A Hybrid Neural Network and ARIMA Model for Energy Consumption Forecasting

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***Abstract*—Energy consumption time series consists of complex linear and non-linear patterns and are difficult to forecast. Neither autoregressive integrated moving average (ARIMA) nor artificial neural networks (ANNs) can be adequate in modeling and predicting energy consumption. The ARIMA model cannot deal with nonlinear relationships while the neural network model alone is not able to handle both linear and nonlinear patterns equally well. In the present study, a hybrid methodology that combines both ARIMA and ANN models is proposed to take advantage of the unique strength of ARIMA and ANN models in linear and nonlinear modeling. The empirical results with energy consumption data of Hebei province in China indicate that the hybrid model can be an effective way to improve the energy consumption forecasting accuracy obtained by either of the models used separately.**

***Index Terms*—artificial neural networks, ARIMA model, hybrid model, energy consumption, time series, forecasting**

I. Introduction

Energy consumption forecasting is the basis for making an energy development plan in decision making. So, it is critical to model and forecast it accurately. This is true especially for Hebei province in China. Since the introduction of reform and an open-door policy, Hebei has experienced rapid economic growth. The consumption of primary energy has also been increasing continuously. Even with an annual growtu rate of 7.7% during the 1980-2008 periods. The total energy consumption amounts has magnified by approximately 7.76 times from 3120.5 million tons of standard coal in 1980 to 24225.68 million tons of standard coal in 2008. accordingly, one-off energy consumption including coal, crude oil and natural gas had rising trend wholly. Recently, the energy consumption in Hebei province accounts for approximately 10% of the country's total energy consumption.

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The rapid growth of energy consumption along with the low efficiency of energy use, the pattern of extensive economic growth and the backward management mode, the energy shortage problem confronted by Hebei is increasingly serious. The primary energy consumption has outpaced its production since 1988. Nowadays, more than 50% of the energy has to be transferred from other provinces or to be imported from abroad. Furthermore, along with the continuous economic development and the acceleration of industriailization and urbanization processes, the energy consumption will increase even more rapidly. It is thus clear that the problem of balance of energy supply and demand deeply threatens the sustainable development of Hebei. Given this fact, the accuracy of energy consumption forecasting is important not only for making scientific energy plan but also for the sustainable development of Hebei province.

A sound forecasting technique is essential for energy consumption forecasting. Multivariate modeling along with co-integrated techniques or regression analysis has been used in a number of studies to analyze and forecast energy consumption[1-3]. One limitation of multivariate models is that they depend on the availability and reliability of data on independent variables over the forecasting period, which requires further efforts in data collection and estimation. On the other hand, univariate time series analysis provides another modeling approach, which only requires the historical data of the variable of interest to forecast its future evolution behavior. The univariate Box–Jenkins autoregressive integrated moving average (ARIMA) analysis has been widely used for modeling and forecasting many medical, environmental, financial, and engineering applications[4–6].

Although ARIMA models are quite flexible in that they can represent several different types of time series, their major limitation is the pre-assumed linear form of the model. ARIMA models assume that future values of a time series have a linear relationship with current and past values as well as with white noise, so approximations by ARIMA models may not be adequate for complex nonlinear real-world problems. However, real world systems are often nonlinear, thus, it is

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unreasonable to assume that a particular realization of a given time series is generated by a linear process.

Recently, artificial neural network (ANN) techniques have also gained popularity in energy demand forecasting[7]. The major advantage of neural networks is their flexible nonlinear modeling capability. With ANNs, there is no need to specify a particular model form. Rather, the model is adaptively formed based on the features presented from the data. This data-driven approach is suitable for many empirical data sets where no theoretical guidance is available to suggest an appropriate data generating process. However, using ANNs to model linear problems have yielded mixed results, and hence, it is not wise to apply ANNs blindly to any type of data[8].

In this paper, a hybrid model by combining ARIMA and ANN is proposed for energy forecasting. The motivation of the hybrid model comes from the following perspectives[9]. First, it is often diffcult in practice to determine whether energy consumption series under study is generated from a linear or nonlinear underlying process or whether one particular method is more effective than the other in out-of-sample forecasting. Thus, it is diffcult to choose the right technique for their unique situations. Typically, a number of different models are tried and the one with the most accurate result is selected. However, the final selected model is not necessarily the best for future uses due to many potential influencing factors such as sampling variation, model uncertainty, and structure change. By combining different methods, the problem of model selection can be eased with little extra effort. Second, real-world time series are rarely pure linear or nonlinear. They often contain both linear and nonlinear patterns. If this is the case, then neither ARIMA nor ANNs can be adequate in modeling and forecasting time series since the ARIMA model cannot deal with nonlinear relationships while the neural network model alone is not able to handle both linear and nonlinear patterns equally well. Hence, by combining ARIMA with ANN models, complex autocorrelation structures in the data can be modeled more accurately. Third, it is almost universally agreed in the forecasting literature that no single method is best in every situation. This is largely due to the fact that a real-world problem is often complex in nature and any single model may not be able to capture different patterns equally well. For example, in the literature of time series forecasting with neural networks, most studies use the ARIMA models as the benchmark to test the effectiveness of the ANN model with mixed results. Many empirical studies including several large-scale forecasting competitions suggest that by combining several different models, forecasting accuracy can often be improved over the individual model without the need to find the "true" or "best" model. Therefore, combining different models can increase the chance to capture different patterns in the data and improve forecasting performance.

The rest of the paper is organized as follows. In the next section, the ARIMA and ANN modeling approaches to time series forecasting were reviewed, and then the hybrid methodology is introduced. Empirical results from the real data set is reported in Section 3. Section 4 contains the concluding remarks.

II. METHODOLOGY

A. The ARIMA Model

Introduced by Box and Jenkins, the ARIMA model has been one of the most popular approaches for forecasting. In an ARIMA model, the future value of a variable is assumed to be a linear function of several past observations and random errors. That is, the underlying process that generate the time series has the form:

$$\begin{aligned} y_t &= \theta_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} \\ &\quad + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \end{aligned} . \tag{1}$$

where y_t and ε_t are the actual value and random error at time t, respectively; $\varphi_i (i = 1,2,\cdots,p)$ and $\theta_j (j = 1,2,\cdots,q)$ are model parameters. p and q are integers and often referred to as autoregressive and moving average orders, respectively. Random errors, ε_t, are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2.

Equation (1) entails several important special cases of the ARIMA family of models. If $q = 0$, then (1) becomes an AR model of order p. When $p = 0$, the model reduces to an MA model of order q. One central task of the ARIMA model building is to determine the appropriate model order (p, q).

Based on the earlier work, Box and Jenkins[2] developed a practical approach to building ARIMA models, which has the fundamental impact on the time series analysis and forecasting applications. The Box–Jenkins methodology includes three iterative steps of model identification, parameter estimation, and diagnostic checking.

The basic idea of model identification is that if a time series is generated from an ARIMA process, it should have some theoretical autocorrelation properties. By matching the empirical autocorrelation patterns with the theoretical ones, it is often possible to identify one or several potential models for the given time series. Box and Jenkins proposed to use the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the sample data as the basic tools to identify the order of the ARIMA model. In the identification step, data transformation is often required to make the time series stationary. Stationarity is a necessary condition in building an ARMA model used for forecasting. A stationary time series is characterized by statistical characteristics such as the mean and the autocorrelations tructure being constant overtime. When the observed time series presents trend and hetero scedasticity, differencing and power transformation are applied to the data to remove the trend and to stabilize the variance before an ARIMA model can be fitted.

Once a tentative model is identified, estimation of the model parameters is straightforward. The parameters are

estimated such that an overall measure of errors is minimized. This can be accomplished using a nonlinear optimization procedure.

The last step in model building is the diagnostic checking of model adequacy. This is basically to check if the model assumptions about the errors, ε_t, are satisfied. Several diagnostic statistics and plots of the residuals can be used to examine the goodness of fit of the tentatively entertained model to the historical data. If the model is not adequate, a new tentative model should be identified, which will again be followed by the steps of parameter estimation and model verification.

This three-step model building process is typically repeated several times until a satisfactory model is finally selected. The final selected model can then be used for prediction purpose.

B. The Artificial Neural Networks Model

Artificial neural networks(ANN) can be described as an attempt by humans to mimic the functioning of the human brain. The models are analytical techniques modeled after the processes of learning in the cognitive system and the neurological functions of the brain and are capable of predicting new observations (of specific variables) from other observations (of the same or other variables) after executing a process of so-called learning from existing data. The models can be built without explicitly formulating the possible relationship that exists between variables. Theoretical results show that ANNs are also able to sufficiently approximate arbitrary mappings to the desired accuracy if given a large enough network. In this sense, ANN may be seen as multivariate, nonlinear and nonparametric methods, and they should be expected to model complex nonlinear relationships much better than the traditional linear models[10].

Single hidden layer feedforward network is the most widely used model form for time series modeling and forecasting[11]. The model is characterized by a network of three layers of simple processing units connected by acyclic links. The relationship between the output (y_t) and the inputs (y_{t-1}, . . ., y_{t-p}) has the following mathematical representation:

$$y_t = \omega_0 + \sum_{j=1}^{q} \omega_j g(\omega_{0j} + \sum_{i=1}^{p} \omega_{i,j} y_{t-i}) + e_t \ . \quad (2)$$

Where ω_j ($j=1,2,...,q$) and $\omega_{i,j}$ ($i=0,1,2,...,p$; $j=1,2,...,q$) are the model parameters often called connection weights; p is the number of input nodes and q is the number of hidden nodes. The sigmoid function is often used as the hidden layer transfer function, that is,

$$sig(x) = \frac{1}{(1+exp(-x))} \ . \quad (3)$$

Hence, the ANN model of (2), in fact, performs a nonlinear functional mapping from the past observations (y_{t-1}, . . ., y_{t-p}) to the future value y_t, i.e.

$$y_t = f(y_{t-1},...,y_{t-p},\omega) + e_t \ . \quad (4)$$

Where ω is a vector of all parameters and f is a function determined by the network structure and connection weights. Thus, the neural network is equivalent to a nonlinear autoregressive model. Note that expression (2) implies one output node in the output layer, which is typically used for one-step-ahead forecasting.

The simple network given by (2) is surprisingly powerful in that it is able to approximate arbitrary function as the number of hidden nodes q is sufficiently large. In practice, simple network structure that has a small number of hidden nodes often works well in out-of-sample forecasting. This may be due to the over-fitting effect typically found in neural network modeling process. An overfitted model has a good fit to the sample used for model building but has poor generalization ability for data out of the sample. The choice of q is data dependent and there is no systematic rule in deciding this parameter.

In addition to choosing an appropriate number of hidden nodes, another important task of ANN modeling is the selection of the number of lagged observations, p, the dimension of the input vector. This is perhaps the most important parameter to be estimated in an ANN model because it plays a major role in determining the (nonlinear) autocorrelation structure of the time series. However, there is no theory that can be used to guide the selection of p. Hence, experiments are often conducted to select an appropriate p as well as q.

Once a network structure (p,q) is specified, the network is ready for training--a process of parameter estimation. As in ARIMA model building, the parameters are estimated such that an overall accuracy criterion such as the mean squared error is minimized. Various types of algorithms have been found to be effective for most practical purposes. Levenberg–Marquardt optimized training algorithms is used in this study.

The estimated model is usually evaluated using a separate hold-out sample that is not exposed to the training process. This practice is different from that in ARIMA model building where one sample is typically used for model identification, estimation and evaluation. The reason lies in the fact that the general (linear) form of the ARIMA model is pre-specified and then the order of the model is estimated from the data. The standard statistical paradigm assumes that under stationary condition, the model best fitted to the historical data is also the optimum model for forecasting. With ANNs, the (nonlinear) model form as well as the order of the model must be estimated from the data. It is, therefore, more likely for an ANN model to overfit the data.

There are some similarities between ARIMA and ANN models. Both of them include a rich class of different models with different model orders. Data transformation is often necessary to get best results. A relatively large sample is required in order to build a successful model. The iterative experimental nature is common to their modeling processes and the subjective judgement is sometimes needed in implementing the model. Because of the potential overfitting effect with both models, parsimony is often a guiding principle in choosing an appropriate model for forecasting.

C. The Hybrid ARIMA-ANN Model

Both ARIMA and ANN models have achieved successes in their own linear or nonlinear domains. However, none of them is a universal model that is suitable for all circumstances. The approximation of ARIMA models to complex nonlinear problems may not be adequate. On the other hand, using ANNs to model linear problems have yielded mixed results. Hence, it is not wise to apply ANNs blindly to any type of data. Since it is difficult to completely know the characteristics of the data in a real problem, hybrid methodology that has both linear and nonlinear modeling capabilities can be a good strategy for predicting energy consumption. By combining different models, different aspects of the underlying patterns may be captured[12-13].

It may be reasonable to consider the energy consumption series to be composed of a linear autocorrelation structure and a nonlinear component. That is,

$$Y_t = L_t + N_t . \quad (5)$$

Where L_t denotes the linear component and N_t denotes the nonlinear component. Both of these two parameters have to be estimated from the time series data. First ARIMA model is used to capture the linear component, then the residuals from the linear model will contain only the nonlinear relationship. Let e_t denote the residuals at time t from the linear model, then:

$$e_t = Y_t - YF_t . \quad (6)$$

Where YF_t is the predicted value of the ARIMA model at time t. The diagnostic check of the residuals is important to determine the adequacy of the ARIMA models. An ARIMA model is not sufficient if there are still linear correlation structures left in the residuals. However, diagnostic check of the residuals is not able to detect any nonlinear patterns in the time series data. For this reason, even if the residuals pass the diagnostic check and the model is an adequate one, the model may still not be sufficient in that nonlinear relationships have not been appropriately modeled. Any significant nonlinear pattern in the residuals will indicate the limitation of the ARIMA. Therefore, the residuals can be modeled by using ANNs to discover nonlinear relationships. With n input nodes, the ANN model for the residuals will be:

$$e_t = f\left(e_{t-1}, e_{t-2}, \cdots, e_{t-n}\right) + u_t . \quad (7)$$

Where f is a nonlinear function determined by the neural network and u_t is the random error. Note that if the model f is not an appropriate one, the error term is not necessarily random. Therefore, the correct model identification is critical. Denote NF_t as the forecast from (7), then the combined prediction will be:

$$YF_t = LF_t + NF_t . \quad (8)$$

In summary, the proposed methodology of the hybrid system consists of two steps. In the first step, an ARIMA model is used to analyze the linear part of the problem. In the second step, a neural network model is developed to model the residuals from the ARIMA model. Since the ARIMA model cannot capture the nonlinear structure of the data, the residuals of linear model will contain information about the nonlinearity. The results from the neural network can be used as predictions of the error terms for the ARIMA model. The hybrid model exploits the unique feature and strength of ARIMA model as well as ANN model in determining different patterns. Thus, it could be advantageous to model linear and nonlinear patterns separately by using different models and then combine the forecasts to improve the overall modeling and forecasting performance.

III. Application of the Hybrid Model to Energy Consumption Forecasting

A. ARIMA Modeling

Taking the energy consumption (EC) of Hebei from 1980 to 2008 as the example. Because of many factors influencing the energy demand, such as the growth of the economy, the industry framework, people's income level, the weather, the government's policy and so on, the historical data of the energy consumption of Hebei from 1980 to 2008 was increasing over time and was not stationary, as shown in figure 1.

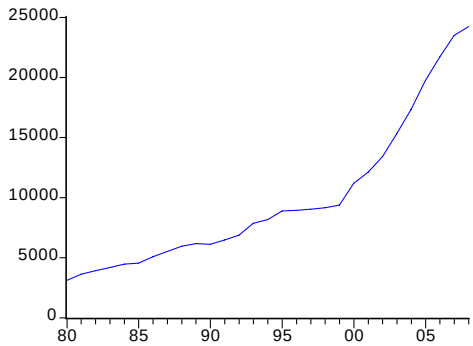

Figure1 Energy consumption of Hebei from 1980 to 2008 (million tons of standard coal).

TABLE I.
Test of the Unit Root Hypothesis

	(C,T,K)	ADF statistic	Critical value		
			1%	5%	10%
X_t	(C,T,1)	-1.5070	-4.3382	-3.5867	-3.2279
Y_t	(C,N,1)	-2.5953	-3.7076	-2.9798	-2.6290
Z_t	(N,N,1)	-4.1494	-2.6603	-1.9955	-1.6228

C,T and K indicate the model statistics with intercept, trend and the number of lags, N indicates without trend or intercept

To eliminate the heteroscedasticity, the logarithmic and then differential function of EC was computed to obtain its stationary series. The logarithmic series of EC was X_t, Y_t and Z_t were the 1-order difference and the 2-order difference series of X_t respectively. Then examined the time series properties of the data using ADF (Augmented Dickey Fuller) test. The results are given in

table I. It can be seen from table I that X_t has a unit root in levels and is stationary in second difference.

After Z_t was identified as stationary, the best fit AR parameters and MA parameters should be estimated according to its partial autocorrelation (PAC) function and autocorrelation (AC) function, respectively. Figure 2 shows the AC and PAC of Z_t. It was obvious that the AC

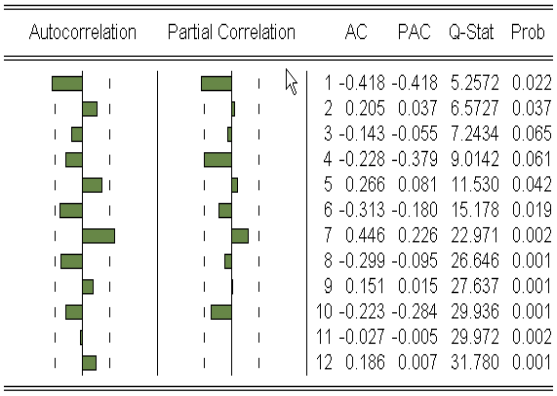

Figure 2 The AC and PAC graph of Z_t

function died off smoothly at a geometric rate after one lag and the PAC declined geometrically after one lag. Therefore, the parameters of AR and MR can be chosen as 1 for the ARIMA model.

However, in the practical fitting process, any other AR/MA parameters could be selected. For instance, the AR parameters can be defined as 1 or 4, the MA parameters can be defined 1 or 7. After fitted, ARIMA(1,2,1) has been found to be the most parsimonious among all ARIMA models. Once the ultimately fittest model was identified, the equations' form of the model could be obtained:

$$Z_t = 0.00178746 + 0.2708 Z_{t-1} - 1.4318 \mu_{t-1}.$$

The series Z_t was the 2-order difference of X_t, The series X_t was the logarithmic function of EC_t, so EC_t could be expressed as:

$$EC_t = e^{2X_{t-1} - X_{t-2} + 0.0018746 + 0.2708 Z_{t-1} - 1.4318 \mu_{t-1}}$$

By this model, the forecasting EC_t of each year was calculated. Based on this, the residual between the original sequence and predicted results e_t can be caculated as:

$$e_t = EC_t - e^{2X_{t-1} - X_{t-2} + 0.0018746 + 0.2708 Z_{t-1} - 1.4318 \mu_{t-1}}$$

B. Neural Network Modeling

A three-layer feedforward neural network model was developed for the prediction of energy consumption using an optimized Levenberg–Marquardt training algorithm. The data for the period between 1980 and 2008 were available for the modeling purposes. Energy consumption time series data were divided into two independent data sets. The first data set of 1980 to 2005 was used for model training, and the second data set of 2006 to 2008 was used for model verification purposes. In the ANN modeling process, the input and output energy consumption data sets for each parameter were normalized to the range of [0, 1].

The number of neurons in the input and output layers have been set as 4 and 1 respectively. In order to determine the optimum number of hidden nodes, a series of different topologies were used. Compared with the training results, it was found that the training set had the

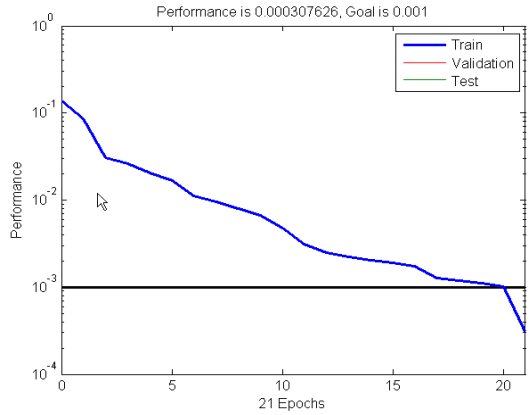

Figure 3 Training performance of ANN model.

lowest error value when the number of hidden units was 9. 9 is chosen as the number of hidden nodes. Thus the number of each layer's neurons in the network was 4-9-1, respectively. The parameters of the network were chosen

TABLE II.
COMPARING THE PREDICTED RESULTS WITH ACTUAL VALUE

	2006	2007	2008
Actual value	21690.4	23489.9	24225.7
ARIMA predicted value	22513.9	23869.9	25484.1
ANN predicted value	20876.29	22530.93	23231.63
ARIMA-ANN predicted value	21693.19	23628.59	24305.71

TABLE III.
FORECASTING PERFORMANCE OF DIFFERENT MODEL

	ARIMA	ANN	ARIMA-ANN
RMSE	895.57	925.66	92.45
MAE	820.7	-16410.1	73.8
MAPE	3.536%	-3.980%	0.311%

TABLE IV.
FORECASTING RESULTS OF ENERGY CONSUMPTION FOR HEBEI PROVINCE FROM 2009 TO 2013

	2009	2010	2011	2012	2013
Forecasting value	24462.03	26096.2	26335.4	29396.9	28856.3
Growth rate	0.9%	3.1%	0.9%	7.8%	1.6%

as follows: the transformation function of hidden neuron was "tansig" and "logsig" was the output layer function. The stop criterion of error function was set to 0.001 and the maximum of number of iteration was 1000. Computer program has been performed under MATLAB 7.0 environment. Figure 3 demonstrates the ANN model training performance for energy consumption parameter.

C. Hybrid Modeling

The proposed algorithm of the hybrid system consisted of two steps. In the first step, to analyze the linear part of the problem, an ARIMA model was employed. In the second step, the residuals from the ARIMA model were modeled by using a neural network model. Since the ARIMA model cannot detect the nonlinear structure of the energy consumption time series data, the residuals of linear model will contain information about the nonlinearity. The outputs from the neural network can be used as predictions of the error terms of the ARIMA model. The hybrid model utilizes the unique feature and strength of ARIMA model as well as ANN model in determining different patterns. Therefore, it may be favorable to model linear and nonlinear patterns separately by using different models and then combine the predictions to improve the overall modeling and predicting performance. In the hybrid modeling algorithm, the input and output energy consumption data sets for each parameter were normalized to the range of [0,1]. In the modeling process, the hybrid model was trained to adjust the model so that the model predicted energy consumption parameters match well with observed data. The verifications results of 2006-2008 listed in table II Table II indicates that the hybrid model prediction results reasonably match the observed energy consumption.

D. Compaison of Model Performance

To evaluate the performance of the forecasting capability, the three evaluation ststistics: root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage forecast error (MAPE) to each model are used. They are expressed as below:

$$RMSE = \sqrt{\sum_{i=1}^{n}(Y_t - YF_t)^2 / n}$$

$$MAE = \sum_{i=1}^{n}\left|Y_t - YF_t\right| / n$$

$$MAPE = \sum_{i=1}^{n}\left|(Y_t - YF_t)/YF_t\right| / n \times 100\%$$

Where Y_t and YF_t are the i-th actural and forecasting values, respectively. And n is the total number of predictions. Table Ⅲ reports the RMSE, MAE and MAPE for the year of 2006 to 2008 from the hybrid, ANN and ARIMA models. From table III, it can be seen that the error levels in the case of the hybrid model are lower than in the other two cases, which leads us to the conclusion that the hybrid neural network presents a better adaptability and consequently produces better results as well. Therefore, we can predict the energy consumption data of Hebei province from 2009 to 2013 with the hybrid model and the forecasting results of energy consumption from 2009 to 2013 are shown in table IV. As shown by prediction, the energy consumption in Hebei province will continue to increase for the next 5 years. In 2013, the energy consumption will reach to 28856.26 million tons of standard coal, at the average annual growth rate of nearly 2.8% during the period of 2009 to 2013. Therefore, policy measures, such as energy taxes, investments in improved energy efficiency, or changes in output composition must be considered explicitly.

IV. Conclusions

Forecasting energy consumption is one of the most important policy tools by the decision makers, specifically for Hebei province in China. It is a challenge for us to develop forecast tools with the energy consumption series obtained due to the complex linear and non-linear patterens. Taking the shortage of ARIMA and ANN forecasting model into account, this study proposes a hybrid model taking advantage of the unique strength of ARIMA and ANN in linear and nonlinear modeling.

The forecasting performance of each model is assessed by three statistical measures: RMSE, MAE, MAPE. The results of the statistical measures suggest that the hybrid model can be an effective tool to improve the forecasting accuracy obtained by either of the models used separtely. Therefore, using the hybrid model, we predict the energy consumption of Hebei province from 2009 to 2013. The results demonstrate that the energy consumption in Hebei province will continue to increase for the next 5 years. In 2013 the energy consumption will reach to 28856.26 million tons of standard coal, at the average annual growth rate of nearly 2.8% during the period of 2009 to 2013. Therefore, policy measures, such as energy taxes, investments in improved energy efficiency, or changes in output composition must be considered explicitly.

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