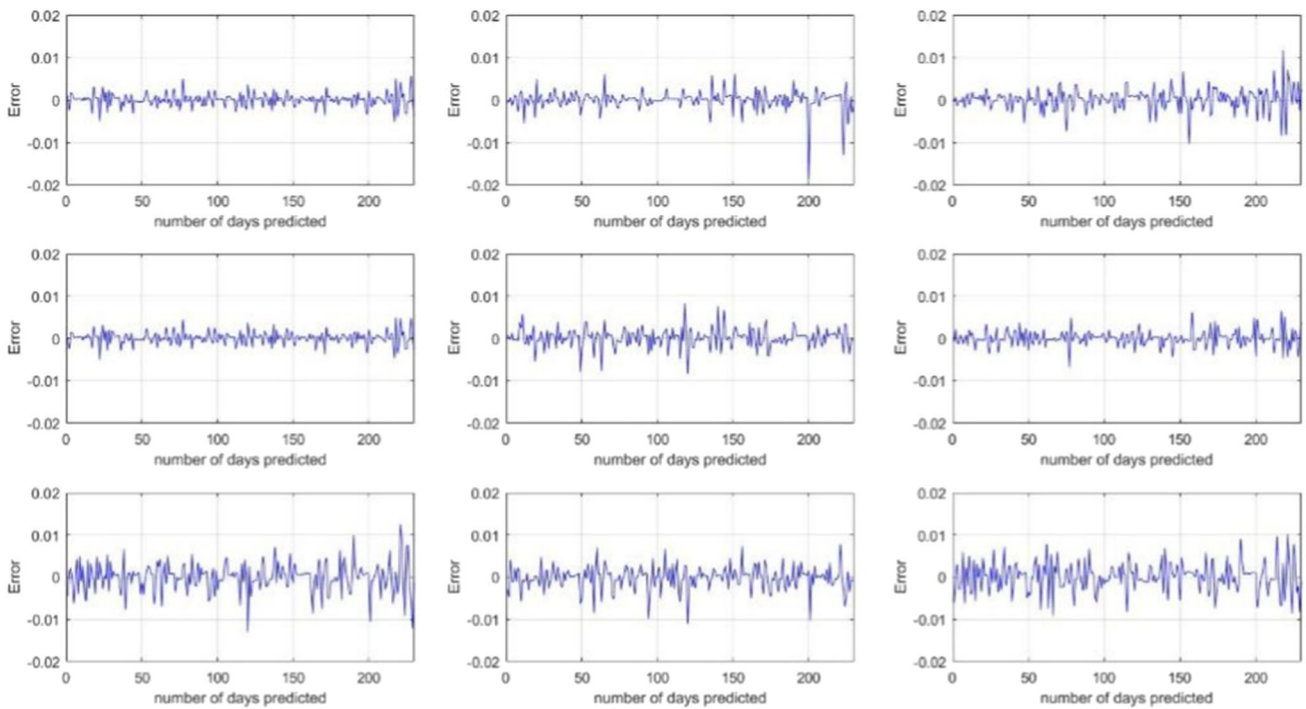


Fig. 10 Error graph of forecast

and the expected rate of return and the actual rate of return are obtained by the algorithm in this section. The abscissa represents the predicted days, and the ordinate is the exchange rate value and the rate of return. It can be seen from the figure that the overall curve fitting effect is good. Figure 11 is the error chart of the algorithm in this section in the prediction of the exchange rate of the nine major currencies over time. It can be seen from this that the algorithm proposed in this section can be controlled within 1% in most cases, which shows that its prediction accuracy is good.

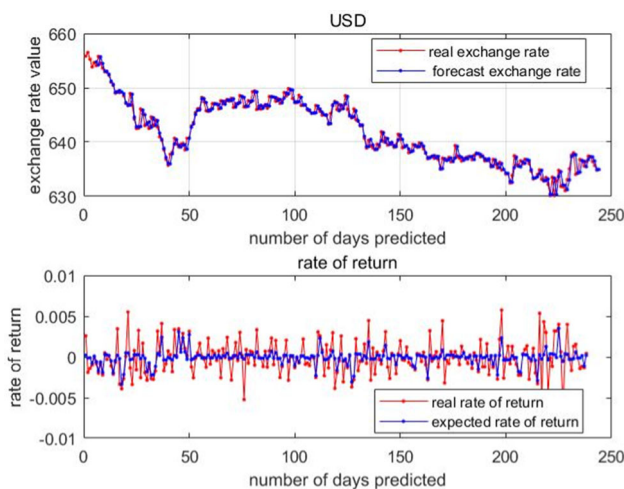


Fig. 11 Comparison chart of the predicted

This section compares and tests various optimization algorithms by introducing five metrics and data from nine currencies. It is precisely because the DETS algorithm combines the breadth search of the differential evolution algorithm and the depth search of the tabu search algorithm, and it can effectively find the optimal parameter combination in the parameter domain and then obtain more accurate foreign exchange forecast data. So in the test results, we can find that the DETS algorithm has the best effect and the best performance among the nine currencies and five metrics. Among them, the MAE obtained by the algorithm in this paper is reduced by 3.79% compared with the MAE of the suboptimal algorithm, and the RMSE is also reduced by 1.47%. At the same time, the trend prediction accuracy rate CTR increased by 2.19% compared with the highest, and the aggregate index was the largest and increased by 4.36 and 3.44%, respectively. Therefore, this paper adopts DETS as the basic algorithm for parameter optimization.

4.4 A new data aggregation method

Although the exchange rate does not generally rise and fall, once the exchange rate fluctuates sharply, many models fail. So how to maintain the basic accuracy and trend correctness of the forecast in this situation has become an urgent problem to be solved. For example, since the Russian–Ukrainian conflict, the ruble has experienced sharp rises and falls. Since April, the average daily fluctuation

has even reached more than 5%. At this time, the handling of fluctuation data is very tested, and there is no way to rely on prediction models alone. Therefore, this section proposes a data processing method that can absorb fluctuation trends and achieves more accurate predictions; the principle has been explained in the previous section.

Below we test this method in two cases:

(1) When encountering severe fluctuations.

This time, the exchange rate data of the ruble against the RMB since April was selected and tested according to the normal data input method and the method proposed in this section, and the forecast results were analyzed and compared.

As can be seen from the left of Fig. 12, the predicted value before the data is not aggregated which is very different from the actual value, and the situation on the right of the figure is significantly improved. According to the calculation, MAE and RMSE decreased by 3.2961 and 3.4928 times, respectively, and the forecast trend increased from 0.5333 to 0.9333, and the forecast effect was significantly improved. Therefore, it can be seen that the data aggregation method proposed in this section works extremely well when the data fluctuate.

(2) When the data fluctuation is not significant.

Due to the relatively small volatility of the US dollar against the RMB in the past year, this time we directly introduce the 244-day change in the US dollar against the RMB exchange rate in Sect. 4.3 for testing. The results are shown in Table 2.

As can be seen from Table 2, all five indicators have been optimized, so the data aggregation method in this section can still improve the prediction model and improve the prediction accuracy when the exchange rate data volatility is small.

To sum up, the research in this section finds that because the data aggregation method in this section is adapted to

Table 2 Comparison table before and after data aggregation

	Before data aggregation	After data aggregation
MAE	0.6370	0.6288
RMSE	0.9534	0.9453
CTR	0.9284	0.9294
CI ₁	0.5838	0.5905
CI ₂	0.6067	0.6138

foreign exchange forecasting, it avoids data fragmentation, absorbs the characteristics of historical data, and also preserves the current data characteristics well. According to the calculation, MAE and RMSE decreased by 3.2961 and 3.4928 times, respectively, and the forecast trend increased from 0.5333 to 0.9333, and the forecast effect was significantly improved. Therefore, after data aggregation, the prediction accuracy of the model will be improved regardless of whether the exchange rate volatility is large or small.

4.5 An empirical study on the solution of foreign exchange portfolio

In order to avoid the overlapping of the research results with the previous section, this section selects the daily data of the central parity rates of nine RMB exchange rates from May 27, 2020, to April 30, 2021, for a comparative test, a total of 228 days of 100 units of foreign currency, the exchange rate value against RMB. Similarly, we set the total capital to be 1 unit and select the 222nd day as the time point of the investment portfolio. From the forecast in the previous section, the forecast exchange rates and expected returns of nine foreign currency assets on the 223rd day can be obtained, and then two actual data, the

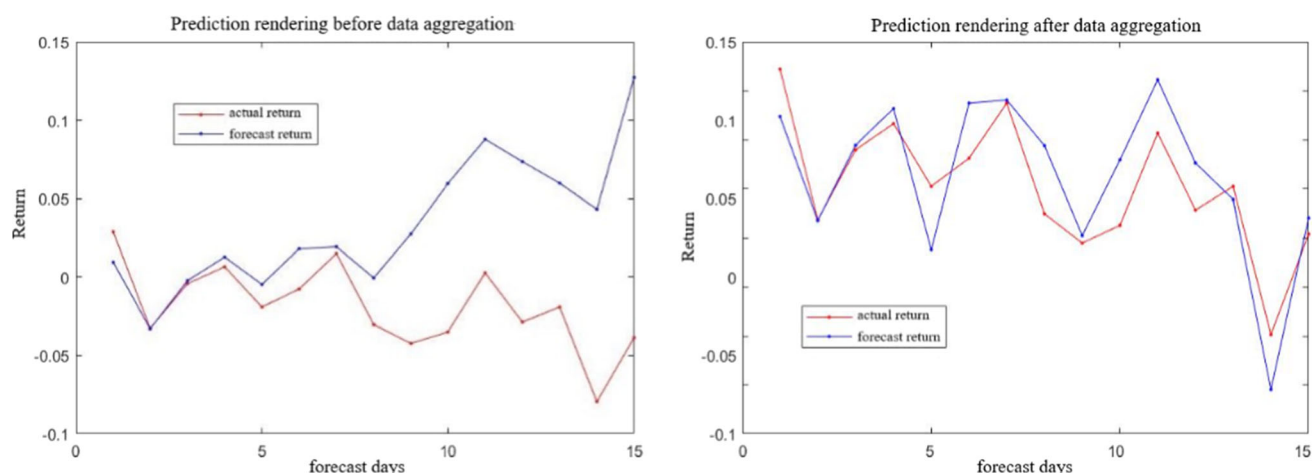


Fig. 12 Comparison of prediction effects before and after data aggregation

actual exchange rate and the actual rate of return, are introduced, as shown in Table 3.

In this section, three algorithms, NSGA-II, NSDE-II, and NSDE-TS, are applied to the multi-objective model of foreign exchange portfolio to solve. There are various options for portfolio options, and the only thing that can be done is to choose the relatively optimal option. This paper uses the convergence index method, the uniformity index method, and the comprehensive evaluation method to evaluate the algorithm performance and solution quality:

1) Evaluation on the algorithm from the viewpoint of convergence. Set the number of different iterations, and draw the distribution figure of Pareto fronts obtained by the three algorithms after operation, as shown in Fig. 13.

Through observation, it is found that the higher the expected rate of return, the higher the corresponding risk. As can be seen from Table 4, the average convergence value of the NSGA-II algorithm is 2.11. In the above figure, the optimal solution of NSGA-II is mainly concentrated in the low-yield and low-risk areas, which are prone to repeated solutions or similar solutions, while high optimal solutions with high returns and high VaR are rare. The average convergence value of the NSDE algorithm is 2.0212, which is higher than that of NSGA-II. The Pareto frontier distribution is obviously also more uniform, and the overall value is better than that of NSGA-II. The average convergence of the NSDE-TS algorithm is 1.7782, and the convergence of the Pareto frontier distribution is greatly improved compared with the previous two algorithms. At the same time, its solutions in the high-yield range are denser, and the solutions are concentrated in the positive-yield range.

2) Evaluation on the algorithm from the viewpoint of uniformity. The above parameter settings are also adopted, and the specific results are shown in Table 5.

According to the results, the average homogeneity of NSGA-II algorithm is 0.1855 and that of NSDE is 0.1688, which has better indicators than that of NSGA-II. The

average homogeneity of NSDE-TS algorithm is 0.1120, and the homogeneity of Pareto front distribution of NSDE-TS algorithm is better than that of the former two.

3) This paper makes a comprehensive evaluation. Compare results with the highest optimization degree of the above algorithms, and results are shown in Fig. 14.

In the low-risk interval, the algorithm is uniform and the income is higher than that of the first two algorithms. In the high-risk area, the algorithm is also uniform and has higher income. According to the comparison, it is quite clear that the effect of the algorithm NSDE-TS for foreign exchange portfolio allocation is excellent.

It can be seen from Fig. 15 and Table 6 that the solution set obtained by NSDE-TS has good convergence, all of which are concentrated in the interval where the return is greater than 0, and the coverage rate of the leading edge solution is high, so that more portfolios meeting the actual investment requirements can be provided. In this paper, 10 experiments are carried out, respectively, to take the average value. Through Table 2, it can be found that the solution set obtained by NSDE-TS algorithm has a small grade difference between each solution, the total number of ranks is lower than the first two, and the number of grade 1 is far ahead of the former two algorithms, which proves that there are many high-quality solutions in the proposed method. Based on the above experiments, it can be found that NSDE-TS can better solve multi-objective optimization problems and provide better solution sets because it can absorb the advantages of DE's global search and TS's depth optimization, respectively.

5 Conclusion

This paper improves the out-of-bounds movement rules and neighborhood movement rules of the algorithm, then proposes a support vector regression algorithm based on improved tabu search and differential evolution algorithm,

Table 3 Actual and forecast foreign currency exchange rate status on day 223

Foreign currency	Forecast exchange rate	Real exchange rate	Expected rate of return (%)	Real rate of return (%)
USD	646.8515	646.72	- 0.0005	- 0.0007
EUR	784.9586	783.97	- 0.0003	- 0.0016
JPY	5.942	5.9382	- 0.0034	- 0.0041
HKD	83.3242	83.306	- 0.0006	- 0.0008
GBP	902.7001	902.01	- 0.0002	- 0.001
MYR	63.402	63.416	0.0003	0.0006
MOP	1148.5	1153.49	0.0006	0.005
CAD	504.4945	502.87	- 0.0006	- 0.0038
SUR	526.3975	526.76	0.0009	0.0016

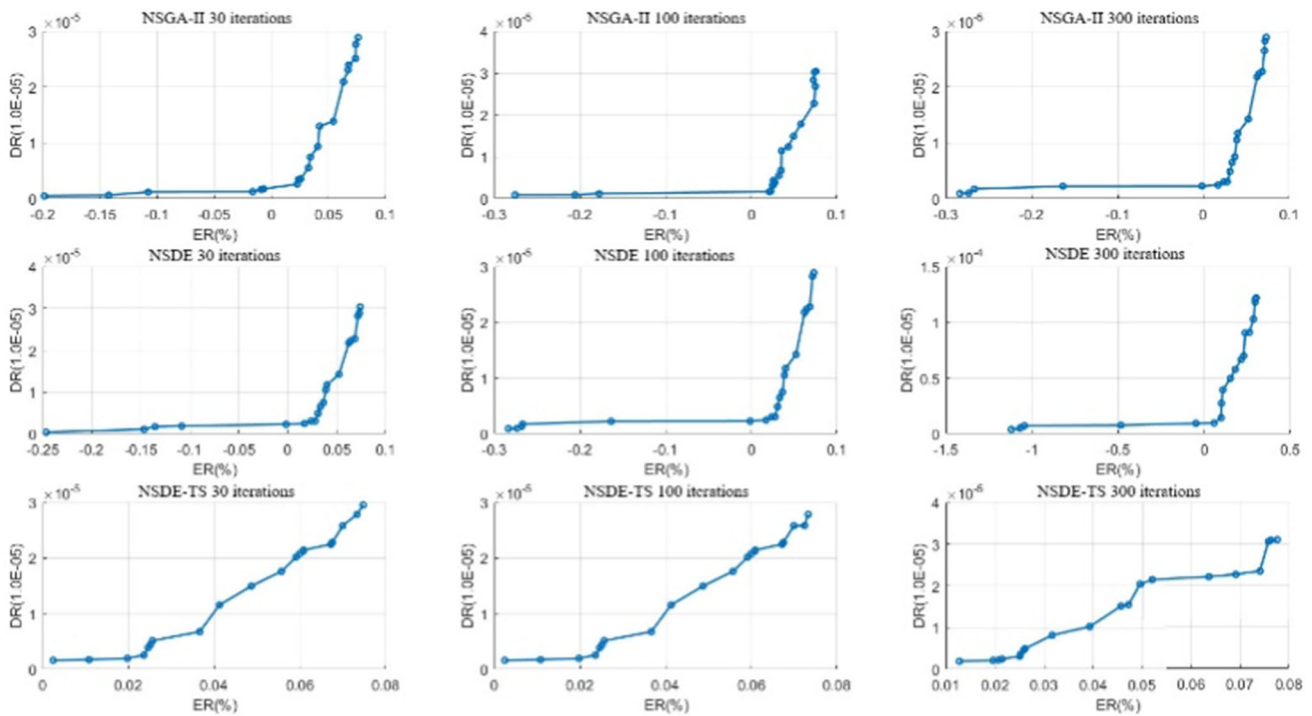


Fig. 13 The frontier average convergence under different iteration numbers (USD)

Table 4 Comparison of the average convergence of each algorithm frontier (USD)

	30 times	100 times	300 times
NSGA-II	2.2789	2.0088	2.0423
NSDE	2.0929	2.0932	1.8775
NSDE-TS	1.8626	1.7464	1.7257

Table 5 Average homogeneity of front edge under different iterations algorithms

	30 times	100 times	300 times
NSGA-II	0.2125	0.1827	0.1613
NSDE	0.2015	0.1470	0.1580
NSDE-TS	0.1324	0.1057	0.0978

named DETS, and uses error indicators to compare related algorithms, and the results prove the efficiency and feasibility of the algorithm in exchange rate prediction. Then combined with the DETS algorithm and Pareto sorting theory, an algorithm suitable for multi-objective optimization was further proposed, named NSDE-TS. Through empirical research and comparison, it is found that the NSDE-TS algorithm can provide a solution set with stronger optimization, better uniformity, and convergence.

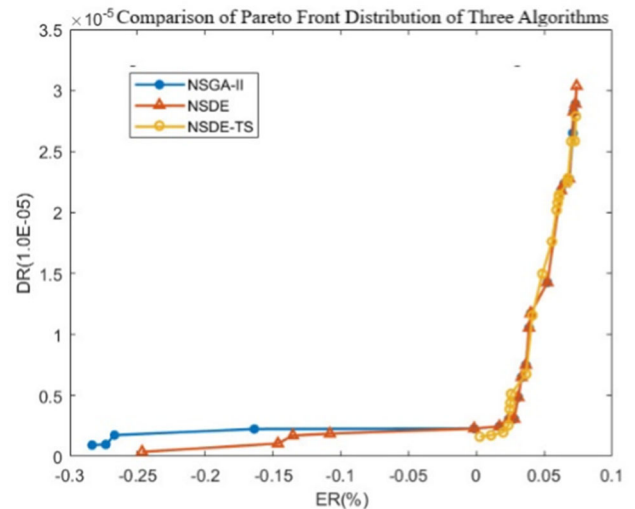


Fig. 14 Comparison of Pareto front distribution of three algorithms

Therefore, the application potential of the algorithm proposed in this paper in the foreign exchange market is unlimited. At the same time, this article only conducts a one-dimensional analysis and there are many factors that affect exchange rate changes, such as interest rates, inflation levels, and exchange rate policies. Follow-up studies can introduce major influencing factors to further enhance the overall forecasting ability. To sum up, this article is aimed at the daily short-term changes of exchange rates for research and recommendations, which have certain guiding

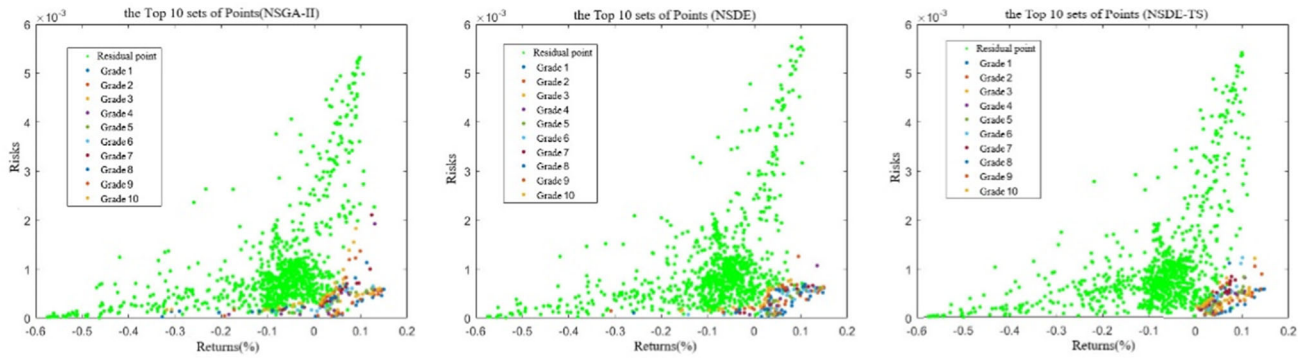


Fig. 15 Top 10 points of the Pareto ranking level of each algorithm

Table 6 The number of different Pareto grades and the total number of grades

	Grade 1	Grade 1–3	Grade 1–10	Total number of grades
NSGA-II	15.9	48.3	202.5	57.4
NSDE	17.2	44.9	214.3	55.9
NSDE-TS	23.1	50.7	232.8	51.0

significance for short-term foreign exchange investment, and follow-up research needs to be in-depth.

Author contribution XZ and CZ contributed to conception and design of the manuscript and interpretation of data, literature searches and analyses, clinical evaluations, manuscript preparation, and writing the paper; LA made substantial contributions to conception and design, literature searches and analyses, participated in revising the article, and gave final approval of the version to be submitted.

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest None to declare.

Ethical approval Unexplored human body or animal experiment.

Informed Consent All participants provided written informed assent and consent before the experiment.

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