Enhanced Hybrid Prediction Models for Time Series Prediction

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Abstract: Statistical techniques have disadvantages in handling the non-linear pattern. Soft Computing (SC) techniques such as artificial neural networks are considered to be better for prediction of data with non-linear patterns. In the real-life, time-series data comprise complex pattern, and hence it may be difficult to obtain high prediction accuracy rates using the statistical or SC techniques individually. We propose two enhanced hybrid models for time series prediction. The first model is an enhanced hybrid model combining statistical and neural network techniques. Using this model, one can select the best statistical technique as well as the best configuration for the neural network for time series prediction. The second model is an enhanced adaptive neuro-fuzzy inference system which combines fuzzy inference system and neural network. The proposed enhanced Adaptive Neuro-Fuzzy Inference Systems (ANFIS) model can determine the optimum input lags for obtaining the best accuracy results. The prediction accuracies of the two proposed hybrid models are compared with those obtained with other models based on three time series data sets. The results indicate that the proposed hybrid models yield better accuracy results compared to Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, moving average, weighted moving average and Neural Network models.

Keywords: Hybrid model, adaptive neuro-fuzzy inference systems, soft computing, neural network, statistical techniques.

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1. Introduction

In recent years, many time series prediction models based on different concepts have been proposed rapidly. The researchers have developed more efficient models to improve the prediction accuracy. The prediction accuracy would depend not only on the model but also on the complexity of the data. Hence, it is very important to choose the best time series prediction model based on the complexity of data. Several statistical techniques such as moving average [23, 45], exponential smoothing, Autoregressive Moving Average (ARMA) [4], Autoregressive Integrated Moving Average (ARIMA) [19, 41] have been reported for time series prediction.

Law has applied Moving Average (MA) technique for impact of financial crisis and demand forecasting [23]. The Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) methods have been used for prediction in various fields [23, 30, 35]. Time series prediction using ARIMA model has been applied in various fields. ARIMA model for tourism demand prediction was reported in [12, 32]. Mishra has applied ARIMA model for natural gas price forecasting [29]. However, these statistical techniques do not yield satisfactory results for complex data patterns [22, 44].

Recent studies have discussed the problem of time series prediction using different concepts, including Artificial Neural Networks (ANN) that have self-learning capabilities [1, 13, 17, 31]. Many researchers have also used ANN model for prediction in various fields.

Liu et al. [25] have applied ANN for wind power plant prediction; Georgarakos et al. [13] have applied this model to predict annual loliginid and ommastrephid landings; Polat and Arslankaya have applied artificial neural network to determine the amount of production [33]; Gosasang et al. have used artificial neural network for Forecasting Container Throughput at Bangkok Port [14]; Buhari and Adamu [6] have applied ANN in forecasting future load demands. Application of neural networks for bridge health prediction has been reported by Suryanita and Adnan [39]. Maizir and Kassim have applied Neural Network model for prediction of axial capacity [26]. Kosanan and Kantanantha have used ARIMA, Neural Networks (NN) and Support Vector Machine (SVM) for Thailand’s Para rubber production forecasting. They reported that neural network model performs better than ARIMA and SVM models [20]. However artificial neural networks yield mixed results in handling linear patterns [44].

In the real-life, time-series data consist of complex patterns. It is difficult to obtain high prediction accuracy rates using the statistical or SC techniques individually. A hybrid model which combines linear and nonlinear methods can be expected to yield high prediction accuracy rates [11, 44]. A hybrid model combining Exponential Smoothing (ES) and neural network method has been employed to predict
Various types of hybrid models have been used in various fields. Hybrid models have been used for financial time series prediction, water quality time series prediction, [11, 22]. The ANFIS model has been applied for prediction of water level in reservoir, weather forecasting, WiMAX traffic prediction, prediction of the power factor in wind turbines and wired-EDM [2, 8, 9, 15, 40].

The statistical technique such as ARIMA model and soft computing technique such as the neural network model have achieved successes in linear and non-linear domains, respectively. The ARIMA model has been employed for prediction in several applications [10, 12, 19, 32, 41]. Unfortunately, the use of ARIMA model has disadvantages for non-linear data [44]. Similarly, the neural network model also has disadvantages for linear data since it is found to yield mixed results [44].

Generally, the time-series data is composed of a linear autocorrelation structure and a non-linear component as expressed in Equation (1) [44]:

\[ y_t = L_t + N_t \]  

(1)

Where \( L_t \) and \( N_t \) represent the linear and non-linear components respectively.

Zhang [44] employs a hybrid method using two steps. In the first step, the statistical technique, namely ARIMA model is employed to predict the linear part (\( \hat{L}_t \)) and in the second step, a neural network (a neural network of 7-6-1) model is used to predict the nonlinear component (\( \hat{N}_t \)) from residual series obtained from the linear model. The residual series \( e_t \) is calculated as in Equation (2):

\[ e_t = y_t - \hat{L}_t \]  

(2)

The final prediction from the hybrid model is calculated as [8]:

\[ \hat{y}_t = \hat{L}_t + \hat{N}_t \]  

(3)

Where \( \hat{y}_t \) represents hybrid model prediction at time \( t \).

### 2.2. Proposed Method

For modeling purposes, three data sets namely time series HIV/AIDS data for the period 1990 to 2009 [28], morbidity of tuberculosis data for the period 1990 to 2007 [42] and New York City Birth (NYB) data set for the period from January-1946 to December-1959 [16] are used. The data sets are used to evaluate the performance of the two proposed hybrid models. The performances of the proposed hybrid models are then compared with those of other models.

The first proposed hybrid model is HM1 model. The HM1 model is an enhanced hybrid model combining the best statistical model with an optimally configured neural network model. The various steps
involved in the functioning of HM1 model are explained below. The first step is to determine the best statistical technique for the given input data. Based on the time-series data, different statistical techniques are applied to predict the linear component. Using the RMSE performance measure values, the best statistical model among Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Moving Average (MA), Weighted Moving Average (WMA) and Autoregressive Integrated Moving Average (ARIMA) is determined. The Residual Series (error) data are then applied to an Multilayer Perceptron (MLP) neural network to determine the non-linear component. The second step, different numbers of input and hidden layer neurons as well as different types of activation functions are employed to identify the optimal MLP configuration which yields the minimum Root Mean Square Error (RMSE) value. The optimum number of neurons in input and hidden layers, and the type of activation functions can be determined in this step.

The overall time series prediction is calculated by combining the best statistical technique with the optimally configured neural network in the third step. The algorithm for the proposed HM1 is shown in Algorithm 1.

**Algorithm 1: Proposed HM1 algorithm.**

```c
n=number_of_training
m=number_of_testing
/* statistical techniques*/
for (i=1 to n)
|
ES[i]=Exponential_Smoothing(yt[i])
MA[i]=Moving_Average (yt[i])
WMA[i]=Weighted_Moving_Average (yt[i])
ARIMA[i]=ARIMA(yt[i])
|
for (i=1 to m)
|
p=RMSE_ES (ys[i])
q=RMSE_MA (ys[i])
r=RMSE_WMA (ys[i])
t=RMSE_ARIMA (ys[i])
Best_RMSE(b, p, q, r, t)
for (i=1 to n)
|
Lt[i]=BestStatistical_Method(yt[i])
error[i]=yt[i]-BestStatistical_Method (yt[i])
/* Neural Network */
/* several types of activation function are used */
for (j=1 to nr) /*nr: number of neuron */
|
for (i=1 to n)
|
Nt[i]= Neural_net (error[i], j)
s=RMSE_NN (error[i], j)
Best_RMSE_NN [b, j]
| /* Hybrid HM1 */
```  

for (i=1 to n)

```
Hybrid1[i]= Lt[i]+Nt[i]
```  

The second proposed hybrid model is HM2 model. The HM2 model is an enhanced ANFIS model combining fuzzy inference system and neural network for univariate time series prediction. The proposed HM2 model is explained as follows:

In the learning process of ANFIS model for the univariate time series prediction, the input data are divided into two sets as inputs and target/output.

Suppose that the univariate time-series data have m-point data sequence \( \{ x_1, x_2, x_3, ..., x_m \} \). Assuming that the ANFIS model has \( p \) inputs and one output, then the model has \( m-p \) training patterns as shown in Table 1. The first pattern comprises \( \{ x_1, x_2, ..., x_p \} \) as the inputs and \( x_{p+1} \) as the output. The second pattern comprises \( \{ x_2, x_3, ..., x_{p+1} \} \) as the inputs and \( x_{p+2} \) as the output. The third pattern is composed of \( \{ x_3, x_4, ..., x_{p+2} \} \) as the inputs and \( x_{p+3} \) as the output. Finally, the last training pattern comprises \( \{ x_m-p, x_{m-p+1}, ..., x_{m-1} \} \) as the inputs and the \( x_m \) for the output. The process of univariate time-series data training for ANFIS is illustrated in Table 1 [34].

**Table 1. The pattern of univariate time series data.**

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Input lag</th>
<th>Output/ Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( x_1, x_2, x_3, ..., x_p )</td>
<td>( x_{p+1} )</td>
</tr>
<tr>
<td>2</td>
<td>( x_2, x_3, x_4, ..., x_{p+1} )</td>
<td>( x_{p+2} )</td>
</tr>
<tr>
<td>3</td>
<td>( x_3, x_4, x_5, ..., x_{p+2} )</td>
<td>( x_{p+3} )</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>( m-p )</td>
<td>( x_{m-p}, x_{m-p+1}, ..., x_{m-1} )</td>
<td>( x_m )</td>
</tr>
</tbody>
</table>

Based on the input univariate time series data as shown Table 1, the ANFIS architecture is illustrated in Figure 1. The ANFIS has \( p \) inputs, namely \( x_{m-p}, x_{m-p+1}, x_{m-p+2}, ..., x_{m} \) and one output \( f \).

The ANFIS for univariate time series has two fuzzy rules with the fuzzy sets, namely \( A_1 \) and \( A_2 \) are presented as follows:

- **Rule 1.** If \( x_{m-p} \) is \( A_1 \) and \( x_{m-p+1} \) is \( A_2 \) and ... and \( x_{m-1} \) is \( A_1 \) then:

\[
\begin{align*}
    f_i &= \sum_{j=1}^{p} w_j x_{m-p+j} + f_i \\
    &\quad + \frac{r_i}{N} \\
\end{align*}
\]

(4)

**Figure 1. ANFIS architecture for univariate time series data.**
Rule 2. If \( x_{m,p} \) is \( A_2 \) and \( x_{m,p+1} \) is \( A_2 \) and ... and \( x_{m,1} \) is \( A_2 \) then: 

\[
f_j = q_m x_{m,p} + q_{m,p+1} \ldots + q_{m,1} + r_i
\]

According to the fuzzy rules, the output of each node in ANFIS model can be given as follows:

**Layer 1.** The output of the node \( i \) in layer 1 denoted as \( O_{1i} \), represents a membership function \( \mu_{A_i} \) or \( \mu_{B_i} \) as shown in Equations (5), (6) and (7).

\[
O_{1i} = \mu_{A_i}(x_{m,p}), \text{ where } i = 1, 2
\]

\[
O_{1i} = \mu_{A_i}(x_{m,p+1}), \text{ where } i = 3, 4
\]

\[
O_{1i} = \mu_{A_i}(x_{m,1}), \text{ where } i = p+1, p+2
\]

Where \( x_{m,p}, x_{m,p+1}, \ldots, x_{m,1} \), are inputs, \( A_i \) are linguistic labels associated with the node.

The membership functions in ANFIS model are the generalized bell functions [34]. The parameters in this layer are called premise parameters. Their values are adaptive and calculated by means of the back-propagation algorithm during the learning state.

**Layer 2.** Each node in layer 2 (labeled as 2) represents the product of the membership function as shown in Equation (8):

\[
O_{2i} = w_i = \mu_{A_i}(x_{m,p}) \mu_{A_i}(x_{m,p+1}) \ldots \mu_{A_i}(x_{m,1})
\]

Where \( i=1, 2 \).

**Layer 3.** Each node in layer 3 (labeled as 3) yields the normalized firing strength as shown in Equation (9):

\[
O_{3i} = \sigma_i = \frac{w_i}{w_1 + w_2}, \text{ where } i = 1, 2
\]

**Layer 4.** The output of each node \( i \) in layer 4 is given as:

\[
O_{4i} = \bar{f}_i = \bar{f}_i(p_1 x_{m,p} + p_{2} x_{m,p+1} + \ldots + p_{q} x_{m,1} + r_i)
\]

\[
O_{4i} = \bar{f}_i = \bar{f}_i(q_1 x_{m,p} + q_{2} x_{m,p+1} + \ldots + q_{p} x_{m,1} + r_i)
\]

Where \( p_1, p_2, \ldots, p_q, q_1, q_2, \ldots, q_p \), \( r_1 \) and \( r_2 \) are the consequent parameters.

**Layer 5.** The single node in layer 5 is labeled as \( \Sigma \). This layer is the output layer. The value of the output is obtained as the summation of all incoming signals. The output of ANFIS is calculated as:

\[
O_{\Sigma} = \sum_{i} \bar{f}_i = \bar{f}_i + \bar{f}_2
\]

Where \( \bar{f}_i \) is the output of node \( i \) in layer 4.

The Algorithm of the proposed HM2 (which is an enhanced version of ANFIS model) is shown in Algorithm 2. In the first step, the time-series data are divided as inputs and target/ output for training and is applied to ANFIS model as illustrated in Table 1. For initialization, ANFIS model uses two numbers of input lags. The next step is to calculate the outputs using Equations (5), (6), (7), (8), (9) and (11) for the layers 1 to 4. Then the Least-Squares Estimator (LSE) method is employed to determine the consequent parameters. Based on the values of consequent parameters, the output of layer 5 is determined. We calculate the Mean Square Error (MSE) value, which is compared with the assumed MSE_{Tolerance}. The Error Back Propagation (EBP) and the Least-Squares Estimator (LSE) methods are repeated to update the values of premise and consequent parameters until MSE < MSE_{Tolerance}. After obtaining the optimal values for the premise and consequent parameters, we calculate RMSE. The input lags are then increased one by one to improve the prediction performance. If the value of RMSE_{旧} is smaller than the value of RMSE_{新}, then the iteration will be stopped. Finally, we calculate the prediction using the best configuration with an optimum number of input lags.

Algorithm 2: Proposed HM2 algorithm.

\[
n = \text{number of training}
\]
\[
k = \text{number of lags}
\]

\[
/* initialization of RMSEold, RMSEN, MSE_{tol} and j */
while ((j<=k) or (RMSEnew <= RMSEold))
{
for (i=1 to n)
{
Fwd [i]=Forward_Anfis (yt[i])
M [j]=MSE(yt[i])
If M[j] < MSE_{tol} then

Back [i]=Back_Anfis (yt[i])

j=j+1
RMSEnew=RMSE(yt[i])
Hybrid2[i]=Anfis (yt[i])
}
}

3. Experimental Results and Discussions

In this study, two performance measures, namely RMSE and MAE are used to compare prediction accuracies of different models [24, 36].

3.1. Statistical Techniques

Several statistical techniques, namely the SES, DES, MA and WMA and ARIMA are used in this study.

3.1.1. Exponential Smoothing Model

The SES and DES models are used for HIV/AIDS time series prediction. The values of RMSE and MAE using SES model with \( \alpha = 0.9 \) are 643.06 and 314.00 respectively. And the values of RMSE and MAE using DES model with \( \alpha = 0.4 \) and \( \beta = 0.5 \) are obtained 670.742 and 477.00 respectively.

3.1.2. Moving Average Model

The MA and WMA models are employed for
HIV/AIDS time series prediction. The performance measures are calculated to obtain RMSE and MAE values. The performance measures obtained using different numbers of inputs are tested. It is found that time series prediction using MA with 2 inputs lags (abbreviated by MA (2)) and WMA with 2 inputs lags (abbreviated by WMA (2)) yield the minimum values of RMSE and MAE for HIV/AIDS data. The values of RMSE and MAE using the MA (2) model are 728.028 and 362.222 respectively. For WMA (2) model, the values of RMSE and MAE are 696.274 and 353.741 respectively. It is found that the WMA (2) model is better than the MA (2) model for HIV/AIDS time series prediction.

Table 2 shows values of RMSE and MAE using different values \( m \) for MA and WMA models.

<table>
<thead>
<tr>
<th>Models (m)</th>
<th>PERFORMANCES</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>MAE</td>
<td></td>
</tr>
<tr>
<td>Moving Average</td>
<td>2</td>
<td>728.028</td>
<td>362.222</td>
</tr>
<tr>
<td>(MA)</td>
<td>5</td>
<td>1193.559</td>
<td>748.613</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>1781.642</td>
<td>1319.384</td>
</tr>
<tr>
<td>Weighted Moving</td>
<td>2</td>
<td>696.274</td>
<td>353.741</td>
</tr>
<tr>
<td>Average</td>
<td>5</td>
<td>997.877</td>
<td>604.027</td>
</tr>
<tr>
<td>(WMA)</td>
<td>9</td>
<td>1494.362</td>
<td>1098.236</td>
</tr>
</tbody>
</table>

3.1.3. Autoregressive Integrated Moving Average Model

Time series prediction using ARIMA models with different parameter \( (p, d, q) \) values are employed for HIV/AIDS time series data to select the optimal ARIMA model. Performance measures using ARIMA models are calculated to obtain RMSE and MAE values. The RMSE and MAE values using ARIMA models for HIV/AIDS time-series data are shown in Table 3.

<table>
<thead>
<tr>
<th>MODELS</th>
<th>Performance Measures</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA(3,1,3)</td>
<td>782.20</td>
<td>385.48</td>
<td></td>
</tr>
<tr>
<td>ARIMA(7,1,3)</td>
<td>767.72</td>
<td>371.32</td>
<td></td>
</tr>
<tr>
<td>ARIMA(3,1,3)</td>
<td>642.20</td>
<td>364.02</td>
<td></td>
</tr>
<tr>
<td>ARIMA(2,1,1)</td>
<td>687.29</td>
<td>420.39</td>
<td></td>
</tr>
<tr>
<td>ARIMA(1,1,1)</td>
<td>664.51</td>
<td>432.04</td>
<td></td>
</tr>
</tbody>
</table>

From Table 3, it is seen that ARIMA (3, 1, 3) model has minimum values of RMSE and MAE. We can conclude that ARIMA (3, 1, 3) model performs better than ARIMA(8,1,3) ARIMA(7, 1, 3) ARIMA(2, 1, 1) and ARIMA(1, 1, 1).

3.2. Neural Network Model

The MLP model is used to predict HIV/AIDS time-series data in this work. We test with different architecture configurations using different numbers of input, hidden layer neurons and activation functions to determine the optimum setup. It is found that the neural network model with 7 input neurons, 12 hidden layer neurons and using hyperbolic tangent activation functions for the hidden and output layers yields the minimum values for RMSE and MAE. The values of RMSE and MAE with the MLP model are presented in Table 4.

<table>
<thead>
<tr>
<th>MODELS</th>
<th>Performance Measures</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>MAE</td>
<td></td>
</tr>
<tr>
<td>NN(6,12,1)</td>
<td>130.015</td>
<td>88.426</td>
<td></td>
</tr>
<tr>
<td>NN(7,12,1)</td>
<td>143.011</td>
<td>87.732</td>
<td></td>
</tr>
<tr>
<td>NN(8,12,1)</td>
<td>181.258</td>
<td>110.169</td>
<td></td>
</tr>
<tr>
<td>NN(8,14,1)</td>
<td>145.149</td>
<td>91.938</td>
<td></td>
</tr>
</tbody>
</table>

From Table 4, it is found that the MLP model with 7 input neurons, 12 hidden layer neurons and 1 output neuron (denoted as NN (7, 12, 1)) yields minimum values of RMSE and MAE.

3.3. Enhanced Hybrid Model Combining Best Statistical Techniques and Optimum Neural Network (HM1 Model)

The HM1 model combines the best statistical technique with an optimally configured neural network. Based on the algorithm of HM1 shown in Algorithm 1 and from the experimental results, the best linear and NN models are obtained as ARIMA (3,1,3) and NN(7,12,1) with hyperbolic tangent activation functions respectively. The HM1 model is shown in Figure 2.

![Figure 2](image)

3.4. Hybrid Model Using an Enhanced ANFIS Model (HM2 model)

The second proposed hybrid model is HM2 model. This model uses an enhanced ANFIS method. The algorithm of HM2 for enhanced ANFIS model is...
shown in Algorithm 2. It should be noted that the proposed HM2 model calculates the time-series prediction using the optimum number of input lags.

The HM2 model for HIV/AIDS data time series prediction is constructed using the number of rules used is 2 and the number of epochs used for training is 1000. By varying the number of input lags, it is found that the optimum number of input lags is obtained 2 and the corresponding RMSE value is obtained 84.698. The value of MAE using HM2 model with optimum input lags is obtained 49.265.

3.5. Comparison of Different Models

The performances of different models are evaluated using the HIV/AIDS data. A comparison of the RMSE and MAE values obtained using SES, DES, MA, WMA, ARIMA, Neural Network and the proposed hybrid models are shown in Figure 3. It is seen that the first Hybrid Model (HM1) gives better results compared to ARIMA, WMA, MA, double ES and single ES models. The second Hybrid Model (HM2) makes use of optimum number of input lags based on the input data also performs better than ARIMA, WMA, MA, double ES, single ES and neural network models.

The results also indicate that the HM1 model is better than the HM2 model.

In this study, three data sets, namely HIV/AIDS, MTB-I and NYB data sets are used to evaluate these models. From the experimental results, the HM1 model makes use of the combination of best linear and optimum NN models for these data sets, as shown in Table 6. For MTB-I data, the HM1 model combines ARIMA (2, 1, 2) and neural network model with 5 input neurons, 10 hidden layer neurons using hyperbolic tangent activation function. And for NYB data, the HM1 model combines ARIMA (4, 1, 3) and neural network model with 30 input neurons, 15 hidden layer neurons using hyperbolic tangent activation function.

The values of the performance measure, namely RMSE and MAE obtained using these models are shown in Table 7. Performances comparison using HM1 and HM2 for univariate time series prediction is also shown in Table 7.

From Table 7, it is noted that the smallest values of RMSE and MAE are obtained for the HM1 model. So, we can conclude that the HM1 model performs better than HM2 model.

4. Conclusions

In this paper, two enhanced hybrid models for time series prediction have been presented. The first Hybrid Model (HM1) combines the best statistical technique with an optimally configured neural network, and the second Hybrid Model (HM2) combines neural network with fuzzy inference system. The HM2 model makes use of an optimum number of input lags for prediction. Experiments were performed to test the performances of various models using HIV/AIDS, MTB-I and NYB data sets. The models were compared using performance measures such as RMSE and MAE. The experimental results show that the
proposed hybrid models perform significantly better than the other known models.

References


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