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Short Paper

Hybrid BPNN-Weighted Grey-CLSP Forecasting*

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Conventional GM(1, 1|α) prediction always produces the huge singleton residual error around the turning point region of a time series and this phenomenon is called overshooting. A novel forecasting technique using a hybrid BPNN-weighted Grey-CLSP (BWGC) prediction that employs a back-propagation neural net (BPNN) to automatically adjust a linear combination of GM(1, 1|α) prediction and the cumulated 3-point least squared linear prediction (C3LPS) is presented herein to resolve this overshooting problem. This is because utilizing an underestimated output from C3LPS to offset an overshoot predicted output from the grey prediction will dramatically reduce the big residual error. This model exhibits a smoothing effect on the forecast to yield better an accuracy for the non-periodic short-term prediction. A three-layer BPNN with a structure of $5 \times 14 \times 2$ multilayer-perceptron is used to tune the weights for both models. This approach was verified to be not only suitable for a stochastic type prediction (international stock price indices forecasting) but also for an inertia type prediction (forecasting the path of a typhoon).

Keywords: BWGC prediction, GM(1, 1|α) prediction, C3LSP prediction, back-propagation neural net, overshooting problem

1. INTRODUCTION

Modeling by historical data fitting can build a predictor applied to short-term, medium-term, or long-term forecasting [1, 2]. Basically, the forecasts are obtained through means of extrapolating a value at the next time instant based on the model's prediction algorithm [3]. However, some of these models require a large amount of observed data for learning/training their long-term behavior so as to achieve better prediction performance [4], e.g., linear regression, Holt-Winters smoothing, and Box-Jenkins. Nevertheless, they are suitable for regular or periodic forecasting applications since modeling depends largely on whether or not data are normally distributed with regular variation [3], typically the seasonal or cyclical time series. In such a way, its approach can significantly

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improve the prediction accuracy for long-term or short-term prediction [5] in view of an extension from the historical data. Alternatively, in order to learn the dynamic behavior of observations, intelligent methods like neural network or fuzzy system [4, 6, 7] have also been introduced into forecasting methods. However, the sufficed pattern/target pairs are required to satisfy the training process so that modeling can be accomplished for advanced applications. Notice that when modeling for non-periodic short-term forecasting while employing a lower order polynomial to fit less available data, one can sometimes obtain more accurate predicted results due to better generalization [8]. In contrast, modeling using a high-order polynomial fitted from a lot of data may encounter the over-fitting/ill-posed problem [9] in non-periodic short-term forecasting. Clearly, a designated prediction with higher complexity might not perform well in the cases of non-periodic short-term forecasting.

A widely applicable predictor, GM(1, 1|α) model [10], has been used for dealing with non-periodic short-term forecasting for years. It is better than Holt-Winters smoothing or Box-Jenkins [10]. It still has a problem in that a huge singleton residual error frequently occurs at the time instants around turning point regions of a time series, that is, the overshooting phenomenon [11] as shown in Fig. 1. In this study, underestimated output has been found to occur at the same time as overshooting, and this situation been the result of the cumulated 3-point least squared linear prediction (C3LSP), as illustrated in Fig. 1. An idea of compensation is made by the combination of a grey model and C3LSP in which an underestimated output from C3LSP is used to offset the overshooting output caused by the GM(1, 1|α) model. A three-layer back-propagation neural network (BPNN) is employed to automatically tune the appropriate weights for both models, GM(1, 1|α) and C3LSP, (a posterior analysis) and subsequently this hybrid system is used to compute the predicted output for any designated-step ahead forecast (a prior validation) in non-periodic short-term forecasting.

2. NON-PERIODIC SHORT-TERM PREDICTION MODELS

2.1 Grey Prediction Model GM(1, 1|α)

Transforming observed data, $x^{(0)}(k)$ with a nonnegative sequence, through the first order accumulated generating operation, denoted by 1-AGO [10], aims to generate an approximately exponential curve. This allows the generated curve to be used to build a pseudo first order ordinary differential equation which can be used as a specific forecast model.

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

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

$$z^{(1)}(k) = \alpha x^{(1)}(k) + (1 - \alpha)x^{(1)}(k - 1), \; 0 \le \alpha \le 1 \tag{3}$$

$$X = [x^{(0)}(2) x^{(0)}(3) \ldots x^{(0)}(n)]^T, \; A = \begin{bmatrix} 1 & 1 & \ldots & 1 \\ -z^{(1)}(2) & -z^{(1)}(3) & \ldots & -z^{(1)}(n) \end{bmatrix}^T, \; B = [a \; b]^T \tag{4}$$

$$X = AB,\ B = A^{+}X,\ A^{+} = (A^{T}A)^{-1}A^{T} \tag{5}$$

$$\frac{d\hat{x}^{(1)}(k)}{dk} + a\hat{x}^{(1)}(k) = b \tag{6}$$

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

2.2 Cumulated 3-Point Least Squared Linear Prediction Model (C3LSP)

We take a linear transformation to generate the non-negative data set. Then 1-AGO is used to form a 3-point least squared linear polynomial as a specific forecast model where γ represents a user defined scaling factor and λ stands for a user defined shift factor.

$$x^{(1)}(i) = \gamma x^{(0)}(i) + \lambda,\ i = 1, 2, 3 \tag{8}$$

$$x^{(2)}(i) = \sum_{j=k-3}^{k-4+i} x^{(1)}(j),\quad i = 1, 2, 3 \tag{9}$$

$$x^{(2)}(k) = c_1 z + c_0,\ z = 1, 2, 3 \tag{10}$$

$$X = [x^{(2)}(1), x^{(2)}(2), x^{(2)}(3)]^T,\ Z = \begin{bmatrix} 111 \\ 123 \end{bmatrix}^T,\ C = [c_1\ \ c_0]^T \tag{11}$$

$$X = ZC,\ C = (Z^T Z)^{-1} Z^T X \tag{12}$$

$$\tilde{x}^{(2)}(k) = c_1 k + c_0,\ \text{s.t. } z = k-3,\ k-2,\ k-1 \tag{13}$$

$$\tilde{x}^{(1)}(k) = \tilde{x}^{(2)}(k) - x^{(2)}(k-1) \tag{14}$$

$$\tilde{x}^{(0)}(k) = \frac{1}{\gamma}(\tilde{x}^{(1)}(k) - \lambda) \tag{15}$$

3. HYBRID BPNN-WEIGHTED GREY-CLSP APPROACH

3.1 Motivation for Hybrid Models Prediction

According to the analysis in [11], by decreasing the number of sampling points as much as possible and lessening the effect of the magnitude of the original data, we can lower the residual error of the GM(1, 1|α) model. However, the predicted value of the GM(1, 1|α) model always has an overshooting or undershooting around the turning point regions of a time series [11]; that is, it leads to the occurrence of extreme magnitude (too high or too low) as shown in Fig. 1.

In addition, at the same or different time instants, a highly interesting phenomenon has also occurred in that a reverse situation, the occurrence of underestimate predicted output, may possibly happen resulting from the cumulated 3-point least squared linear prediction (C3LSP), as indicated at sample point 14 shown in Fig. 1. It is also noted that

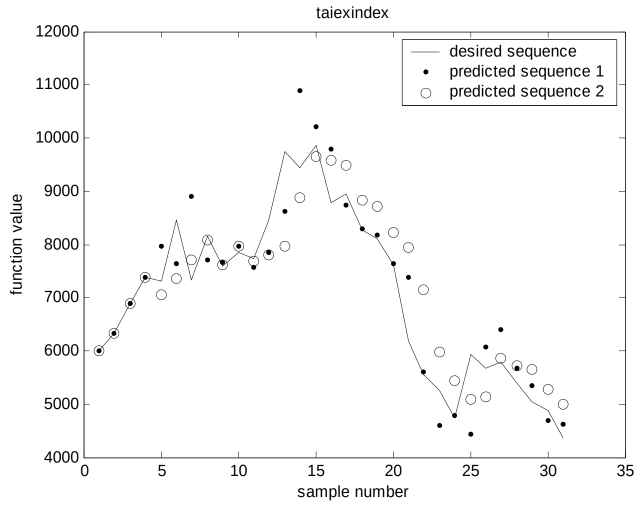

Fig. 1. The desired sequence represents the monthly Taiwan's stock price index for a period of 31 months from January 1999 to July 2001. The outputs of the GM(1, 1|α) model indicted by the predicted sequence 1, denoted by "•", reveal a crucial problem, an overshoot phenomenon that might happen around the turning points at sample numbers 7, 14, 25, 26, and 27. The underestimated predicted outputs may result from a cumulated 3-point least squared linear model indicated by the predicted sequence 2, denoted by "o", around the turning point region at sample numbers 6, 12, 13, 25, and 26.

sometimes the overshoot phenomenon is caused by the C3LSP, and, in contrast, the grey prediction would predict results with underestimated values, as indicated at sample point 23 shown in Fig. 1. In order to simplify the formulation for short-term forecasts, we suggest a linear combination of grey prediction and the prediction of the C3LSP model [12]. Hence, all we have to do is hence to exploit the appropriate weights for the hybrid predicted output $\hat{z}^{(0)}(k)$ as follows.

$$\hat{z}^{(0)}(k) = w_1\hat{x}^{(0)}(k) + w_2\tilde{x}^{(0)}(k), \tag{16}$$

s.t. $w_1 + w_2 = 1$

In Eq. (16), $\hat{x}^{(0)}(k)$ and $\tilde{x}^{(0)}(k)$ denote the predicted values from a grey model on Eq. (7) and a cumulated 3-point least squared linear model on Eq. (15), respectively. In addition, the w_1 and w_2 represent the weight of $\hat{x}^{(0)}(k)$ and $\tilde{x}^{(0)}(k)$, respectively.

3.2 BPNN-Based Weighted Grey-CLSP Output

A well-known intelligent computing machine, the three-layer multilayer preceptron neural net (BPNN) [6], shown in Fig. 2, is used in this hybrid Grey-CLSP predictor for tuning the appropriate weights for the forecasts $\hat{x}^{(0)}(k)$ and $\tilde{x}^{(0)}(k)$ in Eq. (16). By cross-examination among the performance criteria of the forecast outputs in the experimental results section, the prior validation (prediction) shows that the forecasts are acceptable from an accuracy point of view. For this three-layer BPNN, a 5 × 14 × 2

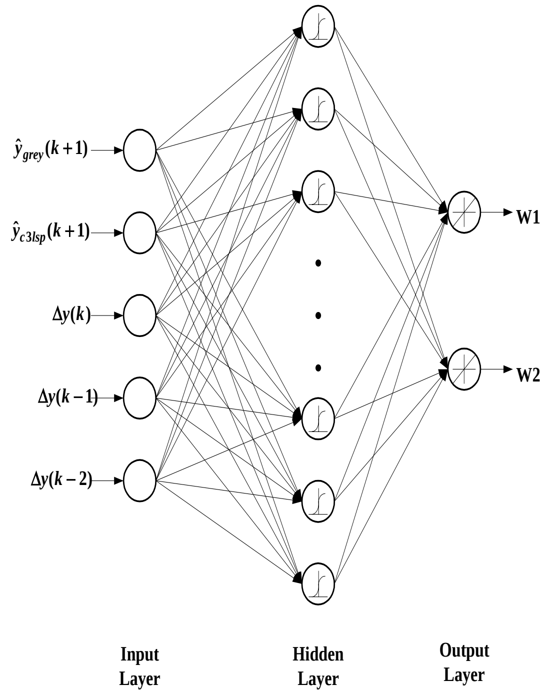

Fig. 2. A typical three-layer BPNN architecture and sigmoid transfer function as the output of activations in the hidden layer.

multilayer-perceptron is used where the input layer has 5 input neurons to catch the input patterns, the hidden layer has 14 neurons to propagate the intermediate signals, and the output layer has 2 neurons to display the computed results (weights). We arrange the input pattern as follows: a single-step-ahead predicted output from the grey model $\hat{y}_{grey}(k + 1)$, a single-step-ahead predicted output from the C3LSP model $\hat{y}_{c3lsp}(k+1)$, and the three most recent differential values of the true observations $\Delta y(k)$, $\Delta y(k-1)$, and $\Delta y(k-2)$. Two weights w_1 and w_2, applied to the hybrid Grey-CLSP prediction, and designed as the outputs. For more training assignments in this three-layer BPNN, the log-sigmoid transfer function is used as the activation function in the hidden layer, the pure-line transfer function is employed in the output layer as the activation function, and the Bayesian regulation with Levenberg-Marquardt training is used as the learning algorithm for this three-layer BPNN.

The block diagram of this hybrid Grey-CLSP non-periodic short-term prediction is depicted in Fig. 3. This diagram shows the procedure for the training phase and simulation (prediction) phase, and explains the operation of hybrid Grey-CLSP forecasting in detail. Applications of non-periodic short-term forecasting can be classified into two types of prediction. The stochastic type of prediction is a kind of irregular time series. In other words, the next output from this system is highly random and fully ambiguous, and hence the forecast of future outcomes is difficult because the predicted values de facto challenge the unforeseen results. The inertia type of prediction belongs to a kind of

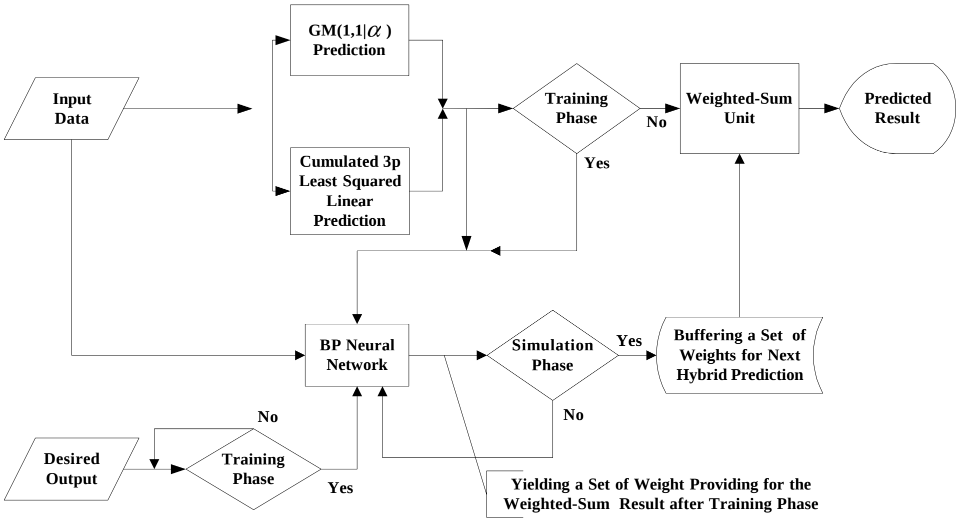

Fig. 3. The block diagram represents the procedure of hybrid BPNN-Weighted GREY-CLSP prediction for the non-periodic short-term forecasting.

persistent time series. The next output from this system is more reliable and steady, and thus the forecast of future outcomes is less complicated since the one-step-ahead trend will preserve for very short time intervals. However, outliers might occur for this inertia type forecasting at any time without any sign in advance. Based on the proposed approach, both stochastic type forecasting (e.g. international stocks, futures, or options price indices) and inertia type forecasting (e.g. typhoon, hurricane, tornado, or cyclone moving trace) can be accomplished successfully.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

4.1 First Experiment: International Stock Price Indices

The proposed hybrid model is applied to the stochastic type forecast on four international stock price indices [13] as shown in Figs. 4, 5, 6, and 7. This forecasting application has been separated into two phases. The first phase has designed as training/learning stage for modeling the BPNN-weighted machine that is of the posterior analysis from observed historical monthly data set for a period of 47 months from January 1997 to November 2000. Next, the second phase, the prior validation stage has proceeded to predict the future results for examining the system performance employing the single-step-ahead forecast on the stock price indices dated from December 2000 to February 2002 for 15 monthly index's values.

In Figs. 4, 5, 6, and 7, predicted sequence 1 shows the output of GM(1, 1|α) prediction, predicted sequence 2 shows the output of cumulated 3-point least squared linear prediction, and predicted sequence 3 shows the output of the proposed hybrid Grey-CLSP prediction.

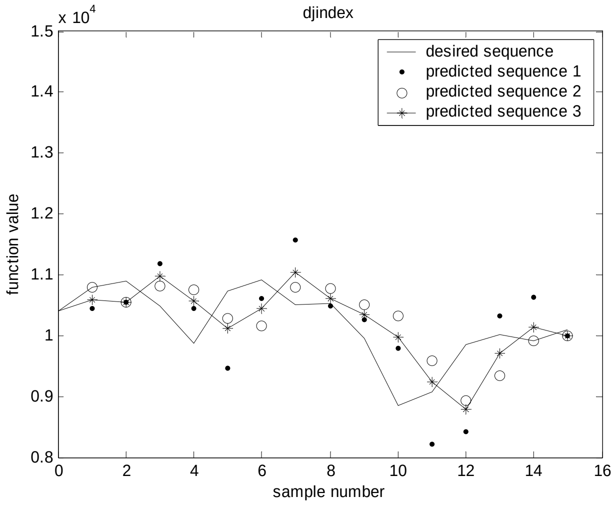

Fig. 4. The stochastic type forecast using the proposed hybrid model applied to the Dow Jones Industrial Average index from December 2000 to February 2002 for monthly values.

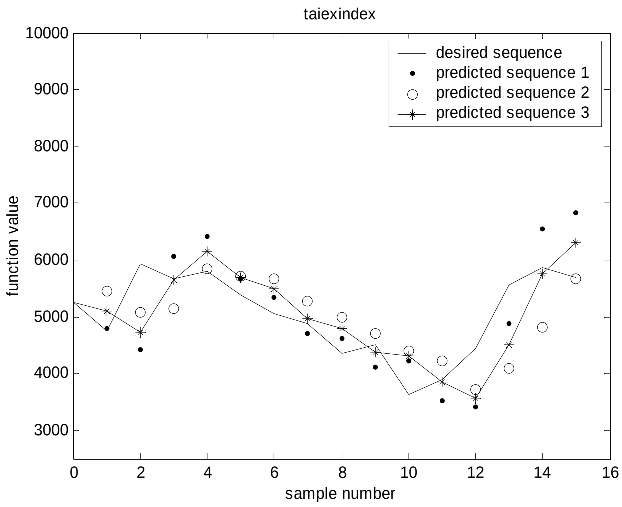

Fig. 5. The stochastic type forecast using the proposed hybrid model applied to Taiwan TAIEX Index from December 2000 to February 2002.

Table 1 gives a comparison between MSE, MAPE, MAD and the proposed hybrid model and the competitive models is given. The one we propose has the best accuracy in this forecast. Furthermore, the goodness of fit for the hybrid BPNN-weighted Grey-CLSP prediction was also tested by the Ljung-Box Q-test [14], and null hypothesis cannot be rejected because p-value is greater than the level of significance (5%).

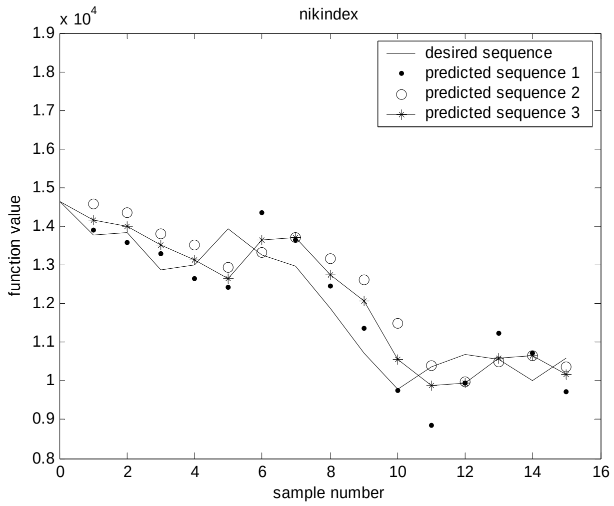

Fig. 6. The stochastic type forecast using the proposed hybrid model applied to Japan Nikkei Index from December 2000 to February 2002.

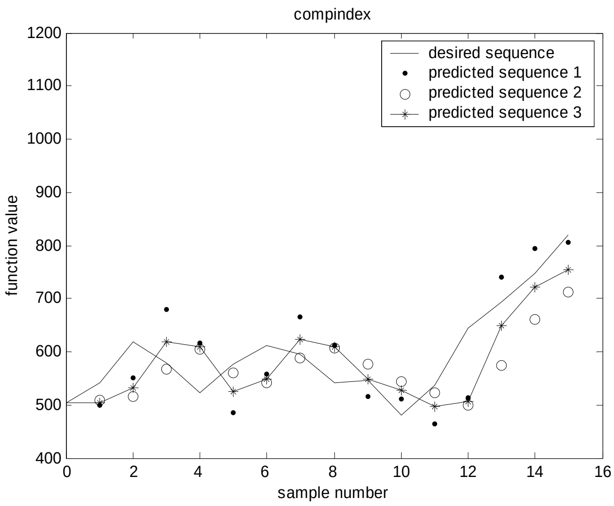

Fig. 7. The stochastic type forecast using the proposed hybrid model applied to Korea Composite Index from December 2000 to February 2002.

4.2 Second Experiment: Typhoon Moving Trace

The proposed hybrid model applied to the inertia type forecast is utilized for the following two tasks have cited in this prediction of typhoon moving trace [15], Toraji and Nari typhoons as shown in Figs. 8, 9, 10, and 11. Typhoon Toraji was sampled for a set of 20 observed historical global positions for training/learning BPNN-weighted machine, that is, a posterior analysis over the first phase. Next, prior to the validation phase,

Table 1. Comparison of mean squared error (MSE), mean absolute percent error (MAPE), and mean absolute deviation (MAD) between the proposed and competitive models on the Dow Jones Industrial Average Index (DJ), Taiwan TAIEX Index (TE), Japan Nikkei Index (NK), and Korea Composite Index (CP) stock price indices forecasting for 15 months from December 2000 to February 2002.

Models	DJ MSE	TE MSE	NK MSE	CP MSE	Avg. MSE	DJ MAPE	TE MAPE	NK MAPE	CP MAPE	Avg. MAPE	DJ MAD	TE MAD	NK MAD	CP MAD	Avg. MAD
GM	5.4701	4.6396	6.5163	0.0499	4.1690	0.0579	0.0905	0.0548	0.0909	0.0735	537.08	448.90	575.03	57.31	404.58
C3LSP	4.0171	4.7252	8.5029	0.0585	4.3259	0.0543	0.0987	0.0677	0.0959	0.0792	499.07	487.74	707.05	62.80	439.16
4LSP	5.2073	5.6145	7.9089	0.0522	4.6957	0.0582	0.0904	0.0563	0.0885	0.0734	542.91	449.23	603.04	56.12	412.83
HW	7.3462	9.2697	12.690	0.0801	7.3466	0.0662	0.1155	0.0758	0.1109	0.0921	616.27	581.17	809.07	69.94	519.11
BJ	13.462	8.9066	6.2920	0.1024	7.1907	0.0708	0.1248	0.0673	0.1161	0.0948	654.08	624.24	688.78	73.37	510.12
RBF	2.8709	3.7655	6.2989	0.0653	3.2501	0.0434	0.0918	0.0560	0.0885	0.0699	395.47	443.14	583.21	56.47	369.57
GRNN	2.5912	3.6922	6.0469	0.0589	3.0973	0.0431	0.0763	0.0512	0.0769	0.0619	396.52	375.08	539.70	49.30	340.15
BWGC	2.5783	3.2496	5.0311	0.0324	2.7229	0.0410	0.0674	0.0486	0.0726	0.0574	371.49	361.10	521.91	49.18	325.92

Method abbreviation as follows: **GM**- GM(1, 1|α) Model, **C3LSP**- Cumulated 3-Point Least Squares Linear Model, **4LSP**- 4-Point Least squares Linear Model, **HW**-Holt-Winters Smoothing Model, **BJ**-Box-Jenkins Forecasting Model, **RBF**- Radial Basis Function Neural Net, **GRNN**- General Regression Neural Net, and **BWGC**- Hybrid BPNN-Weighted Grey-CLSP Algorithm.

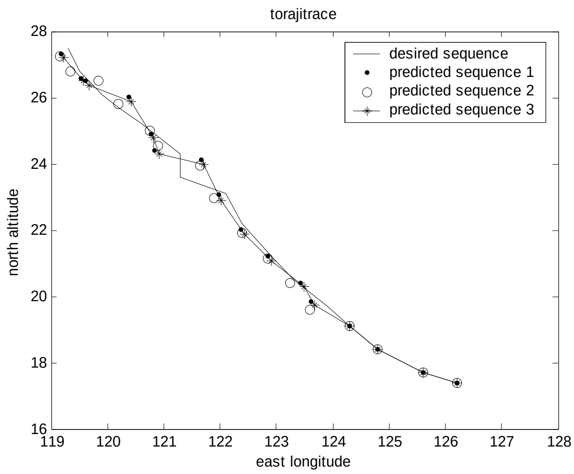

Fig. 8. The inertia type forecast using the proposed hybrid model applied to typhoon Toraji's path depicted for July 28-31, 2001.

the various methods have been employed to predict the future positions at the next 12 successive points in order to track the look-ahead path. Likewise, the first phase for training/learning machine was sampled for a set of 20 observed historical global positions from typhoon Nari. After modeling completely, prior to validation, various methods which have been applied to predict the future global positions on the next successive 44 points. It seems that the complexity of the true motion of typhoon Nari is in fact greater than that of Toraji as seen by examining the true tracks in Figs. 8 and 9. This is because so many motions of Nari show a lack of the stationary property.

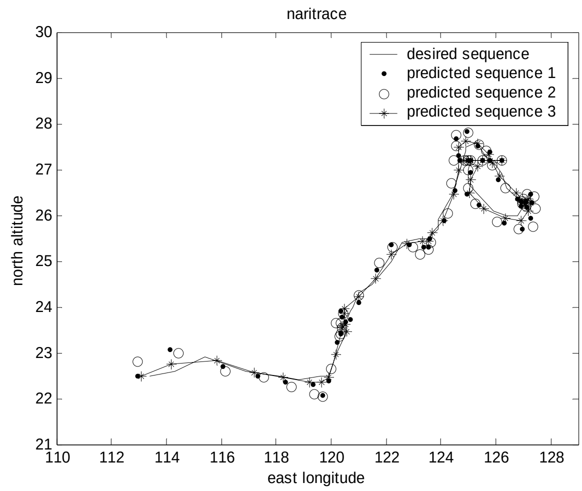

Fig. 9. The inertia type forecast using the proposed hybrid model applied to typhoon Nari's path depicted for September 6-19, 2001.

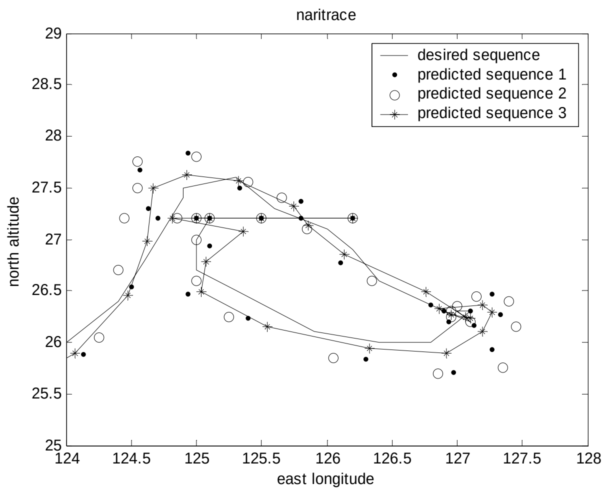

Fig. 10. A zoom-in picture for typhoon Nari's path around north altitude 25 to 29 degrees and east longitude 124 to 129 degrees.

In particular, this is an example of an inertia type forecast in which the GM(1, 1|α) prediction model in fact plays a more important role in forecasting the future position. This is because the inertia type system, e.g., a typhoon belongs to an energy content, and the possibility that the next motion will be diagonal to its original track will be significantly higher as shown in Fig. 8.

Clearly, both Holt-Winters smoothing and Box-Jenkins have performed well for this type forecast due to its highly stationary property or the global position being normally distributed. After carefully examining both Tables 1 and 2, it is seen that the proposed

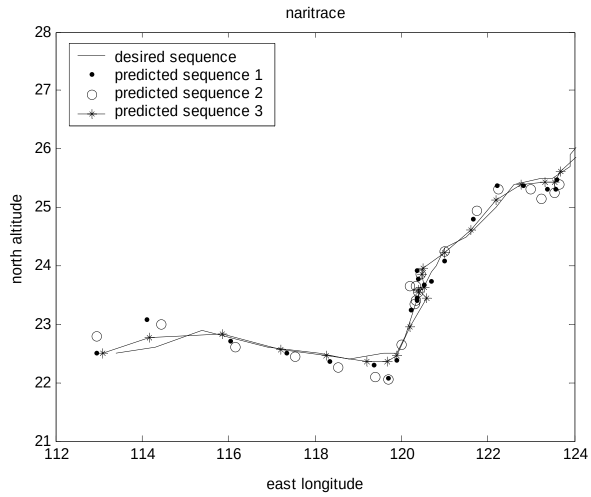

Fig. 11. A zoom-in picture for typhoon Nari's path located around north altitude 21 to 28 degrees and east longitude 124 to 112 degrees.

Table 2. Comparison of performance using mean squared error (MSE), mean absolute percent error (MAPE), and mean absolute deviation (MAD) between the proposed one and the competitive models on typhoons Toraji and Nari moving trace forecast in 2001.

Models	Toraji MSE	Nari MSE	Average MSE	Toraji MAPE	Nari MAPE	Average MAPE	Toraji MAD	Nari MAD	Average MAD
GM	0.0594	0.065	0.0622	0.0022	0.0022	0.0022	0.0859	0.0984	0.0922
C3LSP	0.9681	0.370	0.6691	0.0119	0.3698	0.1909	0.4024	0.2102	0.3063
4LSP	0.0450	0.090	0.0675	0.0019	0.0027	0.0023	0.0733	0.1159	0.0946
HW	0.0024	0.145	0.0737	0.0024	0.0034	0.0029	0.0993	0.1494	0.1244
BJ	0.1438	0.215	0.1794	0.0034	0.0036	0.0035	0.1331	0.1467	0.1399
RBF	0.0809	0.465	0.2730	0.0042	0.0043	0.0043	0.3875	0.0043	0.1959
GRNN	0.0638	0.130	0.0969	0.0017	0.0029	0.0023	0.0857	0.1290	0.1074
BWGC	0.0560	0.025	0.0405	0.0022	0.0020	0.0021	0.0859	0.0971	0.0915

Note: the abbreviation is the same as Table 1.

hybrid model is more easily applied to the inertia type forecast than to the stochastic one. Finally, the Ljung-Box Q-test for the goodness of fit for the hybrid BPNN-weighted Grey-CLSP prediction is also performed and the null hypothesis cannot be rejected due to p-value greater than the level of significance (5%).

5. CONCLUSIONS

The following statements summarize the accomplishment of this proposed hybrid prediction.

(a) Hybrid BPNN-weighted Grey-CLSP prediction is introduced in this study in which an intelligent compensation, namely BPNN adaptation, is applied to automatically tune the weights of the combination of GM(1, 1|α) prediction and cumulated 3-point least squares linear prediction (C3LPS). The goal is to smooth the predicted results and to lessen the overshoot. This uses the underestimate from C3LPS to offset the overestimate from the grey model, effectively reducing a huge singleton residual error from occurring around the turning point region of a time series.
(b) A three-layer BPNN with a $5 \times 14 \times 2$ multilayer perceptron is utilized for optimizing the hybrid model proposed in this study. The computing work by BPNN performs very well even though the task is proceeding in this non-periodic short-term forecasting.
(c) The hybrid BPNN-weighted Grey-CLSP prediction proposed here can be applied into both stochastic and inertia type forecasting. As seen in Tables 1 and 2, the hybrid model is easier to apply to the inertia type forecast to the stochastic one. This is due to the inherent stationary property of the inertia system.

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