Enhanced Hybrid Prediction Models for Time Series Prediction

Purwanto Purwanto[1] and Chikkannan Eswaran[2]
[1]Faculty of Computer Science, Dian Nuswantoro University, Indonesia
[2]Faculty of Computing and Informatics, Multimedia University, Malaysia

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*.

Received March 25, 2015; accepted October 7, 2015

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; Georgakarakos *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 financial time series, and has been found to perform better than the individual models [22]. However, from the results obtained for these hybrid models in different applications, it is clear that the performances of these models vary depending on the type of data used.

Soft computing techniques such as fuzzy logic can tolerate imprecise information, and can also make an approximate reasoning framework. Unfortunately, fuzzy logic lacks self-learning capability. The Adaptive Neuro-Fuzzy Inference System (ANFIS) has been used to predict real- world time-series data [2, 3, 8, 9, 15, 34, 40]. The ANFIS model has been used to predict real world time series data such as water level prediction [9], weather forecasting [40], Worldwide Interoperability for Microwave Access (WiMAX) traffic prediction [15], prediction of power factor in wind turbines [2], and wired-EDM [8]. Tektas has used ANFIS and ARIMA models for weather forecasting [40].

An issue that has gained much attention with regard to the ANFIS model is how to determine the appropriate input lags for univariate time series prediction.

In this study, we propose two enhanced hybrid models (HM1 and HM2) for time series prediction. The first hybrid model HM1 combines the best statistical model with an optimally configured neural network based on the complexity of the input data. The optimum neural network configuration is selected with respect to the number of input and hidden layer neurons, and the activation functions used for the hidden and output layers. The HM2 model is an enhanced ANFIS model which is used to predict univariate time-series data.

Determining the accurate number of input lags remains as a problem in the existing ANFIS model. The proposed HM2 model makes use of a new technique to solve this problem. The two new models HM1 and HM2 are tested using three time-series data sets, and their performances are compared with other models.

This paper consists of five sections. In the next section, we review the concepts of different statistical and soft computing techniques that are used for time series prediction. Section 2 presents research methods for time series prediction. Section 3 describes results and discussion and finally, section 4 presents some conclusions.

2. The Research Method

2.1. Time Series Prediction Models

In this section, the statistical techniques such as Single Exponential Smoothing (SES), double exponential smoothing, Moving Average (MA), weight moving average and ARIMA are used [5, 21, 27]. Soft computing techniques such as neural network [38] and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) models are also used [7, 18, 37, 43].

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]:

$$y_t = L_t + N_t \tag{1}$$

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):

$$e_t = y_t - \hat{L}_t \tag{2}$$

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

$$\hat{y}_t = \hat{L}_t + \hat{N}_t \tag{3}$$

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 HM1 is shown in Algorithm 1.

Algorithm 1: Proposed HM1 algorithm.

```
n=number_of_training
m=number_of_testing
/*  statistical techniques*/
for (i=1 to n)
        {
ES[i]=Exponensial_Smoothing(yt[i])
MA[i]=Moving_Average (yt[i])
WMA[i]=Weight_ 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 $\{x_1, x_2, x_3, \ldots, x_m\}$. 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 $\{x_1, x_2, \ldots, x_p\}$ as the inputs and x_{p+1} as the output. The second pattern comprises $\{x_2, x_3, \ldots, x_{p+1}\}$ as the inputs and x_{p+2} as the output. The third pattern is composed of $\{x_3, x_4, \ldots, x_{p+2}\}$ as the inputs and x_{p+3} as the output. Finally, the last training pattern comprises $\{x_{m-p}, x_{m-p+1}, \ldots, x_{m-1}\}$ as the inputs and the xm 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.

Pattern	Input lag	Output/ Target
1	$x_1, x_2, x_3, x_4, \ldots, x_p$	x_{p+1}
2	$x_2, x_3, x_4, x_5, \ldots, x_{p+1}$	x_{p+2}
3	$x_3, x_4, x_5, x_6, \ldots, x_{p+2}$	x_{p+3}
...	...	....
m-p	$x_{m-p}, x_{m-p+1}, x_{m-p+2}, \ldots, x_{m-1}$	x_m

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-1} 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_1 and … and x_{m-1} is A_1 then:

$$f_1 = p_1 x_{m-p} + p_2 x_{m-p+1} + \ldots + p_p x_{m-1} + r_1 \tag{4}$$

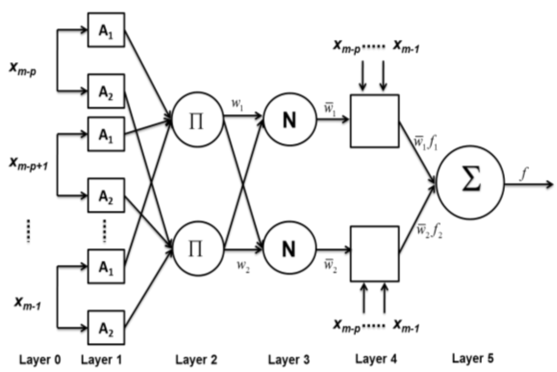

Figure 1. ANFIS architecture for univariate time series data.

- *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: $f_2 = q_1 x_{m-p} + q_2 x_{m-p+1} + ... + q_p x_{m-1} + r_2$

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 $O_{1,i}$ represents a membership function μ_{A_i} (or μ_{B_i}) as shown in Equations (5), (6) and (7).

$$O_{1,i} = \mu_{A_1}(x_{m-p}) \text{ , where } i = 1, 2 \tag{5}$$

$$O_{1,i} = \mu_{A_{-2}}(x_{m-p+1}) \text{ , where } i = 3, 4 \tag{6}$$

$$\cdots$$

$$O_{1,i} = \mu_{A_{-p}}(x_{m-1}) \text{ , where } i = p+1, p+2 \tag{7}$$

Where x_{m-p}, x_{m-p+1},…, 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):

$$O_{2,i} = w_i = \mu_{A_1}(x_{m-p})\mu_{A_1}(x_{m-p+1})...\mu_{A_1}(x_{m-1}) \tag{8}$$

Where *i*=1, 2.

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

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \text{ , i =1, 2} \tag{9}$$

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

$$\begin{aligned} O_{4,1} &= \bar{w}_1 f_1 = \bar{w}_1(p_1 x_{m-p} + p_2 x_{m-p+1} + ... + p_p x_{m-1} + r_1) \\ O_{4,2} &= \bar{w}_2 f_2 = \bar{w}_2(q_1 x_{m-p} + q_2 x_{m-p+1} + ... + q_p x_{m-1} + r_2) \end{aligned} \tag{10}$$

Where p_1, p_2, …, p_p, q_1, q_2, …, q_p , r_1 and r_2 are the consequent parameters.

- *Layer 5.* The single node in layer 5 is labeled as ∑. 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:

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\bar{w}_1 f_1 + \bar{w}_2 f_2}{w_1 + w_2} \tag{11}$$

Where $\bar{w}_i f_i$ 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), (10) 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 $RMSE_{-Old}$ is smaller than the value of $RMSE_{-New}$, 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=number_of_training
k=number_of_lags
/* initialization of RMSEold, RMSEnew, MSEtol 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] < MSEtol 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 α = 0.9 are 643.06 and 314.00 respectively. And the values of RMSE and MAE using DES model with α = 0.4 and β=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 2. Comparison of RMSE and MAE using MA and WMA for HIV/ AIDS data.

Models (m)		**PERFORMANCES**	
		RMSE	**MAE**
Moving Average (MA)	2	728.028	362.222
	5	1193.559	748.613
	9	1781.642	1319.384
Weighted Moving Average (WMA)	2	696.274	353.741
	5	997.877	604.027
	9	1494.362	1098.236

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 3. Performance measures using ARIMA models for HIV/AIDS data.

MODELS	**Performance Measures**	
	RMSE	**MAE**
ARIMA(8,1,3)	782.20	385.48
ARIMA(7,1,3)	767.72	371.32
ARIMA(3,1,3)	642.20	364.02
ARIMA(2,1,1)	687.29	420.39
ARIMA(1,1,1)	664.51	432.04

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 4. Performance measures using neural network models for HIV/AIDS data.

MODELS	**Performance Measures**	
	RMSE	MAE
NN(6,12,1)	150.015	88.426
NN(7,12,1)	143.011	87.732
NN(8,12,1)	181.258	110.169
NN(8,14,1)	145.149	91.938

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.

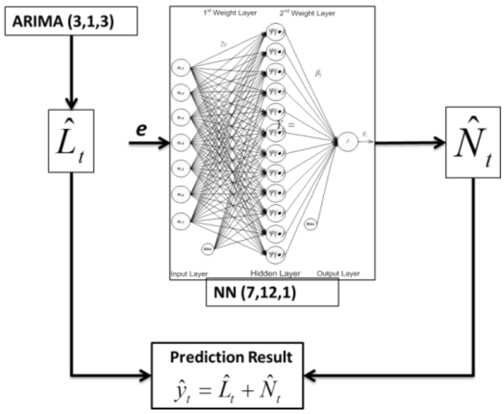

Figure 2. HM1 model combining best statistical techniques and optimum Neural Network for HIV/ AIDS data.

The values of the performance measure, namely RMSE and MAE for the HM1 model are obtained as 28.740 and 22.303 respectively.

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.

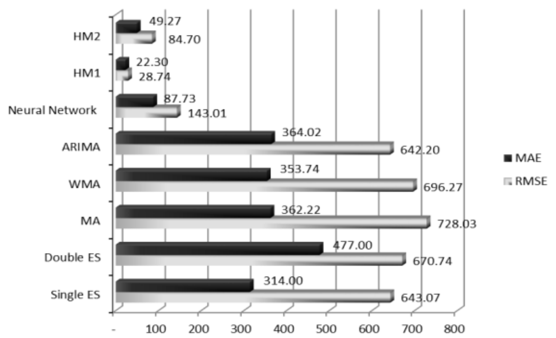

Figure 3. Comparison results of the performance measures for HIV/AIDS data.

The improvement achieved by proposed HM1 over other models for HIV/AIDS data data is shown in Table 5. It is clear from this table that the proposed HM1 model achieves significant performance improvement over other models.

Table 5. Improvement achieved by proposed HM1 over the other models for HIV/AIDS data.

MODELS	IMPROVEMENT ACHIEVED (%)	
	RMSE	MAE
Single ES	95.54	92.90
Double ES	95.72	95.32
ARIMA	95.52	93.87
MA	96.05	93.84
WMA	95.87	93.70
Neural Network	79.90	74.58
HM2	66.07	54.74

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.

Table 6. The best linear and neural network models by HM1 for different data sets.

Data sets	HM1	
	The Best Linear Model	**Optimum NN Model**
HIV/AIDS	ARIMA(3, 1, 3)	NN (7,12,1), Hyperbolic tangent function
MTB-I	ARIMA(2, 1, 2)	NN (5,10,1), Hyperbolic tangent function
NYB	ARIMA(4, 1, 3)	NN (30,15,1), Hyperbolic tangent 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.

Table 7. Comparison using proposed models for univariate time series prediction.

Data sets	Performances			
	HM1		HM2	
	RMSE	MAE	RMSE	MAE
HIV/AIDS	28.74	22.3	84.7	49.27
MTB-I	2.77	2.23	18.05	6.79
NYB	1.23	0.97	1.36	1.13

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

[1] Aminian F., Suarez E., Aminian M., and Walz D., "Forecasting Economic Data with Neural Networks," *Computational Economics*, vol. 28, no.1, pp. 71-88, 2006.

[2] Ata R., "An Adaptive Neuro-Fuzzy Inference System Approach for Prediction of Power Factor in Wind Turbines," *Journal of Electrical and Electronics Engineering*, vol. 9, no. 1, pp. 905-912, 2009.

[3] Atsalakis G. and Valavanis K., "Forecasting Stock Market Short-Term Trends Using a Neuro-Fuzzy Based Methodology," *Expert Systems with Applications*, vol. 36, no. 7, pp. 10696-10707, 2009.

[4] Barbulescu A. and Bautu E., "A Hybrid Approach for Modeling Financial Time Series," *The International Arab Journal of Information Technology*, vol. 9, no. 4, pp. 327-335, 2012.

[5] Brockwell P. and Davis R., *Introduction to Time Series and Forecasting*, Springer, 2002.

[6] Buhari M. and Adamu S., "Short-Term Load Forecasting Using Artificial Neural Network," *in Proceedings of the International Multi Conference of Engineers and Computer Scientists*, Hong Kong, pp. 83-88, 2012.

[7] Campos I., Islas M., González E., Ponce P., and Ramírez G., "Use of Fuzzy Logic for Modeling The Growth of Fe2B Boride Layers During Boronizing," *Surface and Coatings Technology*, vol. 201, no. 6, pp. 2717-2723, 2006.

[8] Caydas U., Hascalik A., and Ekici S., "An Adaptive Neuro-Fuzzy Inference System (ANFIS) Model for Wire-EDM," *Expert Systems with Applications*, vol. 36, no. 3, pp. 6135-6139, 2009.

[9] Chang F. and Chang Y., "Adaptive Neuro-Fuzzy Inference System for Prediction of Water Level in Reservoir," *Advances in Water Resources*, vol. 29, no. 1, pp. 1-10, 2006.

[10] Contreras J., Espínola R., Nogales F., and Conejo A., "ARIMA Models to Predict Next-Day Electricity Prices," *IEEE Transactions on Power Systems*, vol. 18, no. 3, pp. 1014-1020, 2003.

[11] Faruk D., "A Hybrid Neural Network and ARIMA Model for Water Quality Time Series Prediction," *Engineering Applications of Artificial Intelligence*, vol. 23, no. 4, pp. 586-594, 2010.

[12] Fernandes P., Teixeira J., Ferreira J., and Azevedo S., "Modelling Tourism Demand: A Comparative Study between Artificial Neural Networks and the Box-Jenkins Methodology," *Romanian Journal of Economic Forecasting*, vol. 5, no. 3, pp. 30-50, 2008.

[13] Georgakarakos S., Koutsoubas D., and Valavanis V., "Time Series Analysis and Forecasting Techniques Applied on Loliginid and Ommastrephid Landings in Greek Waters," *Fisheries Research*, vol. 78, no. 1, pp. 55-71, 2006.

[14] Gosasang V., Chandraprakaikul W., and Kiattisin S., "An Application of Neural Networks for Forecasting Container Throughput at Bangkok Port," *in Proceedings of the World Congress on Engineering*, London, pp. 137-141, 2010.

[15] Hernandez C., Pedraza L., and Salcedo J., "Comparative Analysis of Time Series Techniques ARIMA and ANFIS to Forecast Wimax Traffic," *The Online Journal on Electronics and Electrical Engineering*, vol. 2, no. 2, pp. 223-228, 2010.

[16] Hyndman R., Time series data library [Online], http://robjhyndman.com/TSDL, Last Visited, 2015.

[17] Jain B. and Nag B., "Performance Evaluation of Neural Network Decision Models," *Manage Information Systems*, vol. 14, no. 2, pp. 201-216, 1997.

[18] Jang J., Sun C., and Mizutani E., *Neuro Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice Hall International, 1997.

[19] Katimon A. and Demun A., "Water Use Trend at Universiti Teknologi Malaysia: Application of ARIMA Model," *Jurnal Teknologi*, vol. 41, no. 1, pp. 47-5, 2004.

[20] Kosanan O. and Kantanantha N., "Thailand's Para Rubber Production Forecasting Comparison," *in Proceedings of the International MultiConference of Engineers and Computer Scientists*, Hong Kong, pp. 979-984, 2014.

[21] Koutroumanidis T., Iliadis L., and Sylaios G., "Time-Series Modeling of Fishery Landings Using ARIMA Models and Fuzzy Expected Intervals Software," *Environmental Modelling and Software*, vol. 21, no. 12, pp. 1711-1721, 2006.

[22] Lai K., Yu L., Wang S., and Huang W., "Hybridizing Exponential Smoothing and Neural Network for Financial Time Series Predication," *in Proceedings of 6th International Conference Computational Science Reading*, UK, pp. 493-500, 2006.

[23] Law R., "The impact of the Asian Financial Crisis On Japanese Demand For Travel to Hong Kong: A Study of Various Forecasting Techniques," *Journal of Travel and Tourism Marketing*, vol. 10, no. 2-3, pp. 47-65, 2001.

[24] Lee Y. and Tong L., "Forecasting Time Series Using A Methodology Based On Autoregressive Integrated Moving Average and Genetic Programming," *Knowl-Based S*ystem, vol. 24, no. 1, pp. 66-72, 2011.

[25] Liu Z., Gao W., Wan Y., and Muljadi E., "Wind Power Plant Prediction By Using Neural Networks," *in Proceedings of IEEE Energy Conversion Conference and Exposition*, Raleigh, pp. 3154-3160, 2012.

[26] Maizir H. and Kassim K., "Neural Network Application in Prediction of Axial Bearing Capacity of Driven Piles," *in Proceedings of the International Multi Conference of Engineers and Computer Scientists*, Hong Kong, pp. 51-55, 2013.

[27] Makridakis S., Wheelwright S., and McGee V., *Forecasting: Methods and Applications*, John Wiley and Sons, 1998.

[28] Ministry of Health (Indonesia), "Indonesia Health Profile: Ministry of Health," http://www.depkes.go.id/download.php?file=download/pusdatin/profil-kesehatan-indonesia/profil-kesehatan-indonesia-2006.pdf, Last Visited, 2008.

[29] Mishra P., "Forecasting Natural Gas Price-Time Series and Nonparametric Approach," *in Proceedings of the World Congress on Engineering*, London, pp. 490-497, 2012.

[30] Nazim A. and Afthanorhan A., "A Comparison Between Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Holt's (Brown) and Adaptive Response Rate Exponential Smoothing (ARRES) Techniques In Forecasting Malaysia Population," *Global Journal of Mathematical Analysis*, vol. 2, no. 4, pp. 276-280, 2014.

[31] Niskaa H., Hiltunena T., Karppinenb A., Ruuskanena J., and Kolehmaine M., "Evolving the Neural Network Model for Forecasting Air Pollution Time Series," *Engineering Applications of Artificial Intelligence*, vol. 17, no. 2, pp. 159-167, 2004.

[32] Papatheodorou A. and Song H., "International Tourism Forecasts: Time-Series Analysis of World Regional Data," *Tourism Economics*, vol. 11, no. 1, pp. 11-23, 2005.

[33] Polat T. and Arslankaya S., "The Cost Forecasting Application in an Enterprise with Artificial Neural Networks," *in Proceedings of the World Congress on Engineering*, London, pp. 2258-2262, 2010.

[34] Purwanto., Eswaran C., and Logeswaran R., Improved Adaptive Neuro-Fuzzy Inference System for HIV/AIDS Time Series Prediction," *in Proceedings of International Conference on Informatics Engineering and Information Science*, Kuala Lumpu, pp. 1-13, 2011.

[35] Razak F., Mahendran S., Hashim A., and Abidin I., "Load Forecasting Using Time Series Models," *Jurnal Kejuruteraan*, vol. 21, pp. 53-62, 2009.

[36] Rojas I., Valenzuela O., Rojas F., Guillen A., Herrera L., Pomares H., Marquez L., and Pasadas M., "Soft-Computing Techniques and ARMA Model for Time Series Prediction," *Neurocomputing*, vol. 17, pp. 519-537, 2008.

[37] Ross T., *Fuzzy Logic with Engineering Applications*, John Wiley and Son, 1997.

[38] Suhartono, "Feedforward Neural Networks for time series Modeling," http://personal.its.ac.id/files/pub/1088-suhartono-statistics-Disertasi_Suhartono_Matematika.pdf, Last Visited, 2014.

[39] Suryanita R. and Adnan A., "Application of Neural Networks in Bridge Health Prediction Based on Acceleration and Displacement Data Domain," *in Proceedings of the International MultiConference of Engineers and Computer Scientists*, Hong Kong, pp. 42-47, 2013.

[40] Tektas M., "Weather Forecasting Using ANFIS and ARIMA Models, A Case Study for Istanbul," *Environmental Research Engineering and Management*, vol. 1, no. 51, pp. 5-10, 2010.

[41] Tabnak F., Zhou T., Sun R., and Azari R., "Time series forecasting of AIDS incidence using mortality series," available at: http://gateway.nlm.nih.gov/MeetingAbstracts/ma?f=102238135.html, Last Visited, 2012.

[42] World Health Organization, "Global tuberculosis control: epidemiology, strategy, financing: WHO report 2009," https://www.ghdonline.org/uploads/WHO_TB_report_without_annexes_2009.pdf, Last Visited, 2009.

[43] Zadeh L., "Fuzzy Algorithms," *Information and Control*, vol. 12, pp. 94-102, 1968.

[44] Zhang G., "Time Series Forecasting Using A Hybrid Arima And Neural Network Model," *Neurocomputing*, vol. 50, pp. 159-175, 2003.

[45] Zhuang Y., Chen L., Wang X., and Lian J., "Weighted Moving Average-Based Approach for Cleaning Sensor Data," *in Proceedings of the 27th International Conference on Distributed Computing Systems*, Toronto, pp. 38-45, 2007.

Purwanto Purwanto is an Assistant Professor in Faculty of Computer Science, Dian Nuswantoro University, Semarang, Indonesia. He received the Ph.D degree from Faculty of Computing and Informatics Multimedia University, Cyberjaya, Malaysia. He has published research papers in reputed international journals and conferences. His current research interests include modelling, time series forecasting, data and text mining, machine learning, soft computing and decision support system.

Chikkannan Eswaran is currently a Professor in the Faculty of Information Technology, Multimedia University, Cyberjaya, Malaysia, where he is also the Chairman of the Centre for Communications Infostructure. He has been a Professor in the Department of Electrical Engineering, Indian Institute of Technology, Madras. He was a Research Fellow/Visiting Faculty at Ruhr University, Bochum, Germany; Concordia University, Montreal, QC, Canada; University of Victoria, BC, Canada; and Nanyang Technological University, Singapore. He received the B.Tech., M.Tech., and Ph.D. degrees from the Indian Institute of Technology, Madras, India. He has published more than 150 research papers in reputed international journals and conferences.