AN INTELLIGENT PREDICTION METHOD FOR SHORT-TERM TIME SERIES FORECAST ON ENGINEERING EDUCATION

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Abstract *¾ Traditional methods usually encounter the problem in which the predicted results cannot reach a satisfactory need because the overshooting prediction value made by the forecasting model cause a big residual error at the turning points where the peak or valley observed values occurred. Therefore, this study introduced a intelligent prediction algorithm (including two types) utilized for the applications of non-periodic short-term time series forecast. This algorithm actually is a hybrid model, combing a grey prediction model and a cumulative least squared linear prediction model, with the technique of automatically compensating a possible overestimated predicted value by a potential damped predicted value for those predicting points having extreme peak or valley value. The verification of this study is also tested successfully in three experiments whose are stock price index, economy growth rate forecasts, and typhoon moving trace. Furthermore, the results of this intelligent algorithm also concluded that the proposed one achieved the best accuracy of predicted values in these experiments when compared with other five traditional forecasting models discussed in the experiments.*

Index Terms ¾ Grey prediction model, Cumulative least squared linear prediction model.

INTRODUCTION

Typically, six traditional models - Simple exponential, Holt-Winters smoothing, Regression method, Causal regression, Time series method, and Box-Jenkins [1][2][3] have been employed into many scientific or economic applications. Basically, the forecast is obtained through means of extrapolating a value at the next time instant according to the forecast model's equation [4][5]. However, some of models as shown above, e.g. Holt-Winters smoothing, Regression method, and Box-Jenkins, usually require many observed data for fitting their models to obtain better approach [5][6] so that these models probably do not be suitable for short-term forecasting case because of only a few data available. Secondly, some of models mentioned above, e.g., Holt-Winters smoothing, Regression method, and Time series method, are applicable for the specified situation where data distribution characterized the wave form with regular variation or normally distributed for a certain system [4][7], for example, the seasonal or cyclical data series. Contrarily, the GM(1,1|a) model introduced in [8] just need a few data for model construction implied the simple and reasonable prediction accuracy. Thus, the GM(1,1|a) model is often utilized in the short-term forecast for years. Although the GM(1,1|a) model has the advantage of simple and fast to predict the future output, the precision is also still arguable in many papers [9][10] since the overshooting prediction value made by the forecasting model cause a big residual error at the turning points where the peak or valley observed values occurred. However, 3 points cumulative least squared linear model introduced in this study might output an damped predicted value at the turning points. Therefore, a proposed intelligent algorithm combing both aforementioned methods to introduce a compensation method for solving the problem of overshooting and damped predicted results so as to improve the prediction accuracy. The verification of this study is also tested successfully in three experiments in which involves two types of applications, non-momentun type and momentum type, respectively.

TRADITIONAL MODELS

Grey Prediction Model

A prototype of grey prediction model GM(1,1|a) is introduced in the grey system theory 1982 [8].

Step 1: accumulated generating operation once (1-AGO)

$$x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(j), \quad k = 1,2,\ldots,n \tag{1}$$

$x^{(0)}(k)$: the original sampled data that is a nonnegative sequence

Step 2: finding developing coefficient and control coefficient by using grey difference equation

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad k = 2,3,\ldots,n \tag{2}$$

$$z^{(1)}(k) = ax^{(1)}(k) + (1-a)x^{(1)}(k-1), \quad 0 \le a \le 1 \tag{3}$$

$z^{(1)}(k)$: the background value

$$a = \frac{\sum_{k=2}^{n} x^{(0)}(k) \sum_{k=2}^{n} z^{(1)}(k) - (n-1)\sum_{k=2}^{n} x^{(0)}(k) z^{(1)}(k)}{(n-1)\sum_{k=2}^{n} z^{(1)}(k)^2 - (\sum_{k=2}^{n} z^{(1)}(k))^2} = \frac{\Delta_a}{\Delta} \tag{4}$$

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$$b=\frac{\sum_{k=2}^{n}x^{(0)}(k)\sum_{k=2}^{n}z^{(1)}(k)^2-\sum_{k=2}^{n}z^{(1)}(k)\sum_{k=2}^{n}x^{(0)}(k)z^{(1)}(k)}{(n-1)\sum_{k=2}^{n}z^{(1)}(k)^2-(\sum_{k=2}^{n}z^{(1)}(k))^2} \tag{5}$$

$$=\frac{\Delta_b}{\Delta}$$

Step 3: solving the predicted value $\hat{x}^{(1)}(k)$ through the grey differential equation and performing inverse of accumulated generating operation once (1-IAGO) to obtain $\hat{x}^{(0)}(k)$

$$\frac{dx^{(1)}(k)}{dk}+ax^{(1)}(k)=b \tag{6}$$

$$\begin{aligned}\hat{x}^{(0)}(k)&=\hat{x}^{(1)}(k)-\hat{x}^{(1)}(k-1)\\&=(x^{(0)}(1)-\frac{b}{a})(e^{-a(k-1)}-e^{-a(k-2)}),\quad k=2,3,\ldots\end{aligned} \tag{7}$$

Least Squared Polynomial Model

The least squared polynomial [3] is applied to study the statistic relation between a set of independent variables and a dependent variable. This model can be utilized for estimating or predicting the future output. Some of phenomena in the real world can be realized to be a multivariate model so that the accuracy of estimated (or predicted) would be improved.

Step 1: Building least squared polynomial model generally in the following way:

$$\hat{y}^{(0)}(i)=b_0+b_1x^{(0)}(i)+b_2x^{(0)^2}(i)+\cdots\cdots+b_kx^{(0)^k}(i) \tag{8}$$

Solving the coefficients $b_0, b_1, \cdots\cdots, b_k$ as follows:

$$\text{min.}\quad q=\sum_{i=1}^{n}e_i^2=\sum_{i=1}^{n}(y^{(0)}(i)-\hat{y}^{(0)}(i))^2 \tag{9}$$

$$\text{s.t.}\quad \hat{y}^{(0)}(i)=b_0+b_1x^{(0)}(i)+b_2x^{(0)^2}(i)+\cdots\cdots+b_kx^{(0)^k}(i)$$

Constructing the best approximation solution for x to the equation of

$$X_aB=Y\,. \tag{10}$$

where

$$X_a=\begin{bmatrix}X_a(1)^T\\X_a(2)^T\\\cdot\\\cdot\\\cdot\\X_a(n)^T\end{bmatrix},\quad X_a(i)=[1,x^{(0)}(i),x^{(0)^2}(i),\ldots,x^{(0)^k}(i)]^T$$

$$Y=[y^{(0)}(1),y^{(0)}(2),\ldots,y^{(0)}(k)]^T,\quad B=[b_0,b_1,b_2,\ldots,b_k]^T$$

Step 2: Derived the normal equation to find pseudo inverse matrix

Solving for Eq. (10) typically turns out to be a normal equation [7],

$$X_a^TX_aB=X_a^TY \tag{11}$$

, in which matrix B is a coefficient vector for $b_0, b_1, \cdots\cdots, b_k$ in Eq. (8) and Y is observed values given by in Eq. (8).

Step 3: Solving the appropriate coefficients and Predicting the next output

The solution to B in the normal equation is equal to X_a^+Y where X_a^+ is a pseudo inverse [7] of matrix X_a defined as $(X_a^TX_a)^{-1}X_a^T$.

$$B=(X_a^TX_a)^{-1}X_a^TY=X_a^+Y \tag{12}$$

$$\hat{y}^{(0)}(n+1)=X_a(n+1)B\,. \tag{13}$$

INTELLIGENT PREDICTION ALGORITHM

According to the analysis mentioned in GM(1,1|a) prediction model, decreasing the number of sampling points as possible as we can, and lessening the effect of the magnitude of original data can lower the residual error of GM(1,1|a) model. Thus, using a few sampled points for GM(1,1|a) prediction would achieve the better prediction accuracy. This imply that this kind of GM(1,1|a) model is therefore applicable for short-term forecasting application. Next, how to alleviate the effect of the magnitude of the original given data so as to reduce the residual error of GM(1,1|a) model is another crucial issue [12]. Based on the phenomena discovered in [12], the prediction of GM(1,1|a) model is always to reveal an overshooting around the turning points as shown in Figure 2. Accordingly, the predicted value from the grey prediction model will turn out to be an overestimated (or underestimated) result at the position of turning points. However, a cumulative least squared linear model using the most recent 3 sampled points is introduced herein to compromise the problem in GM(1,1|a) so as for lessening the effect of the magnitude of the original given data. This 3 points cumulative least squared linear model can be set up in the following steps.

Step 1: accumulated generating operation once (1-AGO)

$$x^{(1)}(i)=\sum_{j=k-3}^{k-4+i}x^{(0)}(j),\quad i=1,2,3 \tag{14}$$

$x^{(0)}(j)$: three successive sampled data $x^{(0)}(k-3)$, $x^{(0)}(k-2)$, and $x^{(0)}(k-1)$ before the next predicted point $\hat{x}^{(0)}(k)$.

Step 2: finding a linear approximate polynomial for fitting three successive sampled data $x^{(1)}(1)$, $x^{(1)}(2)$, and $x^{(1)}(3)$

$$x^{(1)}(k)=c_1k+c_0\,,\quad k=1,2,3 \tag{15}$$

That is,

$$X=KC\,,\quad C=(K^TK)^{-1}K^TX \tag{16}$$

where $X=[x^{(1)}(1),\,x^{(1)}(2),\,x^{(1)}(3)]^T$,

$K=\begin{bmatrix}1&1\\2&1\\3&1\end{bmatrix}$, and $C=[c_1,c_0]^T$

Step 3: obtaining a predicted value from the linear approximate polynomial

$$\tilde{x}^{(1)}(k+1)=c_1(k+1)+c_0\,,\quad k=3 \tag{17}$$

Step 4: inverse accumulated generating operation once (1-IAGO)

$$\tilde{x}^{(0)}(k+1)=\tilde{x}^{(1)}(k+1)-x^{(1)}(k)\,,\quad k=3 \tag{18}$$

This cumulative least squared linear model have the problem about the damped around turning points, as shown in Figure 2, that is conversely to the situation happened to GM(1,1|a) model. Therefore, we can apply this characteristic to offset the magnitude overshooting such that alleviating the effect of the magnitude of the original given data for GM(1,1|a) prediction can be achieved. A 3 points cumulative least squared linear model combining with GM(1,1|a) model thus is exploited for the prediction as follows.

$$\breve{x}^{(0)}(k) = w_1\hat{x}^{(0)}(k) + w_2\tilde{x}^{(0)}(k), \qquad (19)$$

$$w_1 + w_2 = 1$$

In Eq. (19), $\hat{x}^{(0)}(k)$ and $\tilde{x}^{(0)}(k)$ stand for the predicted value of a grey model and the predicted value of a 3 points cumulative least squared linear model, respectively; moreover, the w_1 and w_2 represent the weight of $\hat{x}^{(0)}(k)$ and $\tilde{x}^{(0)}(k)$, respectively.

The value of w_1 or w_2 can be evaluated by a weighting algorithm shown below where $\overline{x}^{(0)}(k)$ represents the predicted output from a least squared linear model using 4 sampled data without cumulative data preprocess. There are two types of this intelligent prediction algorithm described as follows.

Non-momentum Type of Predictive Algorithm

Input Parameters:

e(1)= $x^{(0)}(k-3) - x^{(0)}(k-4)$

e(2)= $x^{(0)}(k-2) - x^{(0)}(k-3)$

e(3)= $x^{(0)}(k-1) - x^{(0)}(k-2)$

m2= $(x^{(0)}(k-1) + x^{(0)}(k-2))/2$

m3= $(x^{(0)}(k-1) + x^{(0)}(k-2) + x^{(0)}(k-3))/3$

m4= $(x^{(0)}(k-1) + x^{(0)}(k-2) + x^{(0)}(k-3) + x^{(0)}(k-4))/4$

prdvalue1= $\hat{x}^{(0)}(k)$

prdvalue2= $\tilde{x}^{(0)}(k)$

refvalue= $\overline{x}^{(0)}(k)$

Output Data: w_1 and w_2

Algorithm:

```
if refvalue is very close to prdvalue2
    t=(prdvalue1+prdvalue2)/2;
elseif refvalue is not located in validation region
  if e(3)* e(2)>0 & e(2)*e(1)>0
    t=m4;
  else
    t=m2;
  end
else
  if e(p-1)* e(p-2)<0 & e(p-2)*e(p-3)<0
    t=(refvalue+m4)/2;
  elseif e(p-1)* e(p-2)<0 & e(p-2)*e(p-3)>0
    t=(refvalue+m4)/2;
  elseif e(p-1)* e(p-2)>0 & e(p-2)*e(p-3)<0
    t=(refvalue+m3f)/2;
  else
    t=(prdvalue1+prdvalue2)/2;
  end
end
q1=abs(t-prdvalue1);
q2=abs(t-prdvalue2);
w1=q2/(q1+q2);
w2=q1/(q1+q2);
```

Momentum Type of Predictive Algorithm

Input Parameters:

e(1)= $x^{(0)}(k-3) - x^{(0)}(k-4)$

e(2)= $x^{(0)}(k-2) - x^{(0)}(k-3)$

e(3)= $x^{(0)}(k-1) - x^{(0)}(k-2)$

m2= $(x^{(0)}(k-1) + x^{(0)}(k-2))/2$

m4= $(x^{(0)}(k-1) + x^{(0)}(k-2) + x^{(0)}(k-3) + x^{(0)}(k-4))/4$

prdvalue1= $\hat{x}^{(0)}(k)$

prdvalue2= $\tilde{x}^{(0)}(k)$

refvalue= $\overline{x}^{(0)}(k)$

Output Data: $\breve{x}^{(0)}(k)$

Algorithm:

```
if refvalue is very close to prdvalue2
    t=(prdvalue1+prdvalue2)/2;
elseif refvalue is not located in validation region
  if e(3)* e(2)>0 & e(2)*e(1)>0
    t=m4;
  else
    t=m2;
  end
else
    prdvalue2=refvalue;
    t=(prdvalue1+prdvalue2)/2;
end
q1=abs(t-prdvalue1);
q2=abs(t-prdvalue2);
w1=q2/(q1+q2);
w2=q1/(q1+q2);
```

$\breve{x}^{(0)}(k) = w_1 * prdvalue1 + w_2 * prdvalue2$

Experimental Results

As shown in Figure 1 to Figure 11, the predicted sequence 1 indicates the predicted results of the intelligent prediction method, the predicted sequence 2 represents the predicted results of the GM(1,1| a) model, the predicted sequence 3 stands for the predicted results of a 3 points least squared linear model, and the predicted sequence 4 is denoted by the predicted results of a 4 points least squared linear model. In these experiments, the most recent four actual values is considered as a set of input data used to modeling for predicting the next desired output. As the next desired value is observed, the first value in the current input data set is discarded and joins this latest desired value to form a new input data set for next prediction.

Indexes of Stock Price

The stock price index prediction for four countries (U.S.A. New York Dow Jones, Taiwan TAIEX, Japan Nikkei Index, and Korea Comp. Index) [13] have been experimented as shown in Figure 1 to Figure 4. Their accuracy of four prediction methods, which are a grey model, a 3 points cumulative least squared linear model, a 4 points least squared linear model without cumulative data preprocess, the proposed method, is also compared and the summary of this experiment is listed in Table 1.

National Economy Growth Rate (EGA)

The national economy growth rate prediction for four countries (U.S.A., Taiwan, Japan, and South Korea) [14] are also tested and their results are demonstrated in Figure 5 to Figure 8. The comparison of the accuracy for four prediction methods, which are a grey model, a 3 points cumulative least squared linear model, a 4 points least squared linear model without cumulative data preprocess, the proposed method, is also made and the brief of this test is listed in Table 2.

Typhoon Moving Trace

The typhoon moving trace [15] has been exemplified herein for verifying the proposed hybrid momentum type prediction algorithm to describe the real storm tracking analysis. Toraji typhoon has sampled a set of data for a period of 4 days during 28-31, July 2001. Besides, Nari typhoon has also sampled a set of data as shown in the following sequence for a period of 2 weeks during 6-19, September 2001. These examples are of the inertia system utilized the momentum type prediction. In the Figure 9, 10, and 11, the predicted sequence 1 represents as the output of the proposed momentum type prediction algorithm, the predicted sequence 2 stands for the output of GM(1,1|a) prediction model, and the predicted sequence 3 stands for the output of the 3 points cumulative least squared linear model. As shown in Table 3, the accuracy of the predictions for two cases of the typhoon moving trace is clarified by the means of the method of Mean Squared Error (MSE) to compare their prediction performance.

Conclusions

This study introduced a intelligent method for the non-periodic short-term forecast that actually is a hybrid model, combing the grey model and cumulative least squared linear model, with the technique of automatically compensating the overestimated or underestimated predicted value around the points having extreme value. As shown in Figure 1 to Figure 11, the proposed method in fact has the advantage of compromising the crucial problem of overshooting occurred in the grey model and the severe issue of damped happened to the 3 points cumulative least squared linear model. According to Table 1,2, and 3, we can conclude that the mean square error (MSE) of the predicted results in the proposed method is less than that of the other models. This implies that the proposed method obtain the satisfactory results for the non-periodic short-term forecasting application.

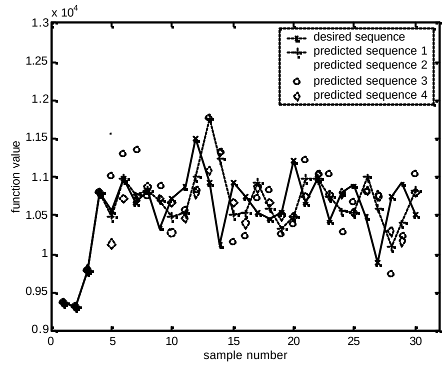

Figure 1. Forecasting results of N. Y. -D. J. Indus. Index.

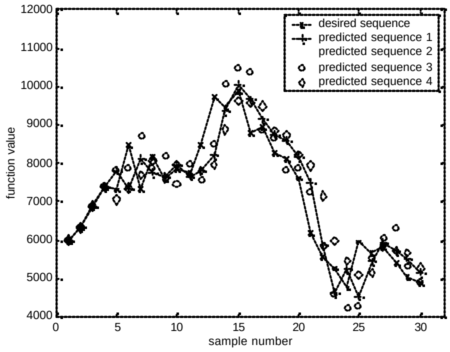

Figure 2. Forecasting results of Taiwan TAIEX sequence.

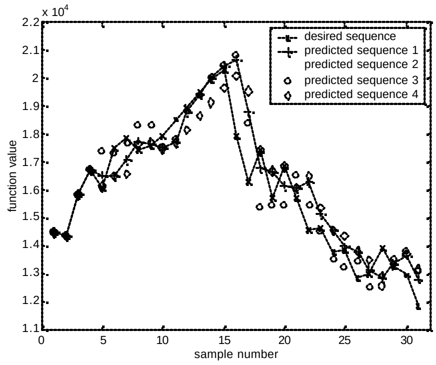

Figure 3. Forecasting results of Japan Nikkei Index.

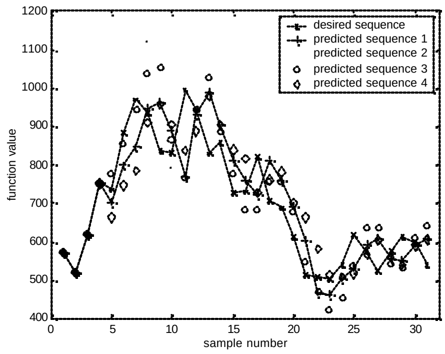

Figure 4. Forecasting results of Korea Comp. Index.

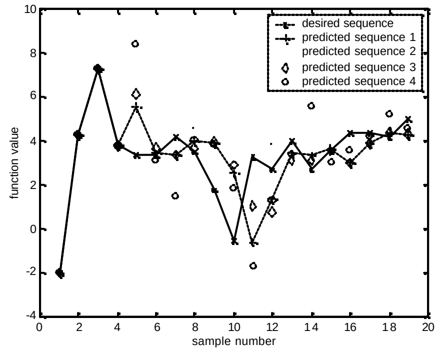

Figure 5. Forecasting results of U.S.A EGA.

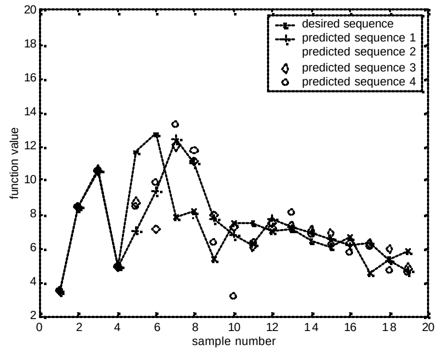

Figure 6. Forecasting results of Taiwan EGA.

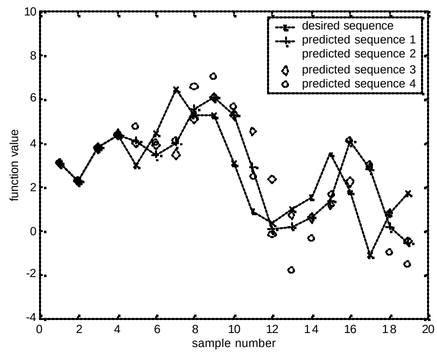

Figure 7. Forecasting results of Japan EGA.

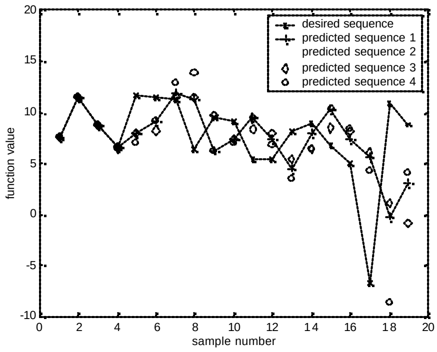

Figure 8. Forecasting results of South Korea EGA.

TABLE 1. The mean squared error (MSE) between the desired values and the predicted results for International Stock Price Indexes up to 31 months from January 1999 to July 2001. (unit=10^5)

Methods	N Y-D.J. Indus. Index	Taiwan TAIEX Index	Japan Nikkei Index	Korea Composite Index	Average of MSE
GM	4.2786	5.2297	13.305	0.1208	5.7335
3CLSP	2.0667	6.0443	11.687	0.0873	4.9716
4LSP	3.5841	5.5522	10.838	0.0912	5.0164
HW	5.1448	9.8316	15.425	0.1220	7.6308
BJ	18.003	10.407	37.719	0.1392	16.5670
IPA	1..9747	4.1780	9.7619	0.0713	3.9965

Note: Method abbreviation

1. GM- GM(1,1|a) Model
2. 3CLSP- 3 Points Cumulative Least Squared Linear Model
3. 4LSP- 4 Points Least Squared Linear Model
4. HW-Holt-Winters Smoothing Model
5. BJ-Box-Jenkins Forecasting Model
6. IPA-Intelligent Prediction Algorithm

TABLE 2. The mean squared error (MSE) between the desired values and the predicted results for National Economy Growth Rate up to 19 years from 1982 to 2000.

Methods	U.S.A.	Taiwan	Japan	South Korea	Average of MSE
GM	2.8236	12.9120	4.9731	37.2338	14.4856
3CLSP	2.4864	5.2981	4.0429	30.3359	10.5408
4LSP	5.4152	5.8641	4.9592	45.7680	15.5016
HW	11.9217	8.9184	6.1925	48.4673	18.8750
BJ	6.1967	9.5694	5.2919	777.72	199.695
IPA	2.2363	4.2253	3.4617	26.5326	9.1140

Note: Method abbreviation

1. GM- GM(1,1|a) Model
2. 3CLSP- 3 Points Cumulative Least Squared Linear Model
3. 4LSP- 4 Points Least Squared Linear Model
4. HW-Holt-Winters Smoothing Model
5. BJ-Box-Jenkins Forecasting Model
6. IPA-Intelligent Prediction Algorithm

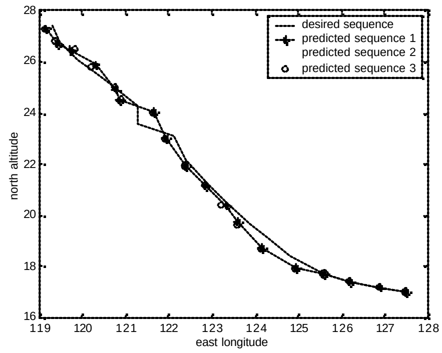

Figure 9. The momentum type prediction algorithm for the forecasting of Toraji typhoon moving trace illustrated during 28-31, July 2001.

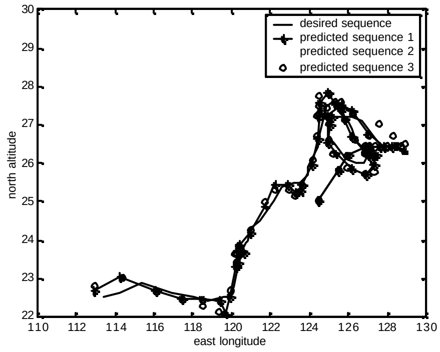

Figure 10. The momentum type prediction algorithm for the forecasting of Nari typhoon moving trace illustrated during 6-19, September 2001.

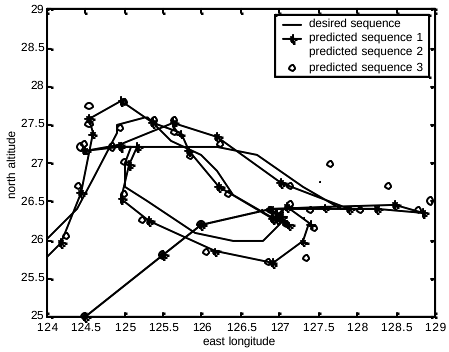

Figure 11. A room-in picture located north altitude from 25 to 29 and east longitude from 124 to 129 illustrated the momentum type prediction algorithm for the forecasting of Nari typhoon moving trace.

TABLE 3. The mean squared error (MSE) between the desired values and the predicted results for Toraji and Nari Typhoon Moving Trace in 2001.

Methods	Toraji Typhoon	Nari Typhoon	Average of MSE
GM	0.3158	0.3467	0.3313
3CLSP	1.3967	0.7191	1.0579
4LSP	0.3005	0.4103	0.3554
HW	0.3828	0.5235	0.4532
BJ	0.4778	0.4901	0.4840
IPA	0.2966	0.3393	0.3179

Note: Method abbreviation

1. GM- GM(1,1|a) Model
2. 3CLSP- 3 Points Cumulative Least Squared Linear Model
3. 4LSP- 4 Points Least Squared Linear Model
4. HW-Holt-Winters Smoothing Model
5. BJ-Box-Jenkins Forecasting Model
6. IPA-Intelligent Prediction Algorithm

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